THE INFLUENCE OF EXTERIOR DESIGN ATTRIBUTES ON CONSUMER PREFERENCE FOR ELECTRIC VEHICLES

By

QUINN E. BUTTON

Bachelor of Science in Textiles & Clothing Design, Business Marketing & Management
University of California, Davis
Davis, California
2009

Master of Science in Entrepreneurship
Oklahoma State University
Stillwater, Oklahoma
2016

Dissertation Prepared for the Degree of
DOCTOR OF PHILOSOPHY
OKLAHOMA STATE UNIVERSITY
July, 2019

THE INFLUENCE OF EXTERIOR DESIGN ATTRIBUTES ON

CONSUMER PREFERENCE FOR ELECTRIC VEHICLES

Dissertation Approval:

Dr. Greg Clare

Dissertation Advisor

Dr. Gina Peek

Dr. Clara Bae

Dr. Isaac Washburn

ACKNOWLEDGEMENTS

Thank you Dr. Clare for all of your incredible support and mentorship throughout this doctoral journey. You have been the best mentor I could have ever asked for—I am grateful to have worked with you for the past three years, and honored to have had you as my advisor. I truly would not have been able to accomplish this without you. Thank you for everything.

Thank you also to my husband, my best friend, my rock, my everything—Dr. Jonathon Button. Just a couple of months ago, we surprised our friends and family with a secret wedding and promised each other forever the same weekend we graduated. We did it our way and we always will because we found ourselves when we found each other. Thank you for your unwavering support and belief in me; thank you for being everything I could ever have imagined and more. We did this together, like we always have, as a team—together we can accomplish anything. Our insatiable curiosity for the world and passion to make the world a better place in everything we do, makes me very excited for what is next for us. I love you with all of my heart.

Name: QUINN ELISE BUTTON

Date of Degree: July, 2019

Title of Study: THE INFLUENCE OF EXTERIOR DESIGN ATTRIBUTES ON CONSUMER PREFERENCE FOR ELECTRIC VEHICLES

Major Field: HUMAN SCIENCES

Abstract: What is the relationship between a product's design and acceptance of the product? We examine consumer preferences relative to the fast changing automotive industry to understand how the various physical design elements of new car models, including electric vehicles, influence consumer vehicle preference. This research explores product design perceptions and aims to understand specific attributes of the visual form that underlie consumer interpretations of products. Eye tracking methods and measurements were employed to empirically examine if attention can predict consumer judgements and behavioral outcomes. Study 1 investigated consumer level *a priori* variables—including prototypicality, processing fluency, and information entropy—which were hypothesized to influence consumer aesthetic liking. In Study 2, car-level attributes were specifically looked at to see if the same variables relative to a cars design influenced annual car sales. Variables in these studies were measured with both conventional eye tracking measurements and newly established composite metrics to analyze the scan paths of participants and understand how the visual entropy of an object influences consumer preferences. Findings reveal the importance of the grille as a feature that consumers rely on to recognize and make judgements about a vehicle's design. This study also confirms Mandler's hypothesis (1989) that a moderate level of prototypicality is preferred by consumers when evaluating vehicles, suggesting that a vehicle's design elements should be moderately unique so that they are memorable, while also consistent relative to the product category's typicality to alleviate confusion. The research findings are relevant to both designers and marketing executives as they attempt to align new model designs with the expectations of consumers while also trying to stand out amongst competitors in a saturated market. Understanding which design features consumers use to make evaluations during the purchasing process is an important first step before launching a new vehicle model to the market. The measures and methods in this study offer useful measures for marketing and design practitioners if design enhancement is of interest.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

Research Question

What is the relationship between a product's design and acceptance of the product? Product design is defined as the "arrangement of the characteristics of a product offering, [which] refer to functionalities and physical appearance/form" (Creusen, 2011), and is a critical component to a consumer acceptance (Bloch, Brunel, & Arnold, 2003). Consumer acceptance is defined as a behavioral response that directs a consumer to prefer particular products (Radford, 2007), and is an essential element to a product's market success. A consumer's behavioral response to products has been measured in several studies including consumer preferences (Noseworthy, Murray, & Di Muro, 2017; Landwehr, Wentzel, & Herrmann, 2012), consumer attitudes (Pieters, Wedel, & Batra, 2010), willingness to adopt (Veryzer & Hutchinson, 1998), purchase decisions (Jindal, Sarangee, Echambadi, & Lee, 2016; Landwehr, McGill, & Herrmann, 2011), product choices (Mugge & Dahl, 2013; Keaveney, Herrmann, Befurt, & Landwehr, 2012; Blijlevens, Carbon, Mugge, & Schoormans, 2012), and evaluation of aesthetics (Landwehr, Wentzel, & Hermann, 2013). The current study uses two measures for consumer product acceptance. In Study 1, consumer acceptance is measured by self-reported evaluations of aesthetic liking for automobiles. In Study 2, consumer acceptance is measured using 2018 sales of the vehicles examined.

The adoption of new products, such as the electric vehicle examined in this study, is hypothesized to influence how consumers cognitively evaluate a product's design. Therefore, understanding a consumer's perceptions of product designs is of central importance to designing and implementing effective marketing communications.

Below are the four primary research questions investigated, followed by descriptions of the literature gaps that they attempt to address.

1. How does the prototypicality of a product's design influence consumer preference toward that product?
2. Can eye tracking methods used to quantify consumer preference towards a product's physical aesthetics to quantify the point at which a product's level of design prototypicality shifts from improving customer preference to reducing their preferences for the vehicles?
3. Can the composite metrics from information entropy, T_{50} and scan path entropy, be used to determine and predict how consumers cognitively acquire visual information of a product's physical design?

Research question 1.

This study will contribute to the field of knowledge about consumer responses to product design in the following ways. First, this study examines the designs of current electric vehicle (EV) offerings to understand how consumers visually respond to the latest designs in this new segment of the automotive market. There has been little research on electric vehicles in marketing and consumer behavior literature, primarily because their market penetration in the automotive industry is a relatively recent phenomenon. The lack of literature on this topic, as well as the exponential growth of EVs in the automotive market, highlight the need for more research. Previous studies have compared the designs of traditional combustion engine vehicles (CVs) based on variables such as price (e.g. economy vs luxury, see Liu, Li, Chen, Haipeng, & Balachander, 2017; Landwehr, Wentzel, & Herrmann, 2013; Landwehr, Labroo, & Herrmann, 2011). This study controls for many of these established market variables and introduces the novel variations in vehicle designs within three different fuel categories (EVs, CVs and HEVs), to better understand how design alterations between these different vehicles affect consumers preferences. Due to the saturation of the automobile industry, companies vying for increased market share amongst competitors must attempt to capture consumer attention with unique designs and innovative technology. However, as the example of Edsel Ford's design failure illustrated earlier, designers must find the optimum design balance between novelty and familiarity to warrant a positive market response. It is of particular interest to find the point at which a product's level of design typicality, or familiarity, shifts from improving to reducing preferences.

Research question 2.

Secondarily, *a priori* variables are hypothesized to influence consumer preferences which can be measured using eye tracking technology. Although eye tracking technology has become more commonly used in marketing research (Pieters & Wedel, 2004; Wedel, Pieters, & Liechty, 2008; Hooge & Camps, 2015), the bridge between eye movements and their role in cognition, such as fluency rate and information entropy, and role in decision making are poorly understood. Studies in the marketing literature have mainly used eye tracking methods to examine how consumers respond to stimuli such as advertisements (Pieters & Wedel, 2004; Wedel, Pieters, & Liechty, 2008; Pieters, Wedel, & Batra, 2010). Eye tracking methods and measurements are used to empirically examine the "mind-eye hypothesis" from information processing theory (Winkielman, Schwarz, Fazendeiro, & Reber, 2003), which suggests attention placement can predict perceived judgements and behavioral outcomes. Eye tracking allows researchers to empirically measure where an individual's attention was placed on stimuli, as well as the ordered search path individuals used between items within a stimulus to acquire information. Additionally, eye movement measures can also reveal the cognitive load elicited by specific areas of interest within the stimulus during the visual process. Insights from these measures have the potential to give researchers a more robust understanding of how visual stimuli are cognitively processed (e.g., versus traditional measures from self-reporting or recall methods) because much of this interaction is executed subconsciously.

Specifically, we use the following eye tracking measures to analyze attention effects on consumer preference: time to first fixation, total fixation duration, average fixation duration, number of fixations, and total dwell time. Each of these measures and their application to our analysis will be further explained throughout the subsequent sections.

Research question 3.

Finally, in addition to conventional eye tracking measurements, recently established composite metrics that combine various eye movement measures are also used to analyze the scan paths of participants. Scan paths measure the visual entropy of an object and can provide insight into how entropy influences consumer preferences. Developed by Shannon (1948), the construct of entropy comes from information theory and measures the amount of disorder, or uncertainty, in a system. In the context of comparing the similarity of one design to another, which is the focus of this study, entropy is a measure of diversity within a system. The composite metrics of scan path entropy and T_{50} are used to examine how the diversity of features within a vehicle's design influences the behavior of participant eye movements when processing different car models. Scan path entropy measures the scan path similarity between participants by looking at the order of fixations made across the various features of a vehicle's exterior design. T_{50} measures the attention drawing power of a vehicle's design features, or areas of interest (AOIs), by calculating the number of first AOI hits and the speed at which eye attraction occurs across all participant observations (Hooge & Camps, 2013). These measurements and methods, which will be further detailed in the subsequent literature review and methods sections, have not been used to empirically examine how the physical design of a product influences consumer preferences. Measures such as total dwell time and scan path entropy are the first to be applied to variables in the investigation of how consumers cognitively acquire visual information of a product's physical design.

In conclusion, this study aims to test the relevance of these composite metrics, in addition to the traditional eye tracking measurements on their own, to advance the understanding of how the physical design of products are processed by looking at where attention is placed and if the order and duration (measured by time) of this attention impacts consumer preference.

Definitions

This section defines additional key terms and important theoretical constructs used in the current study to provide clarity and context prior to the literature review.

Product design definitions.

This examination focuses on consumer responses elicited by product design, which refers to both the process and result of determining the physical execution and arrangement of the characteristics of a product offering. These characteristics refer to functionalities and physical appearance/form, or aesthetics, of a product (Creusen, 2011). The term aesthetics refers to the aesthetic appeal of the product and its ability to please one or more of our senses (Bloch, 2011). Product aesthetics work together with utilitarian benefits to create important first impressions for consumers during the shopping process (Bloch, 2011). Utilitarian attributes are the functional, instrumental, and practical dimensions of a product (Noseworthy & Trudel, 2011). Aesthetic liking is defined as "the sensation that results from the perception of attractiveness (or unattractiveness) in products" (Crilly, Moultrie, & Clarkson 2004, p. 552). Closely aligned with aesthetic liking, the aesthetic value of a product refers to the pleasure derived from seeing the product, without consideration of its utilitarian attributes (Holbrook, 1980; Creusen & Schoormans, 2005).

Categorization-schema definitions.

Categorization-schema theory is used to examine how consumers respond to product design because research suggests that consumers use product appearance for categorization (Bloch, 1995; Veryzer, 1995). The appearance of a product can influence the ease with which a product is categorized and the category to which it will be assigned (Creusen & Schoormans, 2005). Categorical representations consist of information that is stored in an individual's cognitive system to easily process a particular consumer category at a later time (Loken, Barsalou, & Joiner, 2008). Once information has been stored from previous experiences, schemas within these categories are created and used in decision making. Schemas are the cognitive structures that consist of prior knowledge from personal experiences (Fiske, 1982; Fiske & Taylor, 1991). These are the fundamental building blocks of how information is processed and items are quickly categorized based on prior experience. Product schemas are comprised of an individual's understanding of a certain product or product category and are arranged hierarchically (Noseworthy & Trudel, 2011). Product category congruency refers to the degree to which an extension product resembles its category prototype. That is, the level of prototypicality of a product's design and physical attributes relative to its respective product schema (Noseworthy & Trudel, 2011; Meyers-Levy & Tybout, 1989). A prototype is the central representation of a category or as possessing the average or modal value of the attributes in that category (Veryzer & Hutchinson, 1998). Prototypicality refers the degree to which an object is representative of a category (Veryzer & Hutchinson, 1998). Perceived prototypicality, or typicality, is the subjective perception of a product's typicality or category representativeness (Veryzer & Hutchinson, 1998). Product identification has been found to be easier when a product resembles other products in the same category, that is, when it is more prototypical of the category (Loken & Ward, 1990). With respect to product appearance, this means that it should be more visually typical.

An important construct of the categorization-schema process is processing fluency, which is defined as the ease with which consumers process an object and recognize it (Jacoby & Dallas, 1981; Reber, et al., 2004). There are two sub-constructs that make up processing fluency: conceptual and perceptual fluency. Conceptual fluency is the ease with which an object comes to mind and pertains to the processing of meanings (Hamann, 1990). Perceptual fluency refers to the ease with which consumers identify an object on subsequent encounters and involves the processing of physical features (Jacoby & Dallas, 1981). Each of these constructs is discussed extensively in the literature review section below.

Vehicle definitions.

Combustion engine vehicles (CVs) are powered by traditional petroleum or diesel fuel and have been the predominant option in the automotive industry for over a century. Although the electric engine was invented at the dawn of the 20th century, the automotive industry has focused almost solely on creating CVs for the global transportation market. In just the past two decades, however, car companies—such as BMW, Toyota, Tesla Motors, and Nissan—have started offering vehicles that are fueled by alternative energies, such as electricity. Current electric vehicle offerings available in the market can be grouped into two categories: hybrid electric vehicles (HEVs) and plug-ins (Liao, Molin, & van Wee, 2017). HEVs have a battery provides little power to the vehicle overall with its internal combustion engine, and slightly increases fuel efficiency by charging while braking (Liao, Molin, & van Wee, 2017; Moons & De Pelsmacker, 2012). HEVs were initially introduced to the market before plug-in electric vehicles, and have played in important role in the evolution of electric vehicle acceptance and market penetration today.

Plug-ins are powered solely by electric battery and are charged by plugging into a power outlet (Liao et al., 2017). These vehicles can be further categorized into two subgroups: plug-in hybrids (PHEVs, powered by both a battery and/or engine) or full battery electric vehicles (BEVs). PHEVs and BEVs, collectively referred to as electric vehicles (EVs) henceforth, either reduce or entirely negate gasoline or diesel use in the vehicle itself through integration with the electric grid. EVs have reemerged for a variety of reasons – including improvements in battery technology and heightened government vehicle efficiency and air quality standards. EVs may play a role in helping to reduce greenhouse gas emissions, improve local air pollution, and reduce vehicular noise (Brady & O'Mahony, 2011; Hawkins, Singh, Majeau-Bettez, &

Strømman, 2013). In recognition of these benefits, countries around the world, including the European Union, Canada, The United States, China, and Japan, are setting EV adoption targets (IEA, 2019).

In this study, nine 2017 vehicle models from three fuel categories—three EVs, three HEVs, and three CVs—are analyzed to see if the subtle design differences between these different automobile categories influence consumer preference.

Eye tracking definitions.

Visual attention is an influential factor in consumer decision-making. However, little is known about individuals' determinants of visual attention. Visual attention is defined as the degree to which people visually focus on a stimulus within their range of exposure (Solomon, 1983; 2010), and is a precondition for product choice (Audrin, Brosch, Sander, & Chanal, 2018). Attention is the allocation of information processing capacity to a stimulus (Engel, Rumelhart, Wandell, Less, Glover, Chichilinsky, & Shadlin, 1994). Attentional mechanisms allow people to select a subset of information, while suppressing the non-selected information for further processing (Wedel & Pieters, 2008). When a product stands out visually from competitive products, chances are higher that consumers will pay attention to the product in a purchase situation, as it catches their eye (Creusen & Schoormans, 2005). This selection of information through attention is a crucial step in purchase decisions and consumer preference (Milosavljevic & Cerf, 2008). This investigation uses eye tracking methods and measures to quantify individuals' visual attention and better understand the information acquisition process that leads consumers to prefer a particular vehicle design.

Appendix E provides a full list of eye movement measures and definitions frequently used in eye tracking studies throughout the marketing, consumer behavior and product design literature. Although not all measures are used in this study, the following definitions provide context for those who are unfamiliar with eye movement measures and the potential insights eye tracking methods offer researchers.

Motivation For Study

There is increasing interest in how consumers initially visually interpret product design attributes and how these visual signals influence perceptions of the product (Liu et al., 2017; Landwehr, Labroo, & Herrmann, 2011; Bloch, 1995). In businesses today, both marketing scientists and managers suggest that product design is a major tool that can be used to gain competitive advantage (Bloch, 1995). This assumption is particularly pertinent for new products and innovations that are unfamiliar to consumers, as the design can convey information to or inform about the utility that a product may offer, depending on the firm's marketing strategy. Namely, the form of a product, or its design features, allow companies to visually communicate the benefits of new products and innovations to both customers and competitors.

Companies that prioritize design considerations when developing new products can achieve greater returns and market success (Kreuzbauer & Malter, 2005). For example, the electronics manufacturer Apple uses design philosophy and pays acute attention to its products. Their simple, high quality and inherently understandable design aesthetics have made it one of the most successful and recognizable companies in the world (Landwehr, Wentzel & Herrmann, 2012). Conversely, poor aesthetic designs can lead to market failures. The unique-looking Edsel automobile that Ford Motor Company launched with great expectations in 1959 was seen as odd compared to market alternatives and was discontinued in the same year at a significant loss to the company (Barron, 2007). If a design is too easy to understand, it will not capture consumers' attention. On the other hand, if a design is too difficult to understand, it might be ignored. The example of Ford's failed model launch illustrates the consequential balance that car designers must strike between novelty and typicality when creating new products, so that consumers can process the design and make a purchase decision. However, understanding how designs can influence consumer acceptance is of particular interest to both researchers and companies across industries, as market success largely depends on consumers adopting its innovations.

In response to consumer interest and recent environmental policies, the demand for electric cars has gained significant momentum worldwide and has propelled the automotive industry to focus on producing electric vehicles faster than previously anticipated. In 2017, the U.S. saw a record year for EV sales and prominent automakers—such as Ford Motors, Mercedes-Benz, BMW, Volkswagen, General Motors, and more—are now heavily investing into EV models with compelling new features (ChargePoint, Inc., 2017). There were 41 electric vehicle models available for consumers to purchase in 2017, versus only 32 in 2016 (a 28% increase) (ChargePoint, Inc., 2017). Bloomberg Energy Finance (Electric Vehicle Outlook, 2017) predicts that more than 8.5 million EVs will be on the roads globally by 2020 (Raven, 2017). This, however, is only the beginning of electric vehicle growth, as this number of vehicles purchased is predicted to nearly double over the next five years (Ravens, 2017). EV models currently available range from minivans, sport utility vehicles (SUVs), and small luxury crossovers to buses, delivery vehicles, and pickup trucks. The diverse variety of model choices currently available is indicative of the profound shift occurring in the automotive industry toward electric vehicles. The average price of new cars in 2018, regardless of fuel type, was $36,270 (Kelly Blue Book, 2018); however, with consumers incentivized by both federal and state income tax credit offerings (federal income tax credit up to $7,500; state income tax credit ranging from $750-$20,000; Todd, Chen, & Clogston, 2013), EVs are now becoming more financially accessible for every lifestyle and budget (IEA, 2019). An electric vehicle will soon be available for most preferences to replace traditional combustion engine vehicles.

In addition to the top car manufacturers, including Ford Motors, Volkswagen, Mercedes-Benz, BMW, and Toyota, the EV movement has prompted several new electric vehicles to enter the competitive automotive market at a rate not seen since the early 1900s—the dawn of automobile innovation. Recently, several EV manufacturing companies have entered the market such as Tesla Motors, Byton, Polestar (a luxury EV division of Volvo), Faraday, and Nio. Competing for consumers' attention and building loyalty from new brands in a highly competitive and consolidated market may be difficult (Landwehr, Wentzel, & Herrmann, 2013). For these nascent companies, survival depends on both ensuring adequate market penetration and a positive return on early investment. The costs of producing a single concept car are substantial and can range from $100,000 to $300,000 (Arnold, 2000). The high cost of production can make concept car design decisions paramount.

If the change from combustion vehicles (CVs) to electric vehicles (EVs) is, indeed, fueled top down by the manufacturers, rather than bottom up by consumer demand—then the issue of consumer adoption will be an important consideration. Findings from several studies suggest that a significant barrier for EVs is getting consumers to adopt new innovations that change the way products are used on a day-to-day basis, which makes the primary mode of U.S. consumer transportation, the automobile, an appropriate product category to examine (Moons & Pelsmacker, 2012; Radford & Bloch, 2011; Bloch & Richins, 1983).

A fundamental dimension to understanding the barriers to consumer adoption of EVs relates to the current state of the automobile market. Today, consumers must keep up with the constant progress of technology, which can require behavior adjustment (Radford & Bloch, 2011; Radford, 2007). Consumers are averse to risk and uncertainty when presented with an unfamiliar product (Campbell & Goodstein, 2001). Therefore, as new car designs and their innovations disrupt the traditional offerings of the automotive market, it is imperative that industry executives better understand how to lower uncertainty for consumers in order for adoption to occur. Often, the first step of alleviating consumer reluctance towards unfamiliar products is through visual exposure. When an individual is first exposed to a new product, they evaluate the product based on design features before accepting it (Noseworthy & Trudel, 2011; Creusen, 2011). Auto designers should, therefore, better understand how potential customers visually process information about the design features of unfamiliar electric vehicles. Utilizing a consumer-centric design approach is a next step to increase consumer preference for EVs.

Findings from psychology and consumer behavior research suggest that consumers use cognitive schemas, or categories, to store information from prior experience to help understand unfamiliar stimuli. Researchers examining consumer behavior in design have concluded that consumers process the design of products holistically in order to quickly evaluate whether or not they are interested in the product (Reber, Schwarz, & Winkielman, 2004). This is in contrast to the more detailed and narrow way designers think when creating products, mainly due to their level of involvement and expertise. The dissonance between the processing styles of designers and their customers has led to unreliable predictions about initial consumer responses to new products and designs. Thus, research can inform industry of how designs and their visual qualities may improve or harm consumer product acceptance.

Expected Contributions to the Literature

New product introductions are often unpredictable, as more than 50 percent of new products have failed in their respective market (Ogawa & Piller, 2006). This research explores product design perceptions and aims to identify specific attributes of a car's exterior form that underlie consumer evaluations. Product preferences are subjective (Bloch, 1995; Radford, 2007), so consumers' interpretations of visual stimuli can vary. This research explores these individual differences with known psychometric indicators that measure dimensions of product design and consumer acceptance.

Consumer perceptions of innovations have been largely ignored in past innovation research (Barksdale & Darden, 1971; Garcia & Calantone, 2002). Studies on new products have typically focused on the firm level, examining variables such as product performance (Atuahene-Gima, 1995), the development process of new products (Veryzer, 1998), and company traits that encourage adoption (Chandy & Tellis, 2000; Garcia & Calantone, 2002). This dissertation will address this gap in the literature by more fully exploring the concept of consumer acceptance for electric vehicles, a construct that must be investigated from the consumer perspective, and will focus on how the physical design of a product influences consumer vehicle preference. This study aims to contribute to the body of research using eye movement measures to understand how the attention drawing power of design features influences consumer evaluations of products.

Chapter Summary

This chapter introduced the concepts examined in this dissertation, outlined overall purposes and specific objectives, and highlighted the potential contributions of this research to marketing academics and practitioners. The next chapter introduces the theoretical framework employed to explain the relationship between product design and consumer acceptance.

CHAPTER II

LITERATURE REVIEW

This chapter introduces the categorization-schema theoretical framework used in this dissertation, and describes how it may explain end-user reactions to new product forms. In the following sections, a theoretical argument is made for the importance of visual design in product evaluations. Drawing from research in aesthetics and psychology, and the first section highlights the importance of product aesthetics as they relate to the visual-cognitive process when making a decision. The construct of product design will then be defined and specified in relation to related constructs such as schemas, prototypicality, fluency, information entropy, and consumer acceptance. Consumer responses to a product's form will be identified to address the interaction of cognitive and sensory evaluations, and provide a foundation for the empirical studies. Finally, categorization-schema theory is used to examine the way that aesthetics and novelty have been conceptualized and empirically tested.

Theoretical Framework

Categorization theory, also referred to as schema theory, has been widely recognized in marketing and psychology literature to explain how human cognition, memory and learning is processed by individuals (Rosch, Simpson, & Miller, 1976). The premise of the theory is that individuals group objects into "schemas" based on their similarities and differences, and over time develop a set of expectations about each category (Liu et al., 2017). Schemas, also known as knowledge structures, are the fundamental building blocks of how we process information and quickly categorize something based on prior experience.

Within categorization theory, categorical representations are defined as information that is stored in an individual's cognitive system to easily process a particular consumer category at a later time (Loken, Barsalou, & Joiner, 2008). The consumer's goal when categorizing product information is to decode, comprehend, and evaluate product signals through information observed about various products and/or services. These category representations are especially useful during the initial categorization process of a new product or service. Once a product is assigned to a specific consumer category, category representations are used to quickly assess the new product based on information stored earlier in that category. A consumer category, or product schema, is a set of products, services, brands or other means of explicit communication that signal value to consumers (Loken et al., 2008). Consumers might classify a new product such as an electric vehicle by its utilitarian features (e.g., fueled by electricity, engine acceleration, driving range) or aesthetic features (e.g., size, shape, color, etc.) (Voss, Spangenberg, & Grohmann, 2003). Once categorized in a new product schema, this information from the electric vehicle category, for example, can be used to make judgements of new and unfamiliar electric vehicle models.

Product categories and schemas.

Both categories and schemas consist of information about a product and is particularly useful to consumers when formulating judgements about new products, services, or brands. Halkias (2015) notes that the process of schema formation begins where the categorization process ends. While the categorization process distinguishes and classifies a new external stimulus (Lajos, Katona, Chattopadhyay, & Sarvary, 2009; Sujan & Dekleva, 1987), schemas are formed internally using prior knowledge understand more about what has already been categorized (Hoyer & MacInnis, 2008).

Categorization-schema theory suggests that information is organized by individuals in schemas, or cognitive structures, which consist of prior knowledge from personal experiences (Fiske, 1982; Fiske & Taylor, 2013). These schemas allow people to form expectations, process and recall information, categorize stimuli, and streamline decisions (Sujan & Bettman, 1989). Schema theory has provided researchers with insights regarding how the alignment of a product's typicality relative to an individual's product category schema can impact product evaluations (Meyers-Levy & Tybout, 1989). It has also been used to examine how product, brand and attribute knowledge is cognitively arranged by consumers (Halkias, 2015), as well as how brand-advertisement schema congruity can influence response to marketing communications (Halkias & Kokkinaki, 2014).

This study examines the product category schema, which is comprised of an individual's understanding of a certain product or product category. Product schemas are arranged hierarchically by the superordinate level, basic level, and subordinate level; however, the arrangement of this hierarchy is subjective to the individual. The superordinate level schemas are at the very top of this hierarchy and contain very broad information that aids in the most basic level of identification. In the example of vehicle product schemas, the superordinate level would be "vehicles". Product schemas at this level are relatively consistent between individuals, but begin to vary within the subsequent levels of the hierarchy.

The second tier in the product category hierarchy is called the basic level and consists of more detailed information about the superordinate level schema, which aids in one's ability to differentiate between products within the same category. Basic level schemas in the vehicle category, for example, might be based on the shape of vehicles (e.g., truck, sedan, SUV, sports car, etc.) or market segment classifications (e.g., luxury vehicles, economy vehicles). Finally, at the bottom of the hierarchy, subordinate level schemas further categorize information from basic level schemas into very detailed information blocks and are the most subjectively organized. If an individual's basic level schema was grouped by the exterior form of vehicles (e.g., truck, SUV, etc.), then the subsequent subordinate level schemas might include market segment classifications (e.g., luxury vs. economy), fuel type (EV, CV, HEV), or brands (e.g., Tesla Motors, Porsche, etc.).

The subjective nature of how the basic level and subordinate level schemas are created and arranged in an individual's hierarchy has made it difficult for researchers to conclusively predict which schema level is used during the evaluation process. Researchers have suggested that both cars (Rosch & Lloyd, 1978) and sports cars (Sujan & Dekleva, 1987) form a basic category level in consumers' product schema hierarchy. Davvetas and Diamantopoulos (2016) propose that product categories are initially arranged around brands, while brands are typically organized around product attributes. Researchers have also identified brand schemas as essential components of product schemas (Davvetas & Diamantopoulos, 2016; Halkias, 2015), while product attributes are elements of brand schemas (Halkias, 2015; Hoyer & MacInnis, 2008). For example, understanding a product category like EV might begin by the consumer organizing the brands available (e.g., Tesla, Prius), followed by the subsequent evaluation of brand attributes (e.g., unique exterior design features, advanced innovative technology, high speed performance, good for the environment).

The relationship between schemas and working memory has multiple stages. The initial formation of a schema requires the resources of an individual's working memory because one must concurrently process all information chunks and integrate them to construct a new schema (Gerjets & Scheiter, 2003). Once the new schema is created the new construct informs individuals by enabling them to "increase the amount of information that can be held in working memory by chunking individual elements into a single element" (Sweller, 1994, p. 299). Schemas allow the mind to combine subjectively novel or complicated information as one consolidated working memory block (Gerjets & Scheiter, 2003). Cognitive resources are then opened up by schema automation, as it enables one to quickly recall and use stored schemas subconsciously (Gerjets & Scheiter, 2003).

Schema automation describes how schemas may be processed unconsciously, which can aid in freeing up working memory (Paas, Renkl, & Sweller, 2004). A consumer's proficiency of a particular area develops through the construction of greater numbers of ever more complex schemas by combining elements consisting of lower level schemas into higher-level schemas (Paas et al., 2004). The construction of high-level schemas allows an individual to automatically process and retrieve complex information quickly, which enables the advancement of knowledge and skills. According to schema theory, expert knowledge is based on an individual's extensive collection of high-level schemas, which are highly automated when interpreting novel product information. Novices who have not yet constructed these schemas must exert significantly more cognitive effort towards processing unfamiliar information. There is a difference between expert and novice cognitive processes, particularly when it comes to new products. The increased cognitive effort required to formulate schemas for new products that novice consumers encounter may impact the fluency rate (Winkielman, et al., 2003; Schwarz, 2015) during the visual evaluation of a new EV design, thereby altering their affective response to the design.

Fluency, also referred to as processing fluency, is to the level of ease with which consumers process an object and recognize it (Jacoby & Dallas, 1981; Reber, et al., 2004). Research suggests that there are two different fluency constructs that make up processing fluency: perceptual and conceptual fluency. Perceptual fluency is defined as the ease with which consumers identify an object on subsequent encounters and involves the processing of physical features (Jacoby & Dallas, 1981). Conceptual fluency is the ease with which an object comes to mind and pertains to the processing of meanings (Hamann, 1990). The key difference between the two is that while conceptual fluency informs meaning during cognitive processing, perceptual fluency aids in the initial recognition of an object by evaluating the physical features of a product. As they relate to vehicles, for example, perceptual fluency processes basic information by looking at the car's individual features like the grille, and so that it is appropriately recognized and categorized into the first-level vehicle schema. Conceptual fluency then processes the vehicle holistically to inform consumers of its meaning, which can include performance characteristics (e.g., speed, reliability, etc.), brand information (e.g., Mercedes-Benz, Tesla, etc.), and market segments (e.g., luxury, economy, etc.). Both fluency constructs are important in understanding how individuals process a product, so processing fluency, which includes both constructs, is used as a key variable. With several new companies and brands emerging in the current EV market, the schema formation process for new product designs is of particular interest.

Categorization perspectives.

There are three primary viewpoints that offer explanations for how categories are represented in the mind: schemas of prototypicality (Rosch & Mervis, 1975), exemplar (Medin & Schaffer, 1978), and connectionist (McClelland & Rumelhart, 1985). The prototype perspective suggests that categories are represented by abstract combinations of other category members previously experienced, called prototypes (Loken, Barsalou & Joiner, 2008). From this perspective, a prototypical representation is based on a combination of the most salient features associated with that category, which are modelled around personal experience with respective category members (Rosch & Mervis, 1975). Prototypicality refers to how typical or unique a product looks relative to other products in the same product category (Landwehr, Labroo & Hermann, 2011). The hierarchical nature of prototypical features indicates that some category members are more representative of a certain category than others. The prototypicality of a product increases when its features are aligned with or shared with its respective category. Loken, Barsalou, and Joiner (2008) define a new stimulus as “a category member to the extent that it is more similar to the category prototype and less similar to competing category prototypes.” (Loken, Barsalou, & Joiner, 2008, pp. 135).

The exemplar view assumes that categories are represented by specific groupings that provide more common references to the schema set than the more abstract prototypes. An exemplar provides a frame of reference for a specific category and helps to identify the proper category in the mind of consumers. For example, a product category such as MP3 players might be encoded with the iPod (Loken et al., 2008). However, some exemplar theorists such as Medin and Schaffer (1978) suggest that because categories are hierarchical in nature, exemplars can also represent a subset category (e.g., sedans as a subset of automobiles). From this perspective, a new stimulus is a retrieval cue, which allows consumers to retrieve analogous exemplars from prior experiences stored in memory (Medin & Schaffer, 1978). A stimulus is included in a category based on how similar its attributes are relative to the exemplar of that particular category (Medin & Schaffer, 1978).

Lastly, the connectionist perspective (McClelland & Rumelhart, 1985) suggests that categories efficiently guide cognitive attention through a dynamic network of stored associated features. Through the correlation of multiple signals that simultaneously exist within a category, consumers select those that are representative and distinct relative to the observed stimulus. A new stimulus triggers the most similar grouping of associated features within the network and then places the stimulus into its respective category (Loken et al., 2008).

Prior research has suggested that implementing these attribute-based measures requires determining which attributes are salient and accessible for a particular product category, and are then correlated with measures of prototypicality (Barsalou, 1985; Loken & Ward, 1987,1990; Viswanathan & Childers, 1999). Across studies, these attribute-based measures have been found to predict prototypicality measures (Barsalou, 1985; Loken & Ward, 1990).

Information Theory

Entropy is a measure of disorder or uncertainty within a system; in the context of the study of similarity, it is a measure of diversity within a set. Calculating entropy for a set of stimuli incorporates both the number of categories of elements within the set and the relative frequencies of said categories (Young & Wasserman, 2001). Entropy is maximized when all of the elements are different (i.e., belonging to different categories) and is zero when all elements are identical (Shannon, 1948).

Entropy detection offers a powerful and parsimonious explanation of product categorization within the cognitive process because its use does not require an explicit concept of whether information within a stimuli is the same or different. It is possible that an entropy-based mechanism serves as the foundation for the development of explicit representations of prototypicality during the categorization process (Smith, 1989). When calculating the entropy of a transition matrix, Shic, Charwarska, and Scassellati (2008) argue that a high resulting value is aligned with a preference for exploration, while low values indicate transitions mainly between a few AOIs.

Product Design Attributes

Product design consists of the characteristics that provide consumers utilitarian, hedonic, and semiotic attributes (Bloch, 2011; Crilly, Moultrie, & Clarkson, 2004). Utilitarian value is referred to as the usefulness of a product’s function and its ability to simply accomplish what is expected (Boztepe, 2007). The utilitarian features of a car that make it reliable, safe, and convenient to use are factors that influence the consumer decision process (Dhar & Wertenbroch, 2000). Utilitarian concerns may play a role in reducing prevention motivations. Prevention motivations influence behavior that reduces risk, loss, or pain (Landwehr, Wentzel, & Herrmann, 2012), while promotion motivations drive more extroverted behavior that explicitly seeks risk. Research has found that prevention goals may be more closely related with a product’s functional features, while promotional goals are positively associated with hedonic features, like the aesthetics of a design (Dhar & Wertenbroch, 2000). Research has shown that the utilitarian benefits of a product are appraised in the initial stages of the shopping process (Chitturi, Raghunathan, & Mahajan, 2008; Chaudhuri, Aboulnasr, & Ligas, 2010). Once utilitarian needs are met, the aesthetic appraisals of a product's design may ultimately predict the purchase decision (Bloch, 2011; Bloch 1983). There is an inflection point for satisfying utilitarian concerns contingent upon the daily functional use of the product. Once the utilitarian needs are met, consumers place more importance on how the car makes them feel by appraising the car's aesthetic features (Chitturi et al., 2008; Chaudhuri et al., 2010).

Aesthetics refers to the physical design characteristics of a product. Aesthetics can influence emotional responses based on how they are appraised by an individual (Chitturi, 2009; Desmet & Hekkert, 2007), and can also include sensory elements such as sound and touch. The aesthetic appraisal of a car might include the exterior paint color, shape and form, the interior material, dashboard technology, odor, or the sound of a sports car's engine (Bosmans, 2006; Peck & Childers, 2003). Due to the inherent subjectivity of product aesthetics, its centrality is difficult to generalize (Bloch, 2011).

Lastly, semiotic attributes of product design refer to the product's meaning or symbolic value (Van Rompay et al., 2009). The form or design of a product is interpreted by users and can communicate information (Dhar & Wertenbroch, 2000; Bloch, 1983; Monö, 1997), such as its utilitarian uses. These symbols help individuals associate a product's brand origins, category, purpose, and utilization (Bloch, 2011). Design can signal the abstract features of a product, like strength and newness (Radford & Bloch, 2011). Semiotic attributes of a product's design can provide a means of self-expression for consumers by transmitting implicit or explicit messages about the product (Belk, 1988). In sum, all three of these design attributes influence consumer judgments individually but are also very closely related and collectively illustrate the various design considerations consumers must sort through during the shopping process. Each product design attribute, and their impact on the visual consumer evaluation process, is described in further detail in the sections below.

Utilitarian product features.

Utilitarian features help consumers understand what to expect from a good or service and satisfy objective needs that the consumer requires such as its functionality, usefulness, and safety (Noseworthy & Trudel, 2011). Utilitarian benefits serve to meet consumer prevention goals by reducing the risk and uncertainty about how products will actually perform during the evaluation of alternatives (Chitturi et al., 2008; Chaudhuri et al., 2010). The anticipated performance, however, is not guaranteed to be understood by consumers when evaluating new products (Creusen, 2011). Education about the advancements and benefits of an EV's technical features is essential for consumer acceptance.

Technical attributes refer to the technical features of the car that are required for the vehicle to operate effectively, such as driving range, recharging time, and performance. Consumer preference towards a vehicle's design has been primarily observed when utilitarian functions of the car are satisfactory (Bloch, 1995; Creusen & Schoormans, 2005). If the utilitarian functions are not seen as satisfactory to a consumer, or worse, trigger highly negative feelings such as fear and anxiety, the vehicle's design is not even considered (Voss, Spangenberg, & Grohmann, 2003; Chitturi et al., 2008; Petruzzellis, 2010; Bloch, 1995).

According to the product design framework by Rindova and Petkova (2007), utilitarian design decisions can convey the technological novelty of a product. Product innovation is defined as a change in product attributes based on a modification in underlying technologies (Gobeli & Brown, 1987). Product innovations can be categorized as either radical or incremental depending on how different they are from the current technology of the industry (Abernathy & Clark, 1985). Radical innovations exemplify a significant deviation from the industry's current technological direction, while incremental innovations constitute small adjustments from it

(Rindova & Petkova, 2007; Anderson & Tuchman, 1990; Tushman & Anderson, 1986; Abernathy & Utterback, 1978). Perceived incongruity of a new product can be influenced by how much it diverges from technology familiar to consumers relative to the new product's classification. Incremental innovations, such as introducing new performance improvements (Rindova & Petkova, 2007), are likely to be perceived as more congruent because established schemas can accommodate small changes within a configuration of attributes (Mandler, 1982). Innovations are often introduced to consumers as solutions that are meant to communicate higher levels of certainty and safety with little effort required by consumers (Fredrickson, 1998).

The utilitarian attributes signaled through a product's exterior design must be understood and meet expectations before consumers can consider the potential benefits of the product. The more a vehicle's design signals the functional benefits of the vehicle, the more familiar or typical (high prototypicality) the vehicle will be perceived during the visual evaluation process.

Aesthetic product features.

During the often extensive shopping process for automobiles (Dhar & Wertenbroch, 2000), appraisals of individual cars are initially based on the trustworthiness of utilitarian benefits offered. Cars are ultimately selected based on the appraisal features (Chitturi, Raghunathan, & Mahajan, 2007; 2008; Dhar & Wertenbroch, 2000). Related to the purchase of an automobile, aesthetic features refer to the visual elements of a car such as its exterior shape (e.g., sedan, SUV, truck, etc.), the intricate design of its grille, color of paint, the shape of its headlights, the interior material used, or the innovations offered on the dashboard design. This study focuses on the exterior of a vehicle's front design, so the specific elements of interest include the aesthetics of a car's grille, headlights (left and right), hood, bumper, and mirrors (left and right).

Consumers do not simply select an automobile for its utilitarian functions, but also for its aesthetic appeal (Crilly, Moultrie, & Clarkson, 2004; Chitturi et al., 2007; 2008). Aesthetics is cited throughout the marketing, design and psychology literature as being the primary reason for why consumers ultimately choose their car, contingent on the car fulfilling the minimum threshold utilitarian functions expected (Bloch, 1995; Chitturi et al., 2007; 2008).

The aesthetic attributes of a product's design serve as data points to aid in the categorization process. The visual appeal of the car can help consumers identify the product's level of prototypicality relative to others in the corresponding product category (Landwehr et al., 2011; Reber, Schwarz, & Winkielman, 2004). Several studies focused on product design have suggested that prototypicality of a design can significantly influence consumer preference (Landwehr et al., 2011; Liu et al., 2017). If the aesthetics of a design are evaluated as too novel or visually unique (high level of visual appeal), the product will be perceived to have a low level of prototypicality because it is incongruent with existing schemas (Landwehr et al., 2011, Reber et al., 2004; Schwarz, 2015).

Semiotic product features.

Automobiles are an extension of one's identity and symbolizes what an individual's values, mainly because cars are visible to others (Barden, 2013). The cars that consumers drive, or aspire to drive, can provide signals about consumers' values and motivations to others on the road. An understanding of how symbols of an automobile are interpreted by consumers may provide companies with insights into how successful their intended marketing message was received. Semiotics, the study of symbols and symbol systems, has received attention from marketing and consumer behavior academic researchers in the past two decades (Mick, Burroughs, Hetzel, & Brannen, 2004). Cars may non-verbally communicate an individual's achievements and success, identity, and social positions to others (Gatersleben, Niamh, & Wokje, 2014). Automobiles have not only an instrumental value in use, but also symbolic meaning in ownership.

A product is connected to a particular set of perspectives, or symbolic meanings (Levy, 1959). The semiotics of a product's design can illustrate how similar a new product's visual appearance matches with existing product schemas (Rindova & Ptekova, 2007). These design decisions are made to increase processing fluency and, thus, speed up schema retrieval so that incongruity does not impact initial consumer evaluation. Therefore, an increase in symbols is associated with the perception of a more prototypical product.

Empirical Literature Review

Schema congruity & perceived value.

Whether or not a new product matches an existing schema is influenced by its perceived value (Rindova & Petkova, 2007). Perceived value is defined as "a measure of a product's worth in a particular social context" (Baldwin & Clark, 2000, p. 96). Businesses seek value by investing resources into developing new products in order to produce maximum returns (Moran & Ghoshal, 1999). Customers seek new products, in pursuit of enhanced performance and other potential benefits that might improve their life (Carpenter & Nakamoto, 1990). The exact degree to which a new product's value will meet the expectations of a business or a consumer, however, is difficult to predict prior to product launch. Value attribution occurs when actual performance is measured after the point of sale for the producer and consumption by the consumer. The difficulty lies in limiting the dissonance between pre-sale predictions, such as consumption goals or expectations, measured against performance.

When the sales of a company’s new products coincide with their expected goals, this is referred to as intended value (Rindova & Petkova, 2007). From the consumer perspective, expected value relies on product evaluation before use, and is referred to as perceived value (Rindova & Petkova, 2007). Perceived value is actualized when consumers are willing to purchase because the company’s intended value of a new product met their expectations (Priem, 2002). When both the perceived value (consumers) and intended value (businesses) of a new product are closely aligned, the differences between a company’s intended value and the consumer’s perceived value are minimized as well. As a result, the expected return on innovations can be quantified, which enables companies to sustain their efforts and continue developing innovative new products. Company decision makers can understand how they can align the intended value of new products with consumers’ perceived value in order for new innovations to be adopted.

The first step in effectively aligning a company’s product with their customers’ perceived value is assessing value. Psychology literature suggests that value is evaluated through complex assessments of congruity (Meyers-Levy & Tybout 1989; Mandler, 1982). Congruity refers to how well a product's attributes match the attributes within a particular schema used to evaluate that product (Mandler, 1982). Incongruity suggests a mismatch between a product’s attributes and the attributes of constructed schemas (Meyers-Levy & Tybout 1989). A product that is incongruent might have more atypical or unfamiliar attributes, which lowers processing fluency and makes the product more difficult to evaluate. Conversely, a product that is congruent is likely to have attributes that are typical or familiar to the individual and can be quickly assessed with high fluency.

Varying levels of incongruity can elicit a wide range of cognitive and emotional responses, which subsequently impact an individual's perceived value of a product. Mandler's hypothesis (1982) argues that a moderate level of product form typicality is most preferred by consumers, suggesting a curvilinear relationship between the typicality (or congruence) of a product's design and consumer preference. If a product's design is common, consumers may find it uninteresting and automatically process it so their attention can be placed elsewhere. Alternatively, if incongruity level of a product's attributes is too high (i.e., atypical, novel) or the cognitive effort needed to create a new schema is arduous, customers may perceive a product innovation as not useful (Rindova & Petkova, 2007). The challenge for designers is to achieve the delicate balance of communicating the functional value of their new product effectively (Jindal, Sarangee, Echambadi, & Lee, 2016), while also creating designs that capture consumers' visual attention without cognitively overwhelming them (Berlyne, 1971). In order for the value and benefits of new products to be understood by consumers, businesses and designers must consider how to design innovations in a manner that addresses initial incongruities prior to launch. In order to assess the potential value of new products that are incongruent with existing schemas, more cognitive effort must be exerted to create a new schema (Meyers-Levy & Tybout 1989; Moreau, Lehmann, & Markman, 2001).

Prototypicality & product schema congruency.

When an individual evaluates how closely a product fits/does not fit into a certain schema, the marketing literature (Landwehr et al., 2011; Liu et al., 2017) refers to this as the product's prototypicality. Prototypicality, or often referred to as typicality, describes how closely a product fits or does not fit into a certain schema (Bloch, 1995). Typicality has long been studied as a predictor variable in the categorization literature, along with the moderation of fluency it takes a person to understand or categorize an object.

Research has demonstrated that if cognitive difficulty (low fluency) is present when trying to place a product into a schema, the probability of liking of an object is reduced (Schwarz, 2004). The negative relationship between metacognitive difficulty and liking has been attributed to a feeling of unfamiliarity with the object (Lee, 2001). The more unique a product is to its segment, the more difficult it is for an individual to categorize it (Schwarz, 2004). This reduces the aesthetic appeal of that product. Due to the relatively unfamiliar nature of electric cars, the novelty of both their utilitarian features, and aesthetic design features might lead to difficulty in categorization. The low fluency that comes with cognitive difficulty of an unconventional design is predicted to influence consumer response (Graf, Mayer, & Landwehr, 2018; Schwarz, 2004).

In contrast to these considerations, recent studies have demonstrated that the effect of metacognitive difficulty depends on the consumption domain (Pocheptsova, Labroo, & Dhar, 2010; Loken, Barsalou & Joiner, 2008). The consumption domain consists of similar products or services within a defined industry market category (Noseworthy & Trudel, 2011). Pocheptsova, Labroo, and Dhar (2010) observed that while (high) fluency may enhance the liking of ordinary products, consumers might like special-occasion products better when fluency is low. This study will expand on these findings through empirical methods that will measure consumer attributions to aesthetic design features of electric vehicles.

New products & innovations.

This study examines how new products, specifically electric vehicle models, are visually evaluated by individuals. Products are considered innovative based on the perception of individual consumers (Johannessen, Olsen, & Lumpkin, 2001). Similarly, a product is only considered new if the individual perceives it to be new. Rogers (2003) defines an innovation as: "an idea, practice, or object perceived as new by an individual or other unit of adoption" (p. 12). Rather than an objective feature, perceived newness is a product attribute subjectively inferred by a consumer (Blythe, 1999; Hauser, Tellis, & Griffin, 2006) and reflects a comparison of the current product with previous versions in the same or closely correlated categories. Product innovation is defined as a change in product attributes based on modifications in underlying design features (Rindova & Ptekova, 2007). In this study, a car's perceived newness is operationalized by the visual typicality of its exterior design.

While much of the innovation literature refers to new products or services in general (Rogers, 2003; Pinch & Bijker, 1987; Johannessen et al., 2001), Griffith (1999) emphasizes that research must consider innovations for what they really are and how they are perceived by consumers; that is, holistic configurations of various features. Consumers interpret individual features via product form into artifacts with aesthetic and symbolic qualities (Bloch, 1995; Hollins & Pugh, 1990; Lewalski, 1988). As explained previously, the product form design refers to how colors, lines, shapes, materials and proportions combine to inform consumer perceptions a new product (Rindova & Ptekova, 2007; Bloch, 1995). The exterior form of a new product, such as a vehicle, can influence customer perceptions in several ways. For example, the form of a new product can highlight or conceal various aspects of the unfamiliar technologies being introduced to consumers.

The question for companies competing for market share in a new automotive category is as follows: how can a company design an electric vehicle that consumers accept, while communicating information about innovation? The disruption of electric vehicles has changed the ways that cars look, as design requirements and constraints are different for electric vehicles than for traditional gas-powered vehicles. The car grille, for example, no longer serves a utilitarian function for an electric car because it does not require a radiator. Originally designed to allow the radiator to cool in a combustion vehicle, a car's grille is often the most recognized and attention-grabbing features of a car for consumers (Landwehr et al., 2011). The grille has also been used by car companies to rebrand themselves. A large grille on a truck or an SUV can signal power, safety, security, and high performance to some consumers (Landwehr et al., 2011). Although the grille does not serve a utilitarian function for electric cars, it may still be used by consumers to categorize and recognize the product as a car.

Tesla Motors, for example, included a "fake" grille their first design iteration of the Tesla Model S to ensure the vehicle was not too atypical and easier for consumer to accept. This initial design decision for the 2015 Tesla Models S may support consumer's perceived prototypicality so that its design was easy to process as a typical luxury sedan, and thereby potentially alleviating consumer skepticism of an EV's functionality. The most recent design of the 2017 Tesla Model S explicitly eliminated the "fake" grille altogether and did not incorporate a grille design for subsequent model designs such as the Tesla Model X and Tesla Model 3. This is a clear example of how designers can use prominent cues to help consumers process and eventually accept the look of radically new products. The question remains as to whether the design strategy actually influences consumers. Do consumers receive the message manufacturers are sending? If so, how do consumers react to these cues and do they influence consumer preference toward accepting the new innovation?

Recent studies (Radford & Bloch, 2011; Radford, 2007; Rindova & Ptekova, 2007) have examined consumer responses to product designs and provide insight into how changes in a product's design influence product newness perceptions. Radford and Bloch (2011) found that when participants evaluated the newness of a product considered products to be newer innovations if they were minimalist in style. Boxy or busy-looking products, however, were seen as consistent with products currently offered in the marketplace (Radford & Bloch, 2011). Interestingly, as participants accessed schemas from memory, products that were more divergent from their product schema's prototype were also perceived as newer (Radford & Bloch, 2011).

Radford (2007) concluded that consumers exhibited a clear preference for newness. He found that products high in newness elicited more affective and aesthetic responses than products that were lower in newness, which may indicate that high newness products are capable of influencing the consumer to engage in more effortful processing. This is consistent with the findings in technology and innovation literature, which similarly observe that constructed schemas about technologies symbolically influence users' perceptions and promote relevant behaviors toward the technologies (Pinch & Bijker, 1987). In their study, Rosa, Porac, Runser-Spanjol, and Saxon (1999) found that the development of a schema for the minivan product category reduced variation in how participants assessed its value. Although individuals may vary in their use of schemas, their evaluation of a new product is strongly influenced by the value expected from similar products stored in existing schemas (Rindova & Petkova, 2007; Davvetas & Diamantopoulos, 2016).

Visual information transfer.

Several studies have investigated the role of visual attention processes in purchase decisions (Wedel & Pieters, 2008; Hooge & Camps, 2013; Milosavljevic & Cerf, 2008). Visual attention is strongly related to eye movements (Orquin & Loose, 2013), so recording eye movement data allows one to study the visual behavior and how it relates to information processing by measuring eye fixations and saccades. Fixations occur when the eye is still and processing more detailed information (Bojko, 2015). Saccades are rapid eye movements and occur when an individual is scanning for visual information in a stimulus. Eye tracking data not only records the time spent looking at a product, but also the position and duration of each eye fixation (Chandon, Hutchinson, Bradlow, & Young, 2009). Previous research found inconsistencies between self-reported and eye tracking measures (Graham & Jeffery, 2011), suggesting that individuals are not aware of the specific attributes that capture their attention (Chandon et al., 2009). The inability to recall exactly where focus was placed when looking at an object suggests that interpreting visual information might be more complex than simply observing which design features influence decision-making (Chandon et al., 2009). Other variables, such as mood, past experience, cognitive ability, level of expertise, interest, values, and attitudes toward the product category might also influence the interpretation of a visual stimuli during eye tracking.

Studies using eye tracking measures have pointed out that when participants are asked to select a preferred product among several options during a lab experiment, a pre-decisional gaze bias existed toward the preferred option (Chae & Lee, 2013). This bias, referred to as the gaze cascade (Shimojo, Simion, Shimojo, & Scheier, 2003), consists in a shift of attention toward the preferred choice alternative (Krajbich & Rangel, 2011; Willemsen, Neijens, Bronner, & De Ridder, 2011). The preferred option is thus observed during a greater amount of time (Glaholt & Reingold, 2011; Glockner, & Herbold, 2011). The attentional Diffusion Drift Model (aDDM, Krajbich & Rangel, 2011) suggests that gaze fixation is the mechanism by which decision makers retrieve information about each option. According to this model, spending time looking at an option means that we accumulate evidence in favor of the fixated alternative (Krajbich & Rangel, 2011).

Consumer psychology literature suggests that information selection is done through two processes: bottom-up and top-down (Wedel & Pieters, 2008). Bottom-up processes correspond to a rapid and automatic way to capture attention (Milosavljevic, Navalpakkam, Koch, & Rangel, 2012), and refer to factors such as visual saliency and prototypicality (Glaholt & Reingold, 2011; Atalay, Bodur, & Rasolofoarison, 2012; Milosavljevic et al., 2012; Janiszewski et al., 2013). Conversely, top-down processes refer to a voluntary attention capture that requires personal and active search (Wedel & Pieters, 2008). This voluntary focus may be driven by the task, previous knowledge, social identity (Xiao & Van Bavel, 2012), interests or goals (Milosavljevic & Cerf, 2008; Glöckner & Herbold, 2011).

Although researchers have long studied product innovation and adoption (Rogers, 2003; Blythe, 1999; Rindova & Ptekova, 2007), studies have concentrated on the development of new product technology and features, rather than on consumer evaluation of the product's newness. The connection between product innovation and visual design is understudied (Hauser, Tellis, & Griffin, 2006), and is of growing interest in consumer responses to design in general (e.g., Bloch, 1995; Leder, Belke, Oeberst & Augustin, 2004; Veryzer & Hutchinson, 1998; Veryzer, 1999). Research on new product adoption has virtually ignored the visual form, focusing instead on other dimensions such as verbal descriptions (Hoeffler, 2003), mental simulations (Feiereisen, Wong, & Broderick, 2008) and learning effort (Atuahene-Gima, 1995). This study tests to see if new product information is initially communicated visually by the prototypicality of its design.

Conclusions Based on Theoretical and Empirical Literature

Prototypicality & processing fluency.

Prior research in innovation diffusion and acceptance suggests that new products should be designed around prototypicality for high fluency so that consumers can easily understand them (Rogers, 1995). The logic is that innovations may require consumers to establish a new product category and subsequent knowledge structures to process it. Innovations can be presented in a relatively easy to understand manner using cues to speed up and ease the visual information process. Numerous marketing and advertising studies have been done on enhancing marketing materials so that the message is properly communicated to consumers (Pieters & Wedel, 2004; Hooge & Camps, 2013; Wedel & Pieters, 2008; 2012; Sujan & Dekleva, 1987), but very few studies have examined how to enhance the physical design of a product to do the same thing.

Aesthetic design choices highlight the visual appeal of a new product and reflects its prototypicality or level of novelty to consumers. How unique or different product aesthetics are to an individual is hypothesized to influence schema incongruity. This relationship between typicality and attractiveness has been found to be reflected in ratings of aesthetic liking, which is refers to “the sensation that results from the perception of attractiveness (or unattractiveness) in products” (Crilly, Moultrie, & Clarkson, 2004, p. 552; Graf & Landwehr, 2017). In their research, Landwehr et al. (2013) found that typical car designs had higher evaluations of aesthetic liking when participants were asked to quickly rate their liking of the car design after being exposed to them for a short amount of time.

Prototypical objects are, by definition, familiar as a category (Winkielman, Halberstadt, Fazendeiro, & Catty, 2006; Landwehr et al., 2011). In general, greater feature overlap with common features of the category indicates a match in prototypicality (Schwarz, 2015). A new stimulus is classified as a category member to the extent that it is more similar to the category prototype and less similar to competing category prototypes. Novel designs are initially considered atypical (low level of prototypicality), while familiar or traditional designs are considered typical (high level of prototypicality).

Processing efficiency results whenever a design is more prototypical because they require fewer neural resources and are processed quickly, and has been found to cause an intuitive positive affective response (Winkielman & Cacioppo, 2001). Research has reported that prototypical stimuli are easier to process than non-prototypical stimuli (Winkielman et al., 2006). In this study, processing fluency is examined as the underlying psychological construct mediating the effect of prototypicality on consumer evaluations.

Prototypicality & information entropy.

Research in innovation diffusion and consumer acceptance suggests that new products should be designed with prototypical features to increase anticipated fluency, so that consumers can easily understand the product and process it quickly into its appropriate category (Rogers, 1995). The logic is that radical innovations may require consumers to establish a new product category schema, which increases the cognitive load consumers must exert to process it. In order to limit this, companies can consider designing their innovation so that it is easier to understand by using visual cues to guide individuals as they evaluate it.

High fluency may be preferred by most (Rogers, 1995; Winkielman & Cacioppo; Lee & Labroo, 2004; Landwehr et al., 2011) so that information from the visual stimuli is extracted with minimum cognitive effort while the product is accurately categorized. Another independent construct is needed to understand how an individual processed the visual stimuli and how product attribute cues inform decision-making. Research has shown that consumers pay attention to and prioritize objects in advertising messages as a result of the integrated effect of bottom-up and top-down factors (Wedel & Pieters, 2008). Fixated attention on certain objects in advertisements can contribute to post-exposure marketing effects of interest such as preference formation (Wedel & Pieters, 2008). This study will examine the influence that a vehicle's design prototypicality has on consumer attention and information extraction, using eye tracking methods to capture most noticed features.

Processing fluency & consumer evaluations.

Research suggests that perceptual fluency is influenced by the visual features of a stimulus and determines the holistic evaluation of that stimulus (Mandler, Nakamura, & Van Zandt, 1987; Whittlesea, 1993). This attention is mediated by the individual's perceived fluency relative to how quickly the stimuli is understood, resulting in the formation of a final assessment of the target stimuli.

Processing fluency influences judgments because individuals use their subjective experience to form their opinion of a visual stimulus (Reber, et al., 2004). Looking these simple judgments can allow researchers to better understand the processes inherent to the aesthetic experience and other evaluative judgements with similar underlying processes (Bornstein, 1989; Bloch 1995, Winkielman et al., 2003; Crilly et al., 2004). Supporting literature suggests that examining independent variables such as judgments of preference (Landwehr et al., 2011), liking (Winkielman et al., 2003), and beauty (Graf & Landwehr, 2015) are closely related and appropriate variables for this current study. This study proposes that aesthetic experience is a function of the perceiver's processing dynamics—the more fluently an individual can process an object, the more positive his or her aesthetic response will likely be. This study will measure the combined design attributes of an EV model to measure the processing fluency of the vehicle image stimulus.

Information entropy & consumer evaluation.

Product form can convey or conceal information about the utility or the level of performance that a product may offer, depending on marketing. Additionally, design can provide visual cues that are intended to activate schematic memory which may provide additional meaningful information associated with the product. Hirschman and Holbrook (1982) proposed that the meanings of these visual cues are at the heart of consumer response to products, meaning that an automobile's aesthetic design can direct the attention of potential buyers not simply because it is aesthetically pleasing, but because it conveys compelling information that aligns with consumer goals.

Marketing literature defines visual attention as the extent to which consumers visually concentrate on a target stimulus (Solomon, 2010; 1983), and is known to be a factor in product choice (Audrin et al., 2018). How consumers direct their attention ultimately influences the way that they see the world, shapes perspectives, attitudes and behaviors (Hirschman & Holbrook, 1982; Bloch, 1995; Wedel & Pieters, 2008). Attentional frameworks are built by individuals to enable the selection and interpretation of information, while also allowing individuals to restrain from having to further process non-selected information (Wedel & Pieters, 2008). The selected information gained by looking at a product is a critical component of purchase decisions (Milosavljevic & Cerf, 2008). Measuring the visual attention and information acquisition with methods such as eye tracking can strengthen the understanding of how this process influences consumer decisions.

Car companies use a variety of cues to signal specific attributes of a vehicle, to aid in the identification of the model and brand. The emergence of new electric car companies and models, such as Tesla Motors, can elicit uncertainty for consumers unfamiliar with the brand and the benefits they might offer, as is the case for many new market segments when disruptive innovation occurs (Veryzer & Hutchinson, 1998; Veryzer, 1999). Therefore, new brands and their product designs must effectively communicate information to consumer that relieve ambiguity and signal some sort of familiarity (e.g., typicality) to assure consumer acceptance.

How are these attentional frameworks constructed and why do certain areas of interest (e.g., product features) within a visual stimuli capture consumer attention over others? By analyzing the attentional patterns created by participants when looking at the designs of car models, this study aims to shed light on the elusive interaction between the eyes and the brain using various eye movement measures that captures how attention attraction of a design can ultimately influence consumer judgements of preference.

Hypotheses Drawn from Theory and Empirical Literature

Hypothesis 1: Examining prototypicality and fluency.

Processing fluency is a term that describes the ease with which observers process some particular stimuli (Jacoby & Dallas, 1981; Reber, et al., 2004). Research has shown that higher levels of fluency are related to positive attributions and that this positive feedback can significantly influence the evaluation of the target stimuli (Schwarz, 2015). Conversely, Schwarz (2015) suggests that when fluency decreases, consumers require greater cognitive processing including classification and interpretation of the stimuli. This heightened level of processing has been shown to reduce the use of heuristic processing in favor of more complex analytical processes. However, this more complex processing method is not preferred by individuals in every situation, particularly when a product or product category is not of interest.

Visual design variables of products, such as prototypicality, have been found to influence the speed and accuracy of lower level cognitive processing (Schwarz, 2015). The level of prototypicality can directly affect the fluency when visual stimuli are processed because prototypicality indicates congruence match with other products in existing schemas (Winkielman et al., 2006; Schwarz, 2015; Meyer-Levy & Tybout, 1989). If the product is too novel (low prototypicality), then more cognitive load is required to understand it, resulting in low fluency which requires more time to process the product (Schwarz, 2015). Conversely, if the product is familiar (high prototypicality) then less cognitive load is required during the evaluation process, resulting in high fluency (less time is required to process) (Schwarz, 2015). In other words, there is an inverse relationship between the level of prototypicality and cognitive load required to process some target stimuli. Products with low prototypicality, or less familiar design attributes, are likely to require greater visual processing times, as measured by saccades and pupillary fixations when using eye tracking methods. As the consumer recognizes familiar aspects of a design, fewer fixations and saccades are expected when observing more familiar design features.

Research suggests that when forming first impressions, individuals tend to prefer prototypical stimuli (Landwehr et al., 2011). Winkielman et al. (2006), for example, found that prototypical patterns are classified more efficiently and require fewer neural resources. Other studies further establish that this kind of processing fluency is inherently positive and is experienced as an intuitive reaction (Lee, 2001; Lee & Labroo, 2004; Lee & Aaker, 2004; Reber, Winkielman, & Schwarz, 1998; Winkielman & Cacioppo, 2001). Researchers have observed positive affective responses toward easy to process line drawings, abstract paintings, pictures

(Reber et al., 1998), and advertising (Labroo & Lee, 2006). Fluency has also been shown to not only increase the liking of a product, but can also decrease deferral or hesitation from one's initial evaluation (Novemsky, Dhar, Schwarz, & Simonson, 2007). When fluency is high, consumers feel more confident and are likely to form positive judgments toward target stimuli (Schwarz, 2015). In their study on the typicality of car designs, Landwehr, Labroo, and Herrmann (2011) found that fluency mediated the influence that prototypicality had on car model sales, confirming a positive correlation between prototypicality and fluency.

Following findings from the integrative framework that Reber, Schwarz, and Winkielman (2004) proposed, this study examines the relationship between consumer evaluations and the prototypicality of EV models. Reber, et al. (2004) proposed that the strong relationship between prototypicality and attractiveness is attributed to processing fluency, stating "that any variable that increases processing fluency also increases liking" (Reber, et al., 2004, p. 372). In line with their proposition, this study hypothesizes that prototypical stimuli are evaluated more positively because they are easier to process.

Hypothesis 1.

There is a positive relationship between Prototypicality and Processing Fluency.

Hypothesis 2: Examining prototypicality and entropy.

This study uses the measurement of scan path entropy to examine the effectiveness of information transfer. First, an explanation of why eye movements are salient indicators of information acquisition behavior is provided. Second, eye tracking measurements that make up scan path entropy are discussed. Attention is reflected in eye movements, which have long been theorized as the primary indicators of information acquisition behavior (Russo, 1978). Recent advances in technology can allow researchers to accurately quantify and measure eye movements to better understand where individuals place attention as they visually process stimuli.

Saccades are rapid eye movements that last approximately 20-40 milliseconds and are used to project various relevant areas of a scene onto the fovea (Bojko, 2013). Saccades are the fastest movement the human body can create, and the average person makes about 127,000 of them daily (Bojko, 2013). Fixations are still and contiguous eye moments, which last approximately 200-500 milliseconds (Rayner, 1998) and are used to process information that is more detailed. The effortful function of fixations restricts the frequency in which they are utilized, as research estimates that only 8 percent of what people see is actually used for more elaborate processing (Bojko, 2013).

The pattern of fixations and saccades observed as individuals scan an advertising stimulus, such as images of an EV, is called a scan path (Noton & Stark, 1971a; 1971b; 1971c). The amount of information that is transmitted through the optic nerve exceeds what the brain is able to process, so the brain has evolved attentional mechanisms that select a subset of relevant information for enhanced processing. When attention is directed to a particular location or object in a scene, processing of the targeted area is enhanced, and processing of non-selected locations and objects is simultaneously suppressed. The function of suppressing non-selected information within these attentional frameworks is to lower cognitive load or simplify the information transfer process of a visual stimuli, so that evaluations can be made faster. Visual information is extracted during eye fixations, while visual information is suppressed during eye saccades (Wedel & Pieters, 2012).

Research suggests that attention may operate on spatial locations, visual features, or objects in the scene (Hooge & Camps, 2013; Wedel & Pieters, 2008; Chandon et al., 2009).

Areas of interest (henceforth referred to as AOIs) are specified portions of a visual stimulus and are used in eye tracking experiments to measure how much interest specific features receive once they are noticed by the participant (Bojko, 2013). AOIs have been used by researchers to accurately quantify where fixations (i.e. pupillary dilation) and saccades (i.e. sequential scanning behavior) occur during interaction with visual stimuli. Thus, specified AOIs of each EV's exterior design will be measured to compare the observed entropy among the features.

Scan path entropy measures the gaze guiding properties of a visual stimuli. It combines fixations and saccade scan paths to measure attention, and includes spatial and temporal considerations. The temporal and spatial properties, which are inherent within scan paths, may lead to significant variation between participants during an eye tracking examination. Hooge and Camps (2013) explain that "even if different observers follow similar scan paths, their behavior may differ a lot because some people fixate long, where others have a much higher saccade rate" (pp. 2). Scan path entropy attempts to measure the average scan paths across all participants. Hooge and Camps (2013) define gaze guidance as when a visual stimulus has the ability to methodically bias an individual's gaze in a specific direction. In this study, effective gaze guidance will be observed if there is a high number of participants who consistently fixate on a specific design element (e.g., the grille), or if the average time to fixation of a particular area of interest is significantly lower because participants' eyes were guided directly to it.

This study identifies the following key AOIs for each EV model tested in the eye tracking experiment: Grille AOI, No Grille AOI, Fake Grill AOI, Headlight AOIs (2), Side Mirror AOIs (2), Windshield AOI. This study will use these AOIs to test total image entropy, as well as the entropy exhibited in specific AOIs compared across images. From the total image entropy standpoint, typical EV designs are expected to demonstrate high saccade (fluency) value and low fixation (typicality) statistics due to their familiar nature, while atypical EV designs are predicted to yield increased fixation value and decreased saccade value since less familiar design cues require more time to process. Additionally, this study will also compare the entropy exhibited in the three specific grille AOIs (Grille AOI vs. No Grille AOI vs. Fake Grille AOI) across all EV models tested.

Visual stimuli with good gaze guiding capacities is suggested to produce similar scan paths in different observers (Hooge & Camps, 2013). Scan path entropy can provide insight into whether design cues of an EV's product form effectively transfer information that the company/design had intended. Effective information transfer to an individual from the combination of product features will demonstrate lower combined entropy for the vehicle image overall. Low entropy is observed through the scan path if saccades are minimal, there is an increase in average fixation duration, fixations are consolidated in a relatively confined area, and the order of the fixations/saccades are consistent between subjects. Conversely, high entropy denotes ineffective information transfer between the subject and the visual stimuli. The scan path observed for a high entropy design will include more saccades, lower average fixation duration; more fixations across a wide range of areas and the order of the fixations/saccades are significantly consistent between subjects.

Given the empirical support and theoretical consensus (Landwehr et al., 2011; Winkielman & Cacioppo, 2001; Liu et al., 2017) that typical products (vs. atypical) are preferred because they are easier to understand, it is predicted that typical products will result in lower entropy due their designs' ability to transfer information effectively. Atypical products, on the other hand, will result in higher entropy as their inherent novelty will negatively influence effective information transfer. Hence, the relationship between the perceived prototypicality of a vehicle and its design's ability to transfer information effectively (entropy) is directly negative.

Hypothesis 2a.

There is a negative relationship between Prototypicality and Entropy (Total Dwell Time).

Hypothesis 2b.

There is a negative relationship between Prototypicality and Scan Path Entropy (Shannon Entropy).

Hypothesis 2c.

There is a negative relationship between Prototypicality and T_{50}.

Hypothesis 3: Examining fluency and consumer preference.

Processing fluency offers a theoretical explanation for the positive effects that a product's typicality has on consumer liking and attractiveness (Graf & Landwehr, 2015; Reber et al., 2004; Winkielman et al., 2006; Landwehr et al., 2013). As explained earlier, fluency refers to the cognitive effort that people utilize when processing a visual stimulus (Schwarz, 2004; Graf, Mayer, & Landwehr, 2018). The fundamental prediction of processing fluency theory is that the ease of processing a stimulus determines the aesthetic response towards the stimulus (Reber et al., 2004). Higher processing fluency is an intrinsically positive experience interpreted by the individual as an intuitive positive feeling (Winkielman & Cacioppo, 2001). With this knowledge, firms can intentionally construct new products with aesthetic design features that offer to help resolve any incongruity consumers might feel when evaluating their designs and use guiding design cues to enhance the processing fluency overall (Rindova & Petkova, 2007).

Understanding what makes people and things attractive informs about the basic operation of one's affective system and its interactions with cognition (Berntson & Cacioppo, 2009; Zajonc, 1998). The hedonic fluency model suggests that when visual stimuli is easily processed the cognitive fluency implicitly elicits mild positive affect (Winkielman, Schwarz, Fazendeiro, & Reber, 2003). As a result, this pleasant feeling is associated with the target stimulus, which positively influences the individual's evaluation of that stimulus (Winkielman, et al., 2003). Research offers evidence that higher processing fluency improves consumer evaluative judgments (Reber, Schwarz & Winkielman, 2004), preferences (Winkielman & Cacioppo, 2001), choices (Novemsky, et al,, 2007), evaluations of attractiveness (Winkielman, et al., 2003), and brand evaluations (Lee & Labroo, 2004). To examine the relationship between fluency and cognitive evaluations, researchers frequently modify visual features of a target stimulus to examine the influence that specific visual variables have on participant responses, such as the typicality of a product (Landwehr et al, 2011). Landwehr et al. (2011) explored how the typicality of various car models influences their sales and found that processing fluency was the underlying mediating mechanism that affected car sales annually.

Researchers, such as Landwehr et al. (2011) and Weidel and Pieters (2008), use reaction times to verify categorization membership and findings suggest that reaction times are positively related to the prototypicality of a visual stimulus. Studies examining the designs of marketing material stimuli (Weidel & Pieters, 2008) have found that the longer it takes an individual to react to a target stimuli design, the more accurately the design is categorized relative to attributes of other products in established schemas (Rosch, Simpson, & Miller, 1976). Reaction times have been used to verify category membership as a measure of cognitive information processing

(Blijlevens, Carbon, Mugge, & Schoormans, 2012) and are also used in the current study to measure of the fluency with eye tracking.

Therefore, more time (measured by reaction time in seconds) spent looking at the vehicle will indicate lower fluency, while less time will indicate high fluency. As a result, longer times might result in lower aesthetic liking because they were more difficult to process, while shorter times can result in high aesthetic liking because they were fluently processed.

Hypothesis 3a.

There is a positive relationship between Processing Fluency and Consumer Evaluation of Aesthetic Liking.

Hypothesis 3b.

There is a positive relationship between Processing Fluency and Car Sales

Hypothesis 4: Examining entropy and consumer preference

Consumer behavior research has suggested that visual search is not random, but is instead guided by the saliency of objects (e.g., products), their features, and context (Kahn, 2017). The salient features in vehicle exterior design are influenced by a blend of factors that are driven by consumer goals and the visual features of stimulus itself (Hutchinson, Lu & Weingarten, 2017). Stimulus-driven variations, such as altering the prominent product features that tend to grab consumer attention, are invaluable to a product's marketing strategy (Kahn, 2017), and have been found to influence consumer preference (Chandon & Wansink, 2007). Additionally, research has revealed that merely paying attention to specific products within visual stimuli has the ability to influence consumer purchases (Janiszewski, 1998). The attention captured by stimulus-driven factors is only the initial step, as the crucial element of evaluating visual stimuli is the processing fluency that it elicits. Namely, once consumers target their attention to a product, processing fluency helps them make sense of it (Kahn, 2017). The visual variables of a product, such as its design elements (i.e., prototypicality), can influence the rate and precision of low-level processes (Schwarz, 2015), making it easier for consumers to process and evaluate the product.

One contribution this study offers is finding out how consumer attention shifts when presented with unexpected changes in a product's design, and how this shift in attention influences the consumer evaluation of that product. Therefore, this study examines whether or not any particular regions on the vehicle draws attention based on salient adjustments to the exterior design of EVs, such as those that no longer have the grille on the front. New EV models without a grill may produce a novelty effect; consumers might look at the area in anticipation of the grille or turn attention away. Where that attention is directed next on the new EV models from an entropy standpoint is where the value may lie, and would be of interest to marketing researchers and industry stakeholders. Specifically, the examine the grille is examined as an area of interest (AOI) for vehicle designs that have a grille, and will test another AOI of grille typical locations for EV designs without grilles.

Chitturi, Raghunathan, and Mahajan (2007) explain that altering product form is regarded as a hedonic modification in marketing research, and is frequently applied as a strategy to prompt consumer interest and intrigue. Hekkert (2006) suggests that establishing slight incongruity between sensory messages (e.g., the visual form of a car vs. the tactile feel of driving the car) is an effective strategy for designers who want to enhance interest or expand the attention value of a product. Understanding how consumers process a product after hedonic alterations have been made to it, such as the grille, is pertinent to this examination because changes in product form have been found to result in perceptual incongruity (Meyer-Levy & Tybout, 1989), rather than conceptual incongruity. Conceptual incongruity explicitly communicates the functionality of a product. Perceptual incongruity relies on either the consumer to determine its functionality or the designer to convey it (Noseworthy & Trudel, 2011).

By examining participant responses to salient changes, such as the grille of EV models, practical implications for industry leaders may include identifying which features impact evaluations of aesthetic liking. Furthermore, using measures such as the entropy of an exterior vehicle system and its AOI component effects within a 2D representation can further advance the literature as it examines these relationships with eye tracking on the physical form of vehicles.

This study employs scan path entropy to measure participant reaction via eye tracking. Hooge and Camps (2013) explain the relevance of scan path entropy in marketing research and emphasize the value regarding effective information transfer of advertisements, or other marketing communication tools. Accurate and efficient message transfer from marketing elements to consumers relies on where consumer attention is placed. Specifically, eye tracking research suggests that the order of fixations is central to the process of effective message transfer for consumers to understand the story conveyed from visual stimuli.

Hooge and Camps (2013), suggest that the methods and measurements proposed in their study—scan path histograms, scan path entropy and arrow plots—can potentially reveal the information needed to further the understanding of attention placement with eye tracking technology. This research examines where attention is placed, and for how long, and the ordering of areas in which attention is captured. As noted earlier, effective information transfer will be measured by scan path entropy. Hypothesis 1 predicted that car models with effective information transfer will have prominent features or cues that allow participants to accurately categorize the vehicle as electric, and will result in low entropy. Vehicles with few features or cues, will impede information transfer and disorient participants during the visual search process and result in erratic scan path patterns with high entropy.

Hypothesis 4a.

There is a negative relationship between Scan Path Entropy (Total Dwell Time) and Consumer Evaluation of Aesthetic Liking, where low entropy (effective information transfer) will lead to more positive evaluations.

Hypothesis 4b.

There is a negative relationship between Scan Path Entropy (Shannon Entropy) and Annual Vehicle Sales, where low entropy (effective information transfer) will lead to more sales.

Hypothesis 4c.

There is a negative relationship between Scan Path Entropy (T_{50}) and Annual Vehicle Sales, where low entropy (effective information transfer) will lead to more sales.

CHAPTER III

METHODOLOGY

Data Collection

Data collection involved human subjects; as required, Institutional Research Board (IRB) approval was obtained at the beginning of March 2019. Several iterations of pilot study tests were conducted throughout the month of March to prepare for the actual data collection in April. Data from the eye tracking experiments and surveys was collected in April 2019.

Participants.

Intentional convenience sampling strategy was used to recruit a desired representation of relevant subgroups within the sample. Participants recruited for this study included student and faculty members at Oklahoma State University. A total of 111 subjects (n = 111) participated in this study. Participants in the sample were 47.75 percent females and 52.25 percent males, ranging in age from 18 to 58 years (M = 23.25 years, SD = 7.36 years). Participants were recruited via email, in person, and from two classes: Spears School of Business Introduction to Entrepreneurship (EEE 2023) and College of Human Sciences Design Theory & Processes for Design, Housing and Merchandising (DHM 1003). Students recruited from these two courses were offered extra credit; other participants volunteered with no compensation. The only requirement for participation was being a past or current consumer of automobiles. Participants were asked to briefly describe their current vision, and all had normal or corrected-to-normal vision.

Subgroups in this study used Census defined categories of gender, age, and ethnicity. Once participants were classified into subgroups, the appropriate percentage from each subgroup was selected. This allowed the researcher to compare the behavior of participants from these subgroups, and ensure that a representative sample reflected the target population. The percentage of desired participants in each subgroups was based on the 2017 Census population demographics (U.S. Census, 2017). Table 1 provides the 2013-2017 demographic data from the U.S. Census demographic estimates from the American Community Survey report, which was the basis for recruiting participants.

Table 1
2013-2017 Census Demographic Estimates.

Gender	2013-2017 Estimates
Male	48.70%
Female	51.30%
Age	
18 to 19 years	1.65%
20 to 24 years	7.00%
25 to 34 years	13.70%
35 to 44 years	12.70%
Ethnicity	
White	61.50%
Black or African American	12.30%
Asian	5.30%
Hispanic or Latino	17.60%
Other	3.30%

Participants were asked to complete a 55-question survey. The survey included the following control variables: age, gender, education level, current car ownership, past automobile purchase behavior, and knowledge level of electric vehicles. As expected, when asked how much knowledge participants had about electric vehicles (1 = Little to no knowledge, 7 = A great deal of knowledge), the majority reported that they had a low level of knowledge about electric vehicles (M = 3.10, SD = 1.50) The average participant age was 23 years (M = 23.25 years, SD = 7.36 years). If predicted forecasts of EV manufacturing are confirmed, this age strata will comprise of the future mass market for electric vehicles. In order for EV manufacturers to maximize market penetration and lower costs through mass production, companies should consider the interests of this population.

Stimuli.

Nine automobiles were selected and categorized by the type of fuel used, creating three car market classifications: electric vehicles (EV), gas vehicles (GV) and hybrid electric-gas vehicles (HEV). Figure 1 below lists the nine vehicles examined with the actual image stimuli used in the eye tracking experiment for both studies. These car models were selected based on their market share in each respective category, and differed in their perceived performance based on prior research (Jindal, Sarangee, Echambadi & Lee, 2016).

Images were edited through Adobe Photoshop to strip coloring so that they each reflected the same coloring treatment (i.e., consistent levels of black and white), controlling for color bias and preferences. The logos were also removed from the grilles and hoods to control for branding effects, such as brand recognition and preference, so that evaluations would be made based on the vehicle's design.

Figure 1. *Vehicle models used as visual stimuli in eye tracking experiment.*

Experiment procedure.

Participants were given the consent form at the beginning of the procedure. The stimuli were initially presented in random order on a 17-inch laptop with a mounted Tobii X2-30 Compact eye tracker (Tobii Technology, Stockholm, Sweden) with a 1,280 x 1,024-pixel resolution. Participants were asked to sit a distance of approximately 65 centimeters from the screen and to move as little as possible. The researcher assisted participants through the 5-point eye calibration process of Tobii Studio Professional Lab Version 1.73 (Tobii, 2016), to ensure that the hardware and software was properly tracking each participant. The calibration procedure required participants to follow and fixate on the small black dot in the middle of a red circle that moved across the screen randomly five times. Participants' eye movements were recorded at 60 Hz, using the remote eye tracker mounted on the screen on which the car image stimuli were presented. The duration of each trial depended on the time that each participant took to evaluate the nine initial stimuli and respond to the Qualtrics survey items (M = 9.45 minutes).

After calibration, participants were instructed to click "start experiment" when ready and activate the Tobii Pro Studio system's eye tracking data collection. Eye tracking data was collected on every slide presented, including the initial introduction slide, which provided information about the task for each of the subsequent nine image slides in the experiment. The instructions communicated the following: "Please look at each object in the subsequent images entirely. You will have as much time as you need to process each photo. When you feel as though you've processed the image entirely and are ready to evaluate it, please press the spacebar to continue." See Appendix A for sample slide of introduction. Participants were not informed of the number of objects included in the experiment before they proceeded. The recording time of each car image slide was intentionally open ended in order to capture the fluency variable measurement for each participant.

After looking at the nine vehicle images in the Tobii system (Tobii, 2016), participants were asked to complete an online survey and were directed to the online Qualtrics survey. Participants were asked to questions related to age, education, past car purchasing behavior, current car fuel type, and level of electric vehicle knowledge (Moons & De Pelsmacker, 2012). After completing demographic questions, participants were asked questions about the nine vehicles previously viewed. Participants were presented the same vehicles observed in the Tobii program, in randomized order. The questionnaire included four validated scale items, which measured:

1) Evaluation of Aesthetic Liking (DV)

2) Perceived Prototypicality (IV) – 3 scale items (typicality, novelty, product category fit)

The evaluation of aesthetic liking measure asked participants to answer the following question on a 7-point Likert scale: “How much do you like the car’s design?” (Landwehr, Wentzel & Herrmann, 2013). The perceived prototypicality measure asked participants to respond to three questions on a 7-point Likert scale: “How unique is this car?”, “How well does this car model match your expectations for cars in general?”, and “How likely is it that this car is electric?” (Campbell & Goodstein, 2001). After the survey items were completed for all nine car models in Qualtrics, the exit slide asked the participant to press the Escape button (ESC) to conclude the survey and eye tracking collection.

External data collected.

Data for car sales was acquired for each vehicle (*n* = 9) from Automotive News (Jindal, Sarangee, Echambadi & Lee, 2016). Table 3 and 4 list descriptive statistics for variables examined, including the 2018 car sales for each vehicle.

Measures

Study 1: Participant-level measures.

Prototypicality.

Accurately evaluating the typicality of a product design is an essential part in predicting consumers' responses to a design (Mayer & Landwehr, 2017). Additionally, research has suggested that explicitly asking participants to self-report their subjective typicality experience can result in a biased measure because their response to this question can influence their aesthetic evaluation of the product (Mayer & Landwehr, 2017).

To measure subjective prototypicality, the Perceived Typicality scale developed by Campbell and Goodstein (2001) was used. In addition to the aesthetic liking scale item, participants were asked to respond to the following statements on a 7-point Likert scale: "How novel is this product?", "How well does this car model match your expectations for cars in general?", and "How likely is it that this car is electric?" (Campbell & Goodstein, 2001).

Fluency.

Fluency was measured by a participant's total response time participants looked at each vehicle image slide during the experiment (Landwehr et al., 2011), which has frequently been used as a measure for fluency in design and marketing research (Holmqvist et al., 2011).

Design and marketing researchers have used response time to assess the attractiveness of a particular stimulus as an appropriate objective measure of intuitively affective reactions elicited by the fluency of that stimulus (Winkielman et al., 2006; Landwehr et al., 2011; Labroo & Lee, 2006). In their attempt to develop and validate an objective measure of fluency, Landwehr, Labroo and Herrmann (2011) found participant reaction times measuring design fluency corresponded with the Euclidean prototypicality scores ($r = 0.43$, $p = 0.03$), which is the same method employed to obtain the objective prototypicality scores in this study. To further test against preexisting biases and ensure that response time captured fluent processing of the "most basic visual memory traces of each design," they created 30 dot patterns from various vehicle models and the averaged morph car. Participants ($n = 61$) then evaluated the visual fluency of the dot patterns of the vehicles on three fluency-related items ("Constructing a mental image of this car …": 1 = feels difficult, is exhausting, takes a long time; 7 = feels easy, is relaxing, happens instantly; see Labroo & Lee, 2006).

Through their analysis, these researchers found that the objective fluency measure (response times) for images of real cars correlated with participant fluency responses of the car dot patterns ($r = 0.38$, $p = 0.044$) (Landwehr et al., 2011). This suggests that response time includes the basic gut-level reaction to fundamental memory traces of each design. Furthermore, Landwehr, Labroo and Herrmann (2011) found that participants rated the averaged morph dot pattern as the most easy to process (i.e., most fluent) of all the other car dot patterns evaluated. Given this robust validation in a study that includes similar variables, constructs and measurements, this study will operationalize the fluency variable by measuring the average reaction times across participants.

Total Dwell Time.

To examine which vehicle features were used to process and evaluate a vehicle image, the scan paths of each participant was captured by total dwell time during the eye tracking experiment. The total dwell time allows us to gather the duration and number of fixations, saccades and transitions and for each AOI in the image, as well as the transition between AOIs. A dwell is defined as a single visit in an AOI, from entry to exit (Holmqvist et al., 2011). Dwell time has been used as a measure of interest, informativeness, and uncertainty when individuals are tasked with making a conscious choice. Dwell can be measured only when there has been one or more fixations within a specific AOI. Dwell time refers to the entire time spent looking at an area, which includes the total number of individual fixations and their durations, as well as other quick eye movements such as transitions and saccades.

Fixations are often referred to as measures of attention (Bojko, 2015). The number of fixations in an AOI indicates interest, while fixation duration is related to processing. Fixation durations typically range from less than 100 milliseconds to half a second (Bojko, 2015), and have been found to average between 280-330 milliseconds during scene viewing (Bojko, 2015). Longer fixations suggest deeper processing and more information extraction (Bojko, 2015). A transition, also referred to ask a gaze shift, is the eye movement from one AOI to another (Holmqvist et al., 2011). Although similar to saccades, transitions are usually bigger units of measurements because they move from one AOI to the next by fixations in areas outside of the AOIs (Holmqvist et al., 2011). These are also calculated and included in the total dwell time eye tracking measurement used for the scan path entropy variable of this study.

Consumer evaluations of aesthetic liking.

The aesthetic liking of each car model was measured on a 7-point Likert scale (1 = I don't like it, 7 = I like it very much) with a single item, which asked: "How much do you like this car?" (Landwehr, Wentzel & Herrmann, 2013).

Bergkvist and Rossiter (2007) suggest that a single-item measure is sufficient when "(1) the object of the construct is 'concrete singular,' meaning that it consists of one object that is easily and uniformly imagined, and (2) the attribute of the construct is 'concrete,' again meaning that it is easily and uniformly imagined." (p. 176). In the current study, the objects are concretely singular (i.e., front face of car design) and the attribute is concrete as well (i.e., aesthetic liking). Consistent with this contention, several studies on responses to product design have commonly used single-item measures (Hoegg, Alba, & Dahl, 2010; Orth & Malkewitz 2012; Veryzer & Hutchinson, 1998).

Control variables.

To control for variation from exogenous factors, four control variables were also included. The first variable asked whether the respondent currently owned a car that could be used on a daily basis, measured by a yes or no response. The second question asked whether the respondent had any previous experience with electric vehicles, measured on a 7-point Likert scale (1 = No experience at all, 7 = A lot of experience). Three demographic control variables were also included: age, gender, and education level. All control variables are presented in Appendix D.

Study 2: Car-level measures.

Prototypicality.

The objective measure of each vehicle model's design typicality was measured by comparing each car model to the central average exterior proportions (typicality) of all the car models tested (Stanton, Townsend & Kang, 2016). This approach, referred to as manually coded feature point measure (Mayer & Landwehr, 2018), has been applied in several studies examining the typicality of car designs (Landwehr et al., 2011; 2013; Liu et al., 2017). The method requires pre-defining the feature points of an automobile (e.g., vertex of headlights) so these points are set for each vehicle image tested in the experiment. Subsequently, an average morph of all the car models is produced, based on the mean position of the feature points (Mayer & Landwehr, 2018). Details of exactly how this was calculated are discussed in the analysis section below.

Fluency.

The objective fluency variable for Study 2 was obtained by calculating the average time it took all participants to evaluate one vehicle image. Each vehicle tested therefore had one fluency response rate score based on this average from the eye tracking experiment.

Temporal measure: T_{50}.

The temporal measure used in this study is T_{50} (Hooge & Camps, 2013; Montfoort, Frens, Hooge, Lagers-van Haselen & van der Geest, 2007), which measures the attention drawing power of the AOIs in each of the twelve vehicle images tested during the eye tracking experiment. To achieve this, both the number of first AOI hits, as well as the speed at which the eye was attracted to the AOI (Hooge & Camps, 2013) were measured. This method takes into consideration that fixations are not always made within particular AOIs identified by the researcher (Montfoort et al., 2007). The temporal component of visual scanning is just as important to scan path entropy as the spatial component (Hooge & Camps, 2013). Even if different observers follow similar scan paths, their behavior may differ a lot because some people might process stimuli either with longer fixations or at a higher saccade rate.

Several eye tracking studies have attempted to assess the attention attraction power of an AOI by calculating the average time to first AOI hit (Hooge & Erkelens, 1996; Hooge et al., 2007), but this calculation is rather vague. Average time to first fixation on an AOI does not offer concrete evidence that the AOI actually influenced the participant's evaluation, and requires more explanation as to why the eye was first attracted to that particular AOI. To prevent ambiguity in this variable's measurement, the $T_{0.5}$ measure was used (Montfoort et al., 2007). Rather than using averaged reaction time (RT), Montfoort et al. (2017) applied $T_{0.5}$ to compare the RT generated by two groups. In this study, $T_{0.5}$ is referred to as T_{50} (Hooge & Camps, 2013), and use T_{50} to calculate and compare the saccadic reaction times to AOIs between all participants. Rather than simply calculating the average reaction time, $T_{0.5}$ allows researchers to actually compare the reaction times generated within multiple groups.

A single fixation score was generated for every AOIs within a vehicle (7 total AOIs for each vehicle), as well as an averaged T_{50} score across all AOIs for each of the nine vehicles (i.e., a T_{50} score for the entire vehicle). Detailed descriptions of how this composite metric was calculated are discussed in the subsequent analysis and results sections.

Spatial measure: Scan path entropy.

Entropy, originally defined by Shannon (1948), is a measure that calculates the uncertainty in a random variable. In this study, Shannon Entropy is used to measure the level of uncertainty within a vehicle's design by calculating the saccadic eye transitions of participants when evaluating the vehicle. These transitions are calculated by observing the scan paths, also known as a transition matrix, created by participants for each vehicle stimuli. Goldberg and Kotval (1999) define transition matrix density as the number of non-zero entries in the transition matrix divided by the total number of cells. From this calculation (see Figure 8 for equation), matrices with high transition density indicate that visual stimuli elicited random search, while a matrix with low transition density reveals that a visual stimulus effectively guided and directed search (Goldberg & Kotval, 1999).

Transition matrices are referred to as scan paths in this examination, and the transition density is described as scan path entropy. Scan path entropy measures the amount of uncertainty during information search and indicates the attention guiding ability of an image (Shic, Chawarska, & Scassellati, 2008; Jordan & Slater, 2009). Therefore, low scan path entropy (low transition density) indicates effective gaze guidance, while high scan path entropy (high transition density) indicates ineffective search. The purpose of scan path entropy is to compare the similarity between two or more scan paths so that researchers can examine the effective gaze guidance of a visual stimuli (Hooge & Camps, 2013).

Car sales.

The dependent variable is the total annual vehicle sales from 2018. The 2018 sales figures were obtained from Automotive News, which has been a key source of news and data since 1925 for automotive industry executives, vehicle manufacturers, and marketing researchers (Jindal et al., 2016).

CHAPTER IV

RESULTS & ANALYSES

Analysis

Data collection took place for about two weeks and concluded in late April, 2019. Once the desired sample size was acquired, the raw eye tracking data was exported from Tobii Studio and Qualtrics and into STATA/SE Mac version 15.1 for analysis. The proposed measures for variables are examine interactions from two perspectives: participants and cars. The composite metrics, such as entropy and T_{50}, provide information about each car, rather than each participant. The survey and eye tracking measures, on the other hand, provide information about the participants. To avoid the issue of nested data, the conceptual model was adapted for two separate sets of variable measures and analyses in two different studies. The data for both studies were collected during the same eye tracking experiments, but then analyzed separately with different measures. See Figures 2 and 3 for illustrations of the different hypothesized models applied in the separate studies.

Composite metrics, T_{50} and scan path entropy, for Study 2 were then calculated from the eye tracking data so that variables were appropriately operationalized and included in corresponding analyses. Details of these calculations are described individually in the sections below. The finalized data was then exported into STATA/SE Mac version 15.1 and then analyzed for both Study 1 and Study 2. The sections below describe the variable relationships that each study examined and how the different models were analyzed.

Table 2

Summary of Analyzed Variables for Study 1 & 2

STUDY 1 (*n* = 111)					
Variable	N	Mean	Std. Dev	Min	Max
Aesthetic Evaluation	999	4.28	1.82	1	7
Total Dwell Time (s)	999	7.59	5.08	0.42	34.67
Prototypicality	999	4.50	1.61	1	7
Fluency (s)	999	10.41	6.98	0.532	41.17
Grille Dwell Time (s)	942	2.11	1.65	0.05	11.14
Bumper Dwell Time (s)	823	2.65	2.42	0.02	14.74
Hood Dwell Time (s)	707	1.15	1.07	0.05	12.47
HL Dwell Time (s)	914	1.89	1.69	0.02	12.93
HR Dwell Time (s)	684	0.98	0.78	0.05	5.48
ML Dwell Time (s)	189	0.52	0.38	0	2.22
MR Dwell Time (s)	199	0.54	0.36	0.17	2.55

STUDY 2 (*n* = 9)					
Variable	N	Mean	St. Dev	Min	Max
Fluency (s)	9	10.41	0.46	9.66	11.20
Prototypicality Score	9	0.00	1	-1.30	2.59
Sales ($)	9	47404.78	40117.25	4479.00	138000.00
T_{50}	9	1.90	0.43	1.33	2.87
Scan Path Entropy	9	0.05	0.00	0.04	0.053

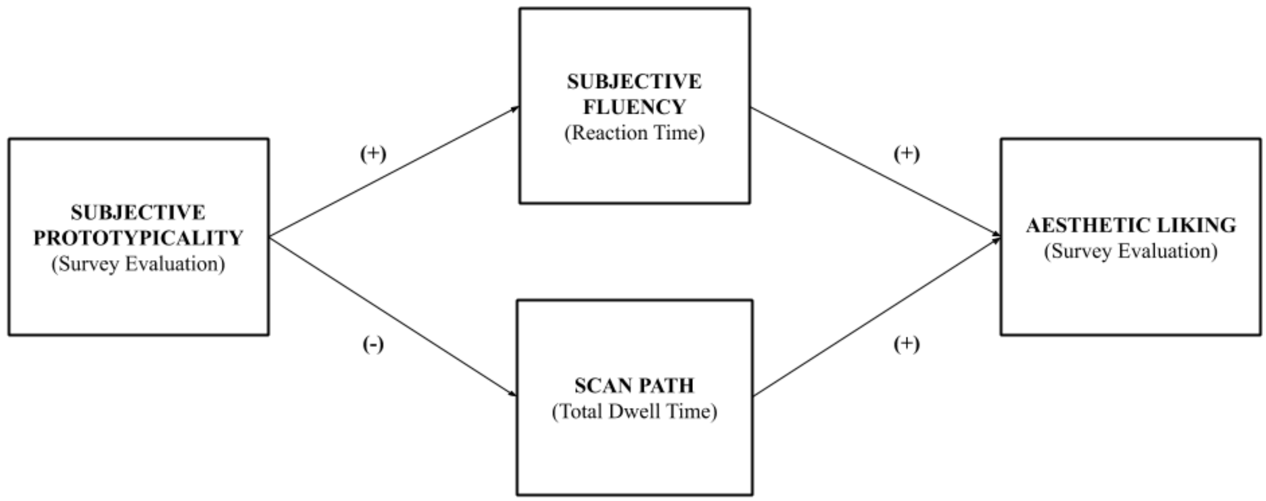
Study 1: Participant-level analysis.

Multiple linear regressions were run to test the relationships between variables in Study 1's conceptual model with a sandwich variance estimator because the residuals in the regression model were predicted to have non-constant residual variance. The sandwich estimator regressions, which adjusted the standard error for the number of participants examined (n = 111) per car (N = 9), were executed through STATA to analyze each hypothesis and the overall model. Below is a brief summary of the Study 1's analysis.

Study 1 analysis overview.

- Model description: Includes subjective survey measures and eye tracking measures for each variable to analyze participant responses
- Sample: 111 participants
- Measures:
    - Prototypicality (IV): Subjective typicality scale asked after each vehicle model image in eye tracking experiment (Campbell & Goodstein, 2001)
    - Fluency (IV): Time to evaluate car image
    - Entropy (IV): Total Dwell Time (across all AOIs)
    - Consumer Evaluation (DV): Consumer Evaluation of Aesthetic Liking scale asked after each vehicle model image in eye tracking experiment (Landwehr, Wentzel & Herrmann, 2013)
- Analysis: Linear regression, using sandwich estimator in STATA

Figure 2. *Study 1 Conceptual Model*



Study 2: Car-level analysis.

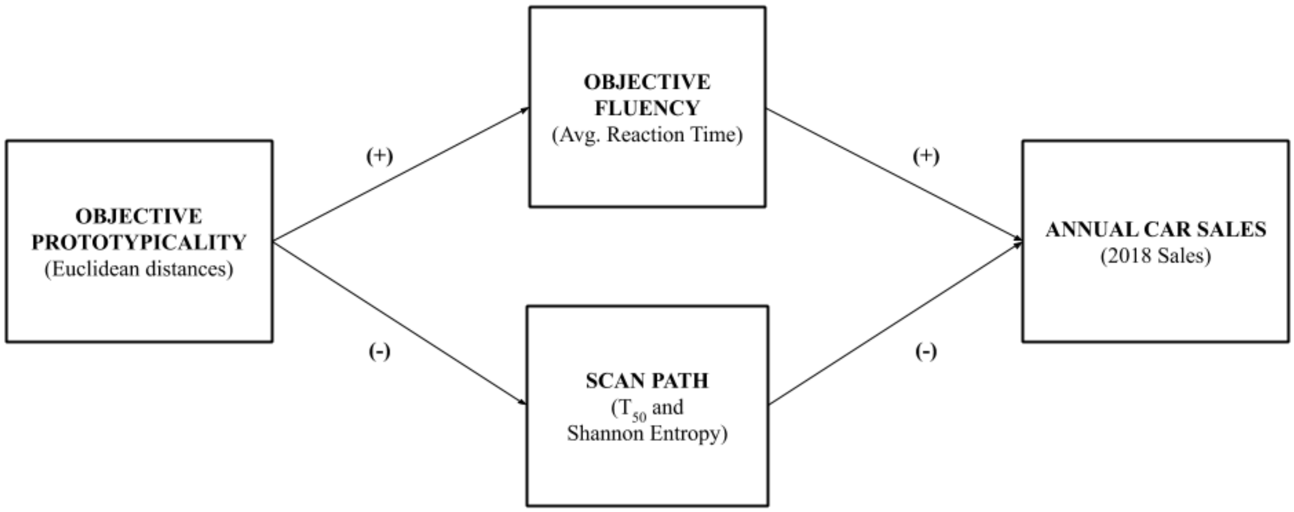
Study 2 employs bootstrapping methodology to analyze hypothesized variable relationships. Bootstrapping is a resampling method that uses an estimator based on a subpopulation of responses taken from the whole population, and is commonly used when dealing with a small sample size. This study examines only nine vehicles, making bootstrapping an appropriate method for analysis. Furthermore, few researchers have actually used the measurements T_{50} and scan path entropy together to analyze the impact they have on consumer product evaluations with eye tracking. To the researcher's knowledge, this study is the first to use both measures in an eye tracking experiment as statistical constructs to predict consumer aesthetic evaluation of a physical product.

Hooge and Camps (2013) suggest that researchers using these measures for statistical analysis should employ bootstrapping methods (Efron, 1979), in order to eliminate doubt about "the sensitivity of T_{50} or scan path entropy in a situation where two visual stimuli produce almost similar values" (Hooge & Camps, 2013, pp. 9). Due to the relative feature similarities of the nine products examined in this study, the difference of these measures between vehicle stimuli might not be enough to warrant statistical analysis. Therefore, considering the small sample size analyzed Study 2 (n = 9) and the sensitivity of measures used to operationalize two of the variables in the model, bootstrap sampling of 5,000 repetitions was used to acquire a more robust estimation for the model's standard error outcomes (Hooge & Camps, 2013). Below is a brief overview of Study 2.

Study 2 analysis overview.

- Model description: Includes objective measures for each variable to analyze design of car models relative to actual sales
- Sample: 9 vehicle models
- Variables & Measures:
    - *Prototypicality (IV):* Average morph score (i.e., typicality score) for each vehicle model tested in Study 1
    - *Fluency (IV):* Average rate to evaluate vehicle image (average time from all participants for each vehicle tested in Study 1)
    - *Entropy (IV):* Average T_{50} score & Shannon entropy score for each vehicle (across all AOIs)
    - *Car Sales (DV):* Total vehicle sales from 2018 (Automotive News, 2019)
- Analysis: Bootstrap (5,000 reps) of multiple linear regressions in STATA

Figure 3. *Study 2 Conceptual Model.*



Calculating prototypicality for Study 2.

Following Landwehr, Labroo and Herrmann's (2011) study, the coordinates (x, y) of 50 feature points for each car model were identified to create an average morph (e.g., headlights, grille, side mirrors, windshield, see Figure 4 for morph example and feature points included from Landwehr et al., 2011). Finally, an objective typicality score was calculated by first summing the Euclidean distances of the 50 feature points of the tested car models and the 50 feature points of the average (prototypical) car morph, and then inverted the overall score (i.e., multiplied by –1). The overall score was inverted because distances from the prototypical morph indicate atypicality (Mayer & Landwehr, 2018).

Figure 4. *Example of averaged morph.*

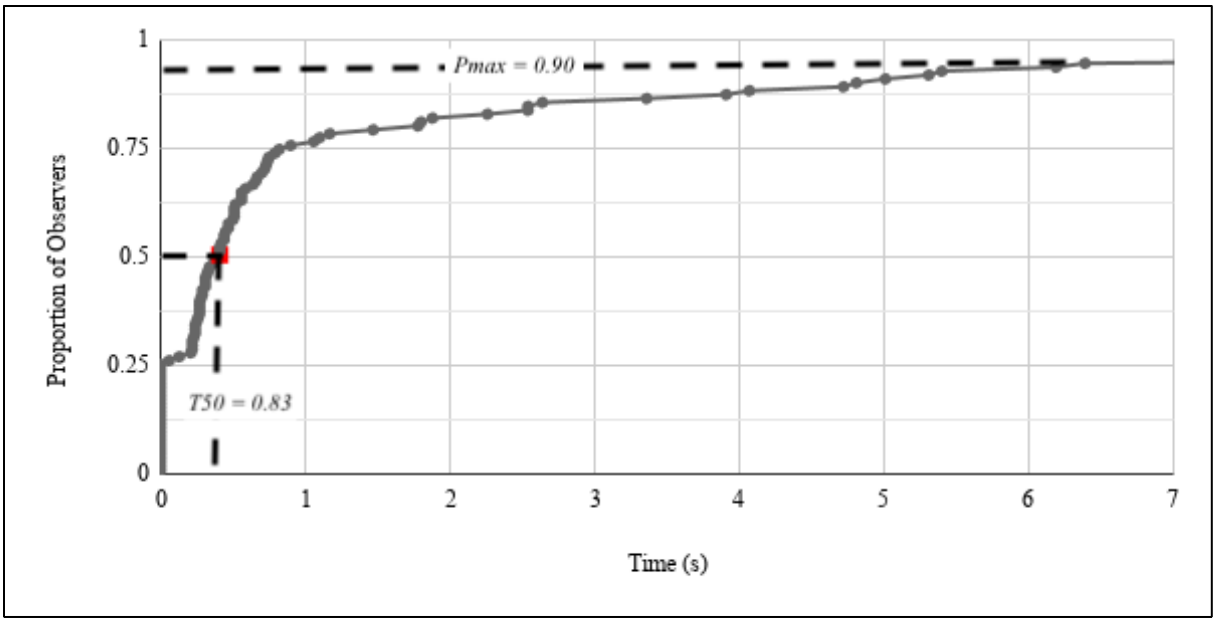
To confirm that this objective measure depicted the proposed construct, the validation method used by Landwehr, Labroo and Herrmann (2011) was replicated. The subjective prototypicality survey response results for each of the nine vehicles from Study 1 (N = 999; n = 111; M = 23.5; SD = 7.36; 52.25% male; 47.75% female) were compared with the z-transformed Euclidean prototypicality scores from each car described above. As expected, the objective prototypicality scores significantly correlated with subjective prototypicality (r = 0.19, p = 0.000)

Calculating T_{50} for Study 2.

To estimate the attention drawing power of the design features for each vehicle, T_{50} of each feature was determined for nine vehicles. The first step in calculating the T_{50} metric for each vehicle was to the average time to first fixation measurement for every AOI and vehicle, which was captured by the Tobii Studio (Tobii, 2016). The time to first fixation for each participant were initially sorted in ascending order from the shortest amount of time to the longest amount of time, which provided a distribution of the first fixations over time for each vehicle's AOI. Illustrations were then used to analyze and determine the fixation behavior of each AOI during participant observations. Figure 5 illustrates an example of the cumulative proportion of participants first fixating a target AOI as a function of time.

Figure 5. *T_{50} Distribution of 2015 Tesla Model S.*

Cumulative proportion of observers fixating the grille AOI of the 2015 Tesla Model S as function of time. 50% of the observers fixated the target AOI in 0.83 s. The maximum proportion of observers fixating the target was 0.90, or 90%. This number is referred to as the fixation score or P_{max}.



Calculating scan path entropy for Study 2.

While T_{50} can reveal to us which feature areas have the most attention drawing power, and the P_{max} or fixation score captures the accuracy of visual search in those areas, the scan path entropy metric provides insight into how effective a design guided participant scan paths. The scan paths of every participant (n = 111) were qualitatively compared for each vehicle, and an entropy score was generated for each of the seven AOIs as well as an average entropy score for each of the nine vehicles overall. In this analysis, designs were considered to have effective gaze guidance and low entropy if less varied scan paths were observed, while those that elicited more diverse scan paths were deemed to have ineffective gaze guidance and higher entropy (Hooge & Camps, 2013).

To find a single entropy score for each AOI and vehicle overall, AOIs were initially identified and then drawn on each vehicle through Tobii Studio. The seven AOIs selected for each vehicle in this examination included: 1) Grille (G), 2) Hood (H), 3) Bumper (B), 4) Headlight Left (HL), 5) Headlight Right (HR), 6) Mirror Left (ML), and 7) Mirror Right (MR). Figure 6 shows the AOIs drawn in Tobii Studio for each vehicle, prior to collecting eye tracking data, as the basis for this analysis and calculation.

The first step in examining gaze guidance effectiveness was to qualitatively observe and record the scan paths of the participant sample (n = 111) by the arrangement of initial fixation hits made in the seven AOIs across each vehicle examined (N = 999). Scan paths were constructed by documenting the sequence of first fixation hits in each AOI, coding each successive AOI hit in a single recording 1 thru 7 by the order it was observed. Only the first fixation for each AOI logged during this process, so any subsequent fixation hits on an AOI were not included in the coding. Also, if an AOI did not elicit a fixation hit, it was not coded in the scan path series so some recordings had less than seven observations in the string of AOI.

Figure 6. *Car Model AOIs.*

Electric | Combustion | Hybrid

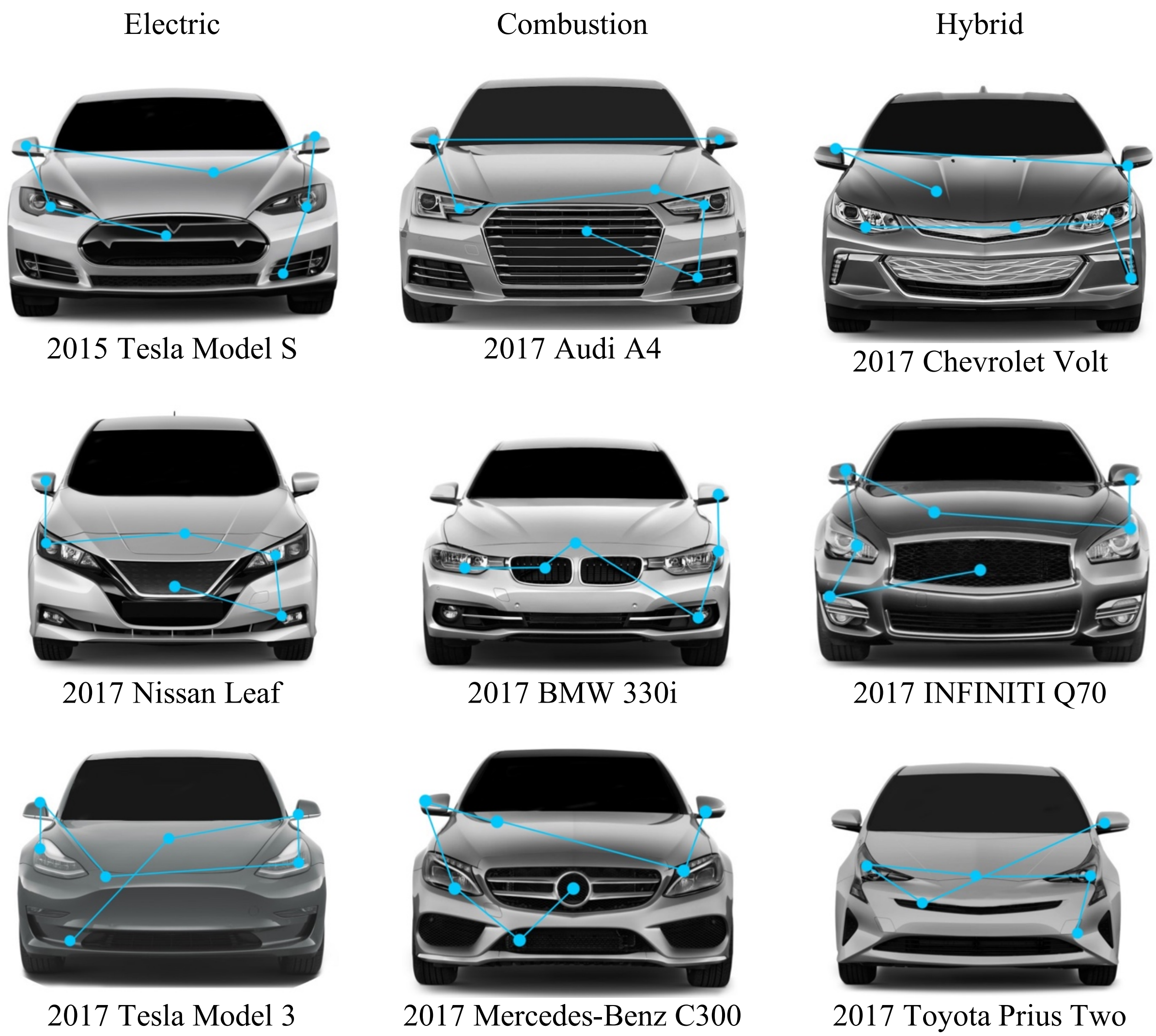
2015 Tesla Model S | 2017 Audi A4 | 2017 Chevrolet Volt

2017 Nissan Leaf | 2017 BMW 330i | 2017 INFINITI Q70

2017 Tesla Model 3 | 2017 Mercedes-Benz C300 | 2017 Toyota Prius Two

Once scan paths were coded from every participant recording (n = 111) for each of the nine vehicles observed (N = 999), the number of fixations per AOI were sorted by the order they were observed and then summed. Figure 7 provides an example of a scan path visualization quantitatively Tobii captured, which was used to qualitatively order AOI fixation hits for this metric.

Figure 7. *Scan Path Illustrations.*



The size of each AOI was controlled for in the final entropy calculation because an AOI's relative size within a stimulus has been found to bias gaze direction (Holmqvist et al., 2011). Pixels have been used as a reliable measure for the size of digital imagery in eye tracking experiments examining stimuli such as webpages, photos, advertisements, and the UX of various software programs (Landwehr et al., 2013; Landwehr et al., 2011). The pixel count of each AOI and overall vehicle was collected to calculate the relative pixel percentage of each AOI in relation to each vehicle's total size. The AOIs were then equally weighted by their pixel percentage (%) so that the bias effect of size was controlled across all AOIs in the final scan path entropy calculations for each vehicle model.

Finally, once the AOIs were weighted and organized by their ordered fixation sequence, the Shannon entropy formula was used to calculate the scan path entropy of each AOI within a vehicle. Shannon entropy is a measure from information theory that describes the information within a variable in terms of ordering (Hooge & Camps, 2013), as illustrated in Figure 8:

Figure 8. *Shannon Entropy Formula (Shannon, 1948)*

$$\mathrm{H(X)} = -\sum_{i=1}^{n} p\,(x_i)^{\,2}\,log\,p(x_i)$$

H(X) is the entropy in bits and $p\ (x_i)$ is the sum of the probabilities of gaze behavior within specific AOIs, which controls for the pixel size of each stimulus and observational order effects as participants process an image visually. Entropy was calculated for every vehicle's AOIs, as was the total vehicle entropy (see Table 3 for results).

Table 3

Entropy and T_{50} Calculation Results

Car Model	AOI	AOI Entropy		AOI T_{50}		
		Pixels (%)	Entropy	Fixations (N)	P_{max}	T_{50}
	Bumper (B)	34.23%	0.04	90	0.81	3.83
	Grille (G)	21.56%	0.06	108	0.97	0.41
	Hood (H)	34.49%	0.01	77	0.96	0.27
2015 Tesla Model S	Headlight Left (HL)	3.54%	0.05	106	0.69	4.61
	Headlight Right (HR)	3.52%	0.04	76	0.68	4.21
	Mirror Left (ML)	1.32%	0.05	15	0.14	N/A
	Mirror Right (MR)	1.33%	0.12	20	0.18	N/A
	Bumper (B)	43.38%	0.04	98	0.88	2.00
	Grille (G)	11.92%	0.09	102	0.92	0.66
	Hood (H)	34.73%	0.01	60	0.96	0.18
2017 Nissan Leaf	Headlight Left (HL)	3.44%	0.04	107	0.54	10.13
	Headlight Right (HR)	3.45%	0.05	60	0.59	7.09
	Mirror Left (ML)	1.63%	0.06	21	0.19	N/A
	Mirror Right (MR)	1.44%	0.05	18	0.16	N/A
	Bumper (B)	42.90%	0.04	105	0.95	1.98
	Grille (G)	18.28%	0.02	100	0.90	0.83
2017 Tesla Model 3	Hood (H)	28.58%	0.03	76	0.99	0.27
	Headlight Left (HL)	3.75%	0.06	110	0.68	3.46
	Headlight Right (HR)	3.75%	0.05	84	0.76	2.75

	Mirror Left (ML)	1.37%	0.03	17	0.15	N/A
	Mirror Right (MR)	1.37%	0.06	21	0.19	N/A
	Bumper (B)	32.86%	0.04	86	0.77	3.08
	Grille (G)	27.49%	0.04	109	0.98	0.50
	Hood (H)	29.64%	0.01	82	0.91	0.27
2017 Audi A4	Headlight Left (HL)	3.71%	0.06	101	0.74	1.93
	Headlight Right (HR)	3.71%	0.06	85	0.77	3.64
	Mirror Left (ML)	1.30%	0.05	32	0.29	N/A
	Mirror Right (MR)	1.30%	0.07	23	0.21	N/A
	Bumper (B)	41.79%	0.03	90	0.81	3.45
	Grille (G)	12.00%	0.07	103	0.93	0.28
	Hood (H)	33.38%	0.02	71	0.95	0.29
2017 BMW 330i	Headlight Left (HL)	4.72%	0.05	106	0.64	3.92
	Headlight Right (HR)	4.72%	0.06	72	0.65	5.55
	Mirror Left (ML)	1.70%	0.04	19	0.17	N/A
	Mirror Right (MR)	1.69%	0.08	24	0.22	N/A
	Bumper (B)	41.53%	0.03	91	0.82	2.86
	Grille (G)	18.67%	0.08	111	1.00	0.25
	Hood (H)	28.15%	0.01	83	0.89	1.01
2017 Mercedes-Benz C300	Headlight Left (HL)	4.38%	0.06	99	0.75	3.53
	Headlight Right (HR)	4.38%	0.05	77	0.69	4.57
	Mirror Left (ML)	1.45%	0.06	26	0.23	N/A
	Mirror Right (MR)	1.44%	0.05	26	0.23	N/A
2017 Chevrolet Volt	Bumper (B)	47.89%	0.04	100	0.90	1.81

	Grille (G)	7.28%	0.07	96	0.86	0.81
	Hood (H)	34.19%	0.01	75	0.98	0.20
	Headlight Left (HL)	3.69%	0.05	109	0.68	6.49
	Headlight Right (HR)	3.69%	0.04	72	0.65	4.81
	Mirror Left (ML)	1.63%	0.04	15	0.14	N/A
	Mirror Right (MR)	1.64%	0.06	26	0.23	N/A
	Bumper (B)	38.91%	0.04	91	0.82	3.05
	Grille (G)	23.19%	0.03	109	0.98	0.27
	Hood (H)	27.40%	0.02	76	0.90	0.72
2017 Infiniti Q70	Headlight Left (HL)	3.82%	0.05	100	0.68	4.04
	Headlight Right (HR)	3.82%	0.04	77	0.69	4.84
	Mirror Left (ML)	1.43%	0.04	24	0.22	N/A
	Mirror Right (MR)	1.43%	0.07	22	0.20	N/A
	Bumper (B)	32.70%	0.04	72	0.65	6.11
	Grille (G)	29.16%	0.04	104	0.94	0.42
	Hood (H)	26.68%	0.01	78	0.95	0.37
2017 Toyota Prius Two	Headlight Left (HL)	3.80%	0.05	105	0.70	3.93
	Headlight Right (HR)	3.78%	0.05	76	0.68	4.26
	Mirror Left (ML)	1.94%	0.03	20	0.18	N/A
	Mirror Right (MR)	1.94%	0.05	19	0.17	N/A

Results

The following sections describe the results of each hypothesis, as well as the main model for Study 1 and Study 2. Subsequently, findings from the overall eye tracking results using traditional eye movement measures, composite metrics (scan path entropy and T_{50}), and survey responses are discussed.

Study 1: Participant-level results.

In the following section, results of the tested hypothesis and overall model from Study 1 are reviewed. Sandwich estimator regressions (often referred to as the robust covariance matrix estimator) were applied to analyze the participant-level variables and their relationships, where aesthetic evaluation is predicted as a function of the independent design measures (typicality, fluency, and information entropy) and their interaction. Table 4 provides descriptive statistics for the variables analyzed in Study 1.

Table 4
Descriptive Statistics for Study 1

STUDY 1 (*n* = 111)						
					Variation Breakdown	
Variable	M	Min	Max	Total Variation	Within Car	Between Car
Participant	56.00	1.00	111.00	32.04	0.00	32.17
Car	5.00	1.00	9.00	2.58	2.58	0.00
Evaluation	4.28	1.00	7.00	1.82	1.62	0.83
Typicality	4.50	1.00	7.00	1.61	1.28	0.98
Total Dwell Time	7.59	0.42	34.67	5.08	2.52	4.43
Fluency	10.41	0.53	41.17	6.98	3.25	6.21

Hypothesis 1: Typicality → Fluency.

Hypothesis 1 predicted that prototypicality would have a positive effect on the fluency rate (s), which produced the following equation (Figure 9):

Figure 9. *Study 1, Hypothesis 1 Equation*

$$\text{FLUENCY}_i = b_0 + b_1 * \text{TYPICALITY}_i + e_i$$

The sandwich estimator regression revealed that prototypicality was positively related to fluency, although the effect was not significant ($b_1 = 0.35$, *Robust SE* = 0.19, $t = 1.83$, $p = 0.07$). Prototypicality only accounted for 0.63% of the fluency variance, which suggests that this variable has little influence on how much time consumers spend examining a design overall. This is seemingly contradictory to recent literature, which has suggested that typical designs elicit high fluency because they're easier to process; however, the relationship between these variables is almost significant at the 0.05 level ($p = 0.07$). A larger sample size might reveal a more significant effect between these variables, which will be discussed further in the discussion on limitations and suggestions for future research.

Hypothesis 2: Typicality → Entropy (total dwell time).

Hypothesis 2 predicted that prototypicality would have a negative effect on entropy (total dwell time), which produced the following equation (Figure 10):

Figure 10. *Study 1, Hypothesis 2 Equation*

$$\text{ENTROPY}_i = b_0 + b_1 * \text{TYPICALITY}_i + e_i$$

Interestingly, the sandwich estimator linear regression analysis indicated that prototypicality had a significant positive effect on the total dwell time ($b_1 = 0.31$, *Robust SE* = 0.14, $t = 2.27$, $p =$

0.03), rather than the predicted negative effect. Prototypicality only accounted for 0.96% of the total dwell time variance, which suggests that this variable has very little influence on how much time consumers spend looking at various areas of a design. This may have to do with the single eye tracking measurement, total dwell time, used to operationalize the entropy variable, which is typically calculated a composite metric (combining multiple eye tracking measures). The positive relationship between these variables suggests that the more prototypical a vehicle's design was, the more dwell time was needed to extract information from the vehicle.

Hypothesis 3: Fluency → Evaluation of aesthetic liking.

Hypothesis 3 predicted that fluency would have a positive effect on the evaluation of aesthetic liking, which produced the following equation (Figure 11):

Figure 11. *Study 1, Hypothesis 3 Equation*

$$\text{EVALUATION}_i = b_0 + b_1 * \text{FLUENCY}_i + e_i$$

The sandwich estimator linear regression revealed that fluency was positively related to evaluation of aesthetic liking, although the effect was not significant ($b_1 = 0.01$, *Robust SE* = 0.01, $t = 1.24$, $p = 0.22$). Fluency only accounted for 0.20% of the aesthetic liking variance, suggesting that this variable has very little influence of consumers' evaluations.

Hypothesis 4: Entropy → Evaluation of aesthetic liking.

Hypothesis 4 predicted that entropy would have a positive effect on the evaluation of aesthetic liking, which produced the following equation (Figure 12):

Figure 12. *Study 1, Hypothesis 4 Equation*

$$\text{EVALUATION}_i = b_0 + b_1\text{*ENTROPY}_i + \text{e}_i$$

The sandwich estimator regression revealed that entropy was positively related to evaluation of aesthetic liking, although the effect was not significant ($b_1 = 0.02$, *Robust SE* = 0.01, $t = 1.33$, $p = 0.19$). Total dwell time only accounted for 0.20% of aesthetic liking variance, suggesting that this independent variable has very little influence of consumers' evaluation.

Prototypicality → Evaluation of aesthetic liking.

A *post-hoc* analysis was conducted to see if prototypicality had a direct positive effect on the evaluation of aesthetic liking, which produced the following equation (Figure 13):

Figure 13. *Direct Effect of Prototypicality on Aesthetic Liking Equation*

$$\text{EVALUATION}_i = b_0 + b_1\text{*TYPICALITY}_i + \text{e}_i$$

The sandwich estimator linear regression revealed that prototypicality was positively related to evaluation of aesthetic liking, and its effect was significant ($b_1 = 0.86$, *Robust SE* = 0.03, $t = 29.15$, $p = 0.00$). The relationship between these two variables accounted for 57% of the variance among aesthetic evaluation, which suggests that prototypicality is the strongest influencing variable on consumers' evaluation of aesthetic liking. This confirms many of the findings in past research, which have also concluded that prototypical designs are evaluated higher than novel designs. However, these results do not necessarily confirm that this is due to the influence of fluency, which has been suggested to elicit positive affect when examining typical designs that feel familiar.

Study 1: Main model.

Once the individual hypothesis were analyzed, overall model was analyzed through a sandwich estimator regression to test effects each independent variable had on the dependent variable, aesthetic liking. Aesthetic evaluation was predicted from perceived prototypicality (7-point Likert scale item), processing fluency (recording time, s), entropy (total dwell time across all AOIs), and effects of these three factors while controlling for the effect of segment (car fuel type: EV, Gas or Hybrid). For each participant, the model equation had the following form (Figure 14):

Figure 14. *Study 1, Main Model Equation*

$$\text{AESTHETIC LIKING}_i = b_0 + b_1{*}\text{TYPICALITY}_i + b_2{*}\text{FLUENCY}_i + b_3{*}\text{ENTROPY}_i + e_i$$

Prototypicality was positively related to aesthetic liking ($b_1 = 0.86$, *Robust SE* = 0.03, $t = 29.31$, $p = 0.00$), as was fluency, although the effect was not significant ($b_2 = 0.02$, *Robust SE* = 0.01, $t = 1.49$, $p = 0.14$). Interestingly, total dwell time was negatively related to aesthetic liking in the model analysis (the relationship was found to be positive in the linear regression of only the variables total dwell time and aesthetic evaluation), but the effect was not significant ($b_3 = -0.04$, *Robust SE* = 0.02, $t = -1.76$, $p = 0.08$). This model explained over half (57.78%) of the aesthetic evaluation variance.

Study 2: Car-level results.

The following section describes the results of Study 2. The main model is then discussed and its results are analyzed, where 2018 annual car model sales is predicted to be a function of each of the following independent variables: objective prototypicality score, average fluency rate (calculated from participant recording times in Study 1), scan path entropy score, and T_{50} score.

Table 5
Descriptive Statistics for Study 2

STUDY 2 (*n = 9)*						
					Variation Breakdown	
Variable	M	Min	Max	Total Variation	Within Car	Between Car
Car	5.00	1.00	9.00	2.58	0.00	2.74
Participant	56.00	1.00	111.00	32.04	32.04	0.00
Sales	47404.78	4479.00	138000.00	40097.17	0.00	42508.18
Prototypicality Score	0.00	-1.30	2.59	0.99	0.00	1.06
Fluency	10.41	9.66	11.20	0.46	0.00	0.49
Shannon Entropy	0.05	0.04	0.05	0.00	0.00	0.01
T_{50} Score	1.90	1.32	2.87	0.43	0.00	0.46

Hypothesis 1: Typicality → Fluency.

Hypothesis 1 predicted that prototypicality would have a positive effect on fluency, which produced the following equation (Figure 15):

Figure 15. *Study 2, Hypothesis 1 Equation*

$$\text{FLUENCY}_i = b_0 + b_1 \text{*TYPICALITY}_i$$

The bootstrapped regression indicated that prototypicality had a negative effect on fluency (b_1 = -0.20, *Bootstrap SE* = 0.50, z = -0.39, p = 0.70), rather than the predicted positive effect. The negative relationship indicates that the less typical a product is, the higher the fluency rate. This finding confirms several emerging findings from the lay theory in consumer behavior research, which have suggested that novel product designs are preferred by consumers because their unique characteristic prompt deeper processing and attract more attention. Rather than frustrate consumers, lay theory suggests that the lower fluency rate caused by these novelty can actually create a deeper connection between consumers and products because more time is spent evaluating them. The potential implications that this finding might have are discussed in the following chapter.

Hypothesis 2: Typicality → Scan path entropy.

Hypothesis 2B predicted that prototypicality would have a negative effect on scan path entropy and Hypothesis 2C predicted that prototypicality would have a negative effect on T_{50}, which produced the two following equations (Figure 16):

Figure 16. *Study 2, Hypothesis 2B and 2C Equations*

$$\text{H2B: ENTROPY}_i = b_0 + b_1\text{*TYPICALITY}_i$$

$$\text{H2C: T}_{50i} = b_0 + b_1\text{*TYPICALITY}_i$$

The bootstrapped regression indicated that prototypicality had a positive effect on scan path entropy ($b_1 = 0.02$, *Bootstrap SE* = 0.05, $z = 0.36$, $p = 0.72$), rather than the predicted negative effect. Prototypicality accounted for 0.22% of the scan path entropy variance, which suggests that this variable has very little influence on a vehicle's level of entropy. T_{50}, on the other hand, was negatively influenced by prototypicality, as predicted, but the effect was not significant (b_1 = -0.09, *Bootstrap SE* = 0.61, $z = -0.15$, $p = 0.88$). Prototypicality accounted for 0.22% of the T_{50}

variance, which suggests that prototypicality has much more influence on T_{50} than on scan path entropy, and some influence on the attention drawing power a vehicle's design. A high correlation between scan path entropy and T_{50} was predicted and, thus, confirmed.

Hypothesis 3: Fluency → Sales.

Hypothesis 3 predicted that fluency would have a positive effect on sales, which produced the following equation (Figure 17):

Figure 17. *Study 2, Hypothesis 3 Equation*

$$\text{H3: SALES}_i = b_0 + b_1\text{*FLUENCY}_i$$

The bootstrapped regression indicated that prototypicality had a significant negative effect on sales (b_1 = -67659.88, *Bootstrap SE* = 24794.05, z = -2.73, p = 0.01), rather than the predicted positive effect. Fluency accounted for 54.92% of the sales variance, which further emphasizes the significant effect that it might have on a vehicle's sales.

Hypothesis 4: T_{50} → Sales.

Hypothesis 4B predicted that scan path entropy would have a negative effect on sales and Hypothesis 4C, predicted that T_{50} would have a negative effect on sales. These hypotheses produced the following equations (Figure 18):

Figure 18. *Study 2, Hypothesis 4B and 4C Equations*

$$\text{H4B: SALES}_i = b_0 + b_1\text{*ENTROPY}_i$$

$$\text{H4C: SALES}_i = b_0 + b_1\text{*T50}_i$$

The bootstrapped regression indicated that both scan path entropy (b_1 = -3643263, *Bootstrap SE* = 2837279, z = -1.28, p = 0.199) and T_{50} (b_1 = -41407.64, *Bootstrap SE* = 49563.25, z = -0.84, p = 0.40) negatively affected sales, although the effects were not significant. Scan path entropy accounted for 8.69% of the sales variance, while T_{50} accounted for 8.39% of the sales variance. This suggests that although their effects are not quite as significant as predicted, both variables do have some impact on sales overall.

Prototypicality → Car Sales.

As in Study 1, a *post-hoc* analysis was also conducted for Study 2 looking at the direct positive effect that prototypicality might have on car sales, which produced the following equation (Figure 19):

Figure 19. *Direct Effect of Prototypicality on Car Sales Equation*

$$\text{SALES}_i = b_0 + b_1 * \text{TYPICALITY}_i$$

The bootstrapped regression indicated that prototypicality had a positive effect on sales (b_1 = 6202.02, *Bootstrap SE* = 30036.88, z = 0.21, p = 0.84), but the effect was not significant.

Study 2: Main model.

After analyzing each of the individual hypotheses, the overall model for Study 2 was analyzed through a bootstrapped linear regression to test the effects that independent variables had on the dependent variable in the model, car sales. Car sales was predicted from perceived prototypicality (z-score), processing fluency (average recording time across all participants, s), entropy (scan path entropy and T_{50} score), and the effects of these three factors. For each vehicle (n = 9), the model had the following form (Figure 20):

Figure 20. *Study 2, Main Model Equation*

$$SALES_i = b_0 + b_1*TYPICALITY_i + b_2*FLUENCY_i + b_3*ENTROPY_i + b_4*T_{50} + e_i$$

Prototypicality was negatively related to car sales (b_1 = -11737.76, *Bootstrap SE* = 211663.70, z = -0.06, p = 0.956), as was fluency (b_2 = -73849.53, *Bootstrap SE* = 27504.90, z = -0.27, p = 0.78) and T_{50} (b_4 = -35384.30, *Bootstrap SE* = 180472, z = -0.20, p = 0.85), although the effects were not significant. Scan path entropy had a positive effect on car sales (b_3 = 88221.09, *Bootstrap SE* = 2.80E+07, z = 0.00, p = 0.99), but the results were not significant. This model explained over half (56.07%) of the car sales variance.

Eye tracking Results.

Tobii (2016) defines time to first fixation as the time from the start of the stimulus display until the participant fixates on the AOI or AOI group for the first time. Using this metric, the data showed the average amount of time it took for participants to first fixate on an AOI across all vehicles was 0.27 seconds. Participants were able to look at each vehicle for as long as they needed to, which resulted in an average fixation time, across all seven AOIs, of 3.38 seconds. The vehicles that did not have a prominent grille produced an average viewing duration across all AOIs in 3.77 seconds, while the vehicles with a prominent grille produced a viewing time of 3.88 seconds (see Table 6).

Among the AOIs across all vehicles, the hood was fixated on first most frequently (f = 505), followed by the grille (f = 349), and left headlight (f = 222). The left mirror (f = 20) and right mirror ($f = 8$) of each vehicle were least frequently the first fixated element in the vehicle images. The right mirror was most frequently viewed last feature ($f = 58$), followed by the left mirror ($f = 51$) across all of the vehicle images.

Considering four of the nine vehicles were not considered to have a prominent grille, it is interesting to note that the grille was nearly the most frequently fixated element across all vehicle images. This supports the premise theoretically hypothesized earlier that the grille would be considered an important feature used by participants to guide their gaze as they processed each vehicle. Furthermore, the bumper and hood AOIs were significantly larger (pixels) on average than the grille AOI for each vehicle, which further emphasizes the important role the grille AOI plays when individuals are visually processing information from the design of vehicles alone.

Table 6
Fixation Duration and Count of Car Model AOIs

		Total Fixation Duration (seconds)					Total Fixation Count
Car Model	AOI	*f*	M	Max	Min	SD	M
2015 Tesla Model S	Bumper (B)	90	0.42	2.78	0.05	0.26	4.06
	Grille (G)	108	0.42	1.71	0	0.25	6.52
	Hood (H)	106	0.36	2.54	0.03	0.23	5.15
	Headlight Left (HL)	77	0.46	2.14	0.06	0.32	1.54
	Headlight Right (HR)	76	0.42	1.22	0.06	0.2	1.49
	Mirror Left (ML)	15	0.37	0.68	0.18	0.15	0.14
	Mirror Right (MR)	20	0.46	0.93	0.2	0.22	0.21
2017 Nissan Leaf	Bumper (B)	98	0.43	3.66	0.03	0.3	5.74
	Grille (G)	102	0.41	2.76	0.03	0.26	4.04
	Hood (H)	107	0.36	1.61	0.01	0.2	5.96
	Headlight Left (HL)	60	0.46	1.43	0.09	0.25	1.14
	Headlight Right (HR)	65	0.45	3.45	0.05	0.36	1.16
	Mirror Left (ML)	21	0.48	2.22	0.07	0.48	0.19
	Mirror Right (MR)	18	0.41	1.07	0.17	0.21	0.21

2017 Tesla Model 3	Bumper (B)	105	0.39	1.92	0.06	0.23	5.96
	Grille (G)	100	0.35	1.74	0.05	0.19	2.86
	Hood (H)	110	0.35	2.62	0	0.21	5.64
	Headlight Left (HL)	76	0.48	1.88	0.18	0.27	1.32
	Headlight Right (HR)	84	0.45	2.36	0.02	0.29	1.5
	Mirror Left (ML)	17	0.5	1.35	0.18	0.31	0.17
	Mirror Right (MR)	21	0.61	2.55	0.21	0.54	0.19
2017 Audi A4	Bumper (B)	86	0.44	1.99	0.01	0.26	4.94
	Grille (G)	109	0.36	2.73	0.04	0.2	5.48
	Hood (H)	101	0.35	1.93	0.01	0.2	4.67
	Headlight Left (HL)	82	0.45	2.19	0.03	0.3	1.77
	Headlight Right (HR)	85	0.47	2.36	0.04	0.29	1.62
	Mirror Left (ML)	32	0.53	1.12	0.17	0.22	0.37
	Mirror Right (MR)	23	0.48	0.88	0.17	0.22	0.25
2017 BMW 330i	Bumper (B)	90	0.42	3.19	0.03	0.29	5.98
	Grille (G)	103	0.41	2.84	0.02	0.26	4.67
	Hood (H)	106	0.36	1.5	0.02	0.19	5.41
	Headlight Left (HL)	71	0.43	1.48	0.11	0.26	1.5
	Headlight Right (HR)	72	0.45	2	0.11	0.3	1.32

	Mirror Left (ML)	19	0.42	1.75	0.19	0.33	0.21
	Mirror Right (MR)	24	0.39	0.92	0.18	0.2	0.27
2017 Mercedes-Benz C300	Bumper (B)	91	0.41	3.17	0.03	0.27	4.76
	Grille (G)	111	0.42	2.49	0.01	0.27	6.02
	Hood (H)	99	0.37	1.82	0.02	0.23	3.92
	Headlight Left (HL)	83	0.5	2.56	0.17	0.37	1.42
	Headlight Right (HR)	77	0.47	1.66	0.16	0.27	1.5
	Mirror Left (ML)	26	0.41	1.52	0.08	0.32	0.28
	Mirror Right (MR)	26	0.48	2.35	0.16	0.42	0.27
2017 Chevrolet Volt	Bumper (B)	100	0.39	4.31	0.03	0.26	7.01
	Grille (G)	96	0.4	2.69	0.03	0.25	3.02
	Hood (H)	109	0.38	4.06	0.01	0.26	6.03
	Headlight Left (HL)	75	0.44	2.05	0.12	0.26	1.59
	Headlight Right (HR)	72	0.51	2.22	0.09	0.34	1.37
	Mirror Left (ML)	15	0.48	1.23	0.23	0.26	0.16
	Mirror Right (MR)	26	0.49	1.19	0.21	0.28	0.27
2017 Infiniti Q70	Bumper (B)	91	0.45	5.53	0.03	0.36	5.25
	Grille (G)	109	0.41	2.88	0.01	0.27	5.95
	Hood (H)	100	0.35	1.54	0.02	0.18	4.5

	Headlight Left (HL)	76	0.42	1.37	0.13	0.22	1.51
	Headlight Right (HR)	77	0.51	3.35	0.14	0.4	1.4
	Mirror Left (ML)	24	0.37	0.94	0.11	0.19	0.24
	Mirror Right (MR)	22	0.46	1.01	0.19	0.22	0.25
2017 Toyota Prius Two	Bumper (B)	72	0.41	1.62	0.04	0.23	2.93
	Grille (G)	104	0.39	1.59	0.01	0.2	5.87
	Hood (H)	105	0.54	1.98	0.03	0.39	4.49
	Headlight Left (HL)	78	0.36	2.15	0.02	0.21	1.39
	Headlight Right (HR)	76	0.49	1.75	0.18	0.29	1.41
	Mirror Left (ML)	20	0.45	2.08	0	0.42	0.2
	Mirror Right (MR)	19	0.37	0.65	0.21	0.13	0.21

Average fixation duration was calculated to analyze the amount of time participants spent looking at each AOI within the design of vehicles. Tobii (2016) defines fixation duration as the total duration of all fixations within an AOI. Average fixation duration has been used by researchers as a measure of performance (Bojko, 2013), such as cognitive processing difficulty (Bojko, 2013; Holmqvist et al., 2011), and can help evaluate specific areas of a stimulus. Average fixation duration is sometimes confused with dwell time, but dwell time refers to the entire time spent looking at an area, which includes all individual fixation durations. Average fixation duration, however, is the sum of fixation durations (seconds) divided by the total number of fixations. On average, the longest amount of time spent looking at an AOI was 5.53 seconds, while the shortest amount of time was 0.1 seconds. In the 2017 Tesla Model 3 image, whose design did not include a grille, the grille area was fixated on for the least amount of time compared to all other vehicle models (see Table 6).

Fixation count statistics were also calculated for each AOI in all vehicle models (see Table 6). Tobii (2016) defines fixation count as the number of times a participant fixates on an AOI. The grille produced the greatest fixation count in five of the nine (56.6%) vehicles. The average fixation count on the grille AOI across all vehicle models was 4.94 fixations. Three of the vehicles where the grille did not produce the greatest fixation count were considered to have little to no prominent grille AOI. The other six designs containing a prominent grille AOI received an average of 94.5 fixations and the designs with little to no prominent grille received an average of 109.75 fixations (see Table 6).

The time to first fixation measurements (Table 7) for each vehicle were also used to discern common scan paths among participants, or the scan path entropy of each vehicle, as well as the attention drawing power of AOIs had measured by T_{50}.

Table 7
Time to First Fixation Results Across Vehicle AOIs

(n = 111)		Time to First Fixation (seconds)				
Car Model	AOI	*f*	M	Max	Min	SD
2015 Tesla Model S	Bumper (B)	90	3.43	15.93	0	2.59
	Grille (G)	108	1.27	24.26	0	2.92
	Hood (H)	106	1.63	17.15	0	3.11
	Headlight Left (HL)	77	3.38	13.27	0	3.04
	Headlight Right (HR)	76	4.19	21.31	0	4.61
	Mirror Left (ML)	15	7.42	17.96	0	5.65
	Mirror Right (MR)	20	7.66	25.81	1.16	5.29
2017 Nissan Leaf	Bumper (B)	98	2.38	18.03	0	2.44
	Grille (G)	102	1.73	22.74	0	3.21
	Hood (H)	107	0.96	17.67	0	2.26
	Headlight Left (HL)	60	3.39	15.69	0	3.92
	Headlight Right (HR)	65	3.53	22.57	0	3.83
	Mirror Left (ML)	21	6.67	14.06	0	4.23

	Mirror Right (MR)	18	5.91	14.17	0	3.69
2017 Tesla Model 3	Bumper (B)	105	2.43	13.18	0	2.41
	Grille (G)	100	2.04	24.77	0	3.46
	Hood (H)	110	1.2	17.14	0	2.68
	Headlight Left (HL)	76	2.72	16.06	0	3.12
	Headlight Right (HR)	84	2.85	17.8	0	3.5
	Mirror Left (ML)	17	6.6	23.42	0	6.41
	Mirror Right (MR)	21	6.65	20.74	1.36	4.99
2017 Audi A4 Sedan	Bumper (B)	86	2.87	12.16	0	2.61
	Grille (G)	109	1.41	14.88	0	2.44
	Hood (H)	101	1.29	12.05	0	2.34
	Headlight Left (HL)	82	2.62	17.36	0	3.55
	Headlight Right (HR)	85	3.61	21.8	0.02	3.9
	Mirror Left (ML)	32	6.68	26.16	0.42	5.2
	Mirror Right (MR)	23	7.46	18.73	2.2	4.06
2017 BMW 330i Sedan	Bumper (B)	90	3.05	12.69	0	2.45
	Grille (G)	103	1.15	10.8	0	2.17
	Hood (H)	106	1.3	18.19	0	2.63

	Headlight Left (HL)	71	3.13	20.76	0	4.01
	Headlight Right (HR)	72	3.8	17.39	0	3.54
	Mirror Left (ML)	19	7.42	30.43	0	7.76
	Mirror Right (MR)	24	6.69	19.27	1.62	4.42
2017 Mercedes-Benz C300 Sedan	Bumper (B)	91	2.97	11.95	0	2.61
	Grille (G)	111	0.65	8.3	0	1.43
	Hood (H)	99	2.25	23.49	0	3.88
	Headlight Left (HL)	83	3.26	22.15	0	3.6
	Headlight Right (HR)	77	3.85	20.21	0	3.8
	Mirror Left (ML)	26	5.75	12.82	1.23	3.18
	Mirror Right (MR)	26	7.39	19.93	0	4.57
2017 Chevrolet Volt Hatchback	Bumper (B)	100	2.19	19.37	0	2.68
	Grille (G)	96	1.88	17.71	0	3.21
	Hood (H)	109	0.89	11.23	0	1.93
	Headlight Left (HL)	75	4.02	24.55	0.22	4.48
	Headlight Right (HR)	72	3.69	19.12	0.18	3.77
	Mirror Left (ML)	15	5.88	15.91	1.42	4.03
	Mirror Right (MR)	26	9.74	33.93	2.11	7.03

2017 Infiniti Q70 Hybrid Sedan	Bumper (B)	91	2.99	14.65	0	2.71
	Grille (G)	109	0.84	13.01	0	1.87
	Hood (H)	100	1.61	13.56	0	2.65
	Headlight Left (HL)	76	3.32	22.65	0	3.77
	Headlight Right (HR)	77	3.6	17.04	0.19	3.58
	Mirror Left (ML)	24	8.21	24.04	1.31	5.93
	Mirror Right (MR)	22	7.58	18.15	1.23	4.91
2017 Toyota Prius Two Hatchback	Bumper (B)	72	3.85	15.9	0	3.1
	Grille (G)	104	1	7.82	0	1.59
	Hood (H)	105	1.82	22.26	0	3.71
	Headlight Left (HL)	78	3.01	11.83	0	2.67
	Headlight Right (HR)	76	3.31	16.1	0	3.26
	Mirror Left (ML)	20	7.2	15.39	0	4.86
	Mirror Right (MR)	19	7.92	31.91	2.59	7.32

The observed scan paths revealed a centralized viewing pattern that primarily show eye movements being guided from the center, then left to right. Grille prominence in the design of each individual vehicle visually convey these scan path trends. When the grille was not a prominent feature or was completely removed from the vehicle's design, the surrounding design elements, such as the left and right headlight, were more frequently fixated (see Figure 23 for fixation heat map of Tesla Model 3). In the vehicles with a prominent grille AOI, the grille was most frequently fixated on first and for the longest amount of time. In the one vehicle where the grille was not there at all (2017 Tesla Model 3), the grille area was still fixated on by most of the participants at least once ($f = 97$; 87.39%) participants.

Composite Metrics Results.

Since the grille element of the vehicle was initially predicted to be the key feature participants would use to visually process and evaluate each vehicle, this analysis will focus only on the results of the grille AOI. Additionally, as mentioned briefly earlier, the grille AOI was the only feature found to have a significant effect in both studies when analyzed for grille T_{50}, grille Entropy, and grille dwell times. Potential implications that findings from these calculations reveal are discussed in the subsequent sections.

T_{50} results.

Findings from the eye tracking results and composite metrics suggests that the grille of this particular vehicle was a key feature used by participants to guide their gaze and process its design. While calculating the T_{50} score for each vehicle's AOIs, the P_{max} or fixation score was also determined in this free viewing task, which corresponds with the accuracy in a visual search task (Hooge & Camps, 2013).

Table 8

Shannon Entropy & T_{50} Descriptive Statistics of Vehicle Areas of Interest (AOIs)

		AOI Entropy			AOI T_{50}	
Car Model	AOI	Pixels (%)	Scan Path Entropy	P_{max}	Fixations (N)	T_{50}
2015 Tesla Model S	Bumper (B)	34.23%	0.04	0.81	90	3.83
	Grille (G)	21.56%	0.06	0.97	108	0.41
	Hood (H)	34.49%	0.01	0.96	77	0.27
	Headlight Left (HL)	3.54%	0.05	0.69	106	4.61
	Headlight Right (HR)	3.52%	0.04	0.68	76	4.21
	Mirror Left (ML)	1.32%	0.05	0.14	15	N/A
	Mirror Right (MR)	1.33%	0.12	0.18	20	N/A
2017 Nissan Leaf	Bumper (B)	43.38%	0.04	0.88	98	2.00
	Grille (G)	11.92%	0.09	0.92	102	0.66
	Hood (H)	34.73%	0.01	0.96	60	0.18
	Headlight Left (HL)	3.44%	0.04	0.54	107	10.13
	Headlight Right (HR)	3.45%	0.05	0.59	60	7.09
	Mirror Left (ML)	1.63%	0.06	0.19	21	N/A
	Mirror Right (MR)	1.44%	0.05	0.16	18	N/A

2017 Tesla Model 3	Bumper (B)	42.90%	0.04	0.95	105	1.98
	Grille (G)	18.28%	0.02	0.90	100	0.83
	Hood (H)	28.58%	0.03	0.99	76	0.27
	Headlight Left (HL)	3.75%	0.06	0.68	110	3.46
	Headlight Right (HR)	3.75%	0.05	0.76	84	2.75
	Mirror Left (ML)	1.37%	0.03	0.15	17	N/A
	Mirror Right (MR)	1.37%	0.06	0.19	21	N/A
2017 Audi A4 Sedan	Bumper (B)	32.86%	0.04	0.77	86	3.08
	Grille (G)	27.49%	0.04	0.98	109	0.50
	Hood (H)	29.64%	0.01	0.91	82	0.27
	Headlight Left (HL)	3.71%	0.06	0.74	101	1.93
	Headlight Right (HR)	3.71%	0.06	0.77	85	3.64
	Mirror Left (ML)	1.30%	0.05	0.29	32	N/A
	Mirror Right (MR)	1.30%	0.07	0.21	23	N/A
2017 BMW 330i Sedan	Bumper (B)	41.79%	0.03	0.81	90	3.45
	Grille (G)	12.00%	0.07	0.93	103	0.28
	Hood (H)	33.38%	0.02	0.95	71	0.29
	Headlight Left (HL)	4.72%	0.05	0.64	106	3.92
	Headlight Right (HR)	4.72%	0.06	0.65	72	5.55

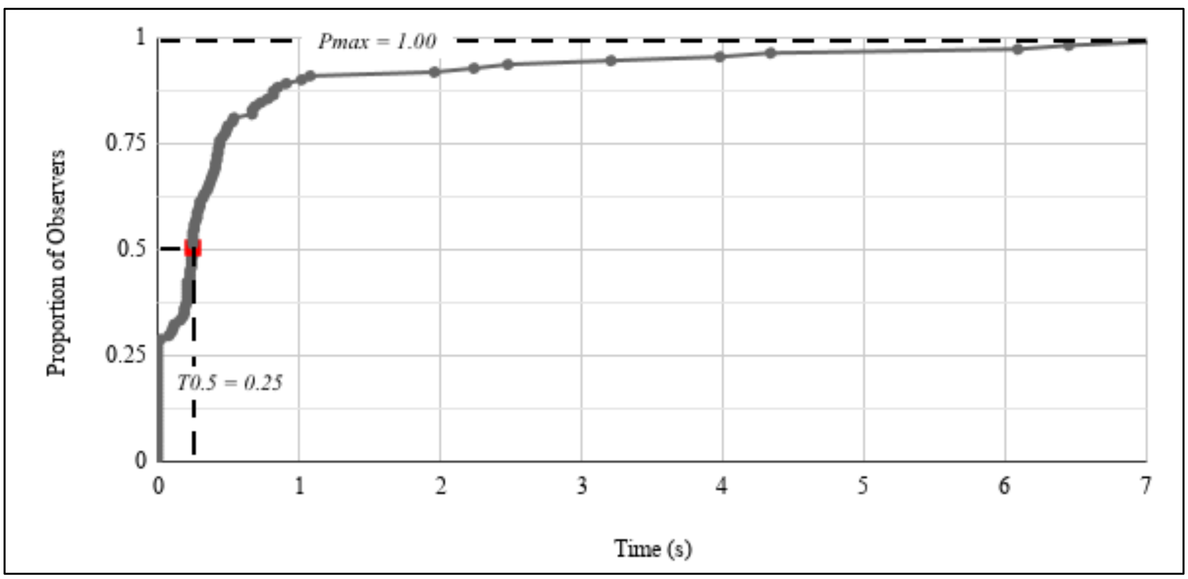
	Mirror Left (ML)	1.70%	0.04	0.17	19	N/A
	Mirror Right (MR)	1.69%	0.08	0.22	24	N/A
2017 Mercedes-Benz C300 Sedan	Bumper (B)	41.53%	0.03	0.82	91	2.86
	Grille (G)	18.67%	0.08	1.00	111	0.25
	Hood (H)	28.15%	0.01	0.89	83	1.01
	Headlight Left (HL)	4.38%	0.06	0.75	99	3.53
	Headlight Right (HR)	4.38%	0.05	0.69	77	4.57
	Mirror Left (ML)	1.45%	0.06	0.23	26	N/A
	Mirror Right (MR)	1.44%	0.05	0.23	26	N/A
2017 Chevrolet Volt Hatchback	Bumper (B)	47.89%	0.04	0.90	100	1.81
	Grille (G)	7.28%	0.07	0.86	96	0.81
	Hood (H)	34.19%	0.01	0.98	75	0.20
	Headlight Left (HL)	3.69%	0.05	0.68	109	6.49
	Headlight Right (HR)	3.69%	0.04	0.65	72	4.81
	Mirror Left (ML)	1.63%	0.04	0.14	15	N/A
	Mirror Right (MR)	1.64%	0.06	0.23	26	N/A
2017 Infiniti Q70 Hybrid Sedan	Bumper (B)	38.91%	0.04	0.82	91	3.05
	Grille (G)	23.19%	0.03	0.98	109	0.27
	Hood (H)	27.40%	0.02	0.90	76	0.72

	Headlight Left (HL)	3.82%	0.05	0.68	100	4.04
	Headlight Right (HR)	3.82%	0.04	0.69	77	4.84
	Mirror Left (ML)	1.43%	0.04	0.22	24	N/A
	Mirror Right (MR)	1.43%	0.07	0.20	22	N/A
2017 Toyota Prius Two Hatchback	Bumper (B)	32.70%	0.04	0.65	72	6.11
	Grille (G)	29.16%	0.04	0.94	104	0.42
	Hood (H)	26.68%	0.01	0.95	78	0.37
	Headlight Left (HL)	3.80%	0.05	0.70	105	3.93
	Headlight Right (HR)	3.78%	0.05	0.68	76	4.26
	Mirror Left (ML)	1.94%	0.03	0.18	20	N/A
	Mirror Right (MR)	1.94%	0.05	0.17	19	N/A

Figure 21 shows the distribution of fixations made by participants on the grille of the 2017 Mercedes-Benz C300 (prominent grille, CV) to illustrate findings from the T_{50} and P_{max} calculations. Analysis of the results show that every participant (*n* = 111) fixated on the grille area of this vehicle at least once during the evaluations, and it only took 0.25 seconds for half (50%) of participants to fixate on the grille.

Figure 21. *T_{50} Distribution of 2017 Mercedes-Benz C300 Grille.*

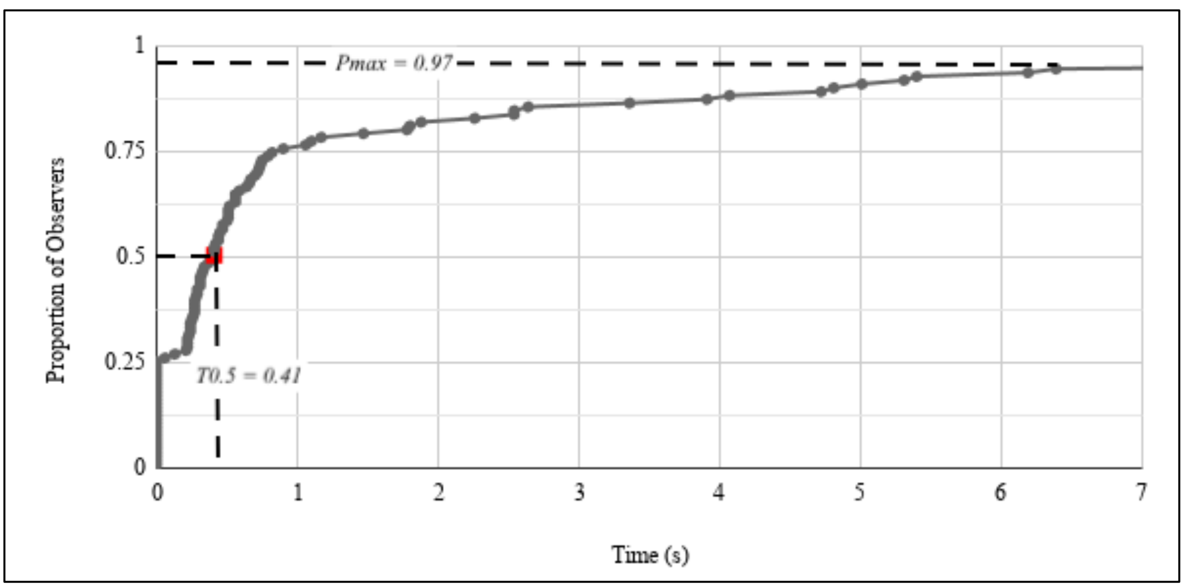
Cumulative proportion of observers fixating the grille AOI of the 2017 Mercedes-Benz C300 as function of time. 50% of the observers fixated the target AOI in 0.25 s. The maximum proportion of observers fixating the target was 1.00, or 100%. This number is referred to as the fixation score or P_{max}.



To illustrate how these effects might differ when a car model has no grille in its design, T_{50} findings of the 2017 Tesla Model 3 was of primary interest in the investigation as well. Figure 22 (below) shows the distribution of the fixations made by participants on the grille AOI of the 2018 Tesla Model 3 (no grille, EV) during the eye tracking experiment. In this example, 97% of participants (*n* = 111) fixated on the grille area at least once during evaluation, and 50% of participants fixated on the grille region within 0.41 seconds. This suggests that even though there was no actual grille included in this vehicle's design, the grille area was still looked at by participants in attempts to acquire information as they processed its design.

Figure 22. *T_{50} Distribution of 2017 Tesla Model 3.*

Cumulative proportion of observers fixating the grille AOI of the 2017 Tesla Model 3 as function of time. 50% of the observers fixated the target AOI in 0.41 s. The maximum proportion of observers fixating the target was 0.97, or 97%. This number is referred to as the fixation score or P_{max}.

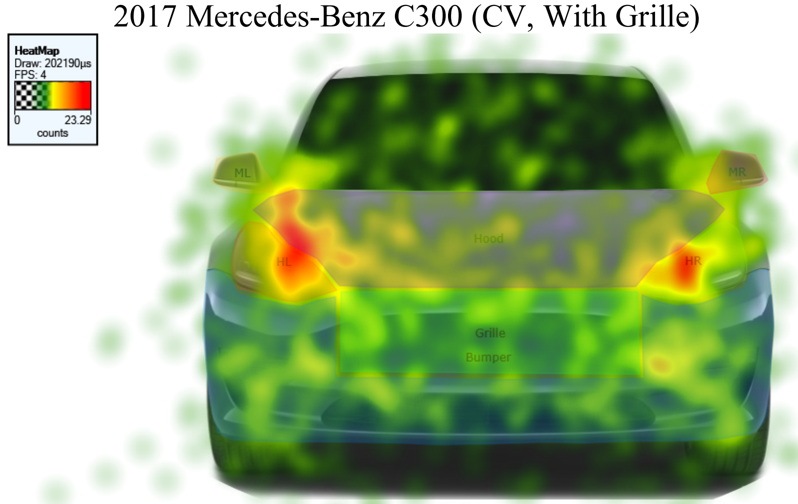


Since the lack of a grille is itself a novel design decision relative to vehicles on the current market, this region garnered the attention of the majority of participants (f = 100) in less than a second but, interestingly, it did not seem to increase cognitive load ($M_{Fixation\ Duration}$ = 0.35, $M_{Fixation\ Count}$ = 2.86) as much as the 2017 Mercedes-Benz C300 empty circle design did. Although many participants did fixate on this region first during evaluations (f = 30), the most amount of time fixated here was less than two seconds ($Max_{Fixation\ Duration}$ = 1.74). Instead, most participant fixations were disseminated around the grille region to other AOIs such as the headlights, hood and bumper regions. Figure 23 shows heat maps of the 2017 Tesla Model 3 and the 2017 Mercedes-Benz C300, which demonstrate the distinctly different fixation patterns made by participants when looking at these two different vehicles.

Figure 23. *Heat maps of 2017 Tesla Model 3 vs. 2017 Mercedes-Benz C300.*

When comparing the fixation patterns of the two cars, the empty circle that normally displays the Mercedes-Benz star logo was a prominent area of attraction during the visual search process. The fixation patterns of the Tesla Model 3 are quite different because there was no grille design to look at, so attention was dispersed to other surrounding areas of interest such as the two headlight features.

2017 Mercedes-Benz C300 (CV, With Grille)



2018 Tesla Model 3 (EV, Without Grille)

Entropy results.

All vehicle images and their design features (AOIs) were found to have relatively low entropy compared to other stimuli examined by previous studies, such as advertisements with both text and image elements (Pieters & Wedel, 2004; Pieters, Wedel & Batra, 2010). This was anticipated prior to the experiment due to the simplicity of the stimuli chosen for this study. The minimal imagery of a single vehicle in the center of a white background was intentionally selected so that data collection would remain primarily focused the vehicle's design and specific features. To further control for extraneous variables that could affect the objectives of the target investigation, all color was removed from each image to control for its potential effect on attention.

When analyzing the entropy results, vehicles with effective gaze guidance (low scan path entropy) yielded similar scan paths across participants, while those with relatively ineffective gaze guidance (high scan path entropy) produced random and inconsistent scan paths across participants. The three vehicles with the most effective gaze guidance and lowest entropy were the 2018 Tesla Model 3 (M = 0.04, SD = 0.02), the 2017 Infiniti Q70 (M = 0.04, SD = 0.02), and the 2017 Toyota Prius Two (M = 0.04, SD = 0.01). The vehicles with the highest entropy were the 2015 Tesla Model S (M = 0.05, SD = 0.03), the 2017 Nissan Leaf (M = 0.05, SD = 0.02), and the 2017 Mercedes-Benz C300 (M = 0.05, SD = 0.02). The scan paths were very similar for all vehicles, likely because there was little variance between stimuli in terms of how elements were arranged. The location of features within each vehicle (i.e., headlights, mirrors, hood, grille, and bumper) were relatively consistent across all vehicle images, and this homogeneity among stimuli allowed participants to use a similar scan path for each vehicle observed.

In terms of AOIs, however, the entropy metric provides useful insight into how the scan paths of participants changed when there was little to no prominent grille feature on vehicle. For vehicles with a prominent grille design, such as the 2017 Mercedes-Benz C300, the grille entropy ($H(X)$ = 0.08 bits) was higher than any other AOI entropy within the vehicle. However, when looking at a vehicle without a grille design, such as the 2018 Tesla Model 3, the entropy of the grille area ($H(X)$ = 0.02 bits) was the lowest of all the AOIs.

Survey response results.

Descriptive statistics assessed which vehicles received the highest aesthetic evaluation ratings and how prototypical participants thought the designs were. The 2017 Mercedes-Benz C300 (M = 5.32, SD = 1.28), 2017 Tesla Model 3 (M = 4.94, SD = 1.84), and the 2015 Tesla Model S (M = 4.87, SD = 1.37) had the highest aesthetic evaluation rating. In response to how typical a car's design was, participants rated the 2017 Mercedes-Benz C300 (M = 5.20, SD = 1.28), 2015 Tesla Model S (M = 5.06, SD = 1.37), and the 2017 BMW 330i (M = 4.77, SD = 1.43) as having the most prototypical designs. In terms of how participants perceived the uniqueness of each car design, the 2017 Tesla Model 3 (M = 5.05, SD = 1.68), the 2017 Mercedes-Benz C300 (M = 4.62, SD = 1.47), and the 2015 Tesla Model S (M = 4.50, SD = 1.42) were rated as having the most unique designs. Interestingly, the vehicle designs that were perceived as the most unique were also the vehicles rated as the most preferred by participants in their aesthetic evaluations. This is a bit contrary to other design research findings, which have suggested that consumers prefer typical product designs over unique ones because they are easier to process. The vehicle designs rated the most typical were almost the same as those with the highest aesthetic evaluation rating, with the exception of the 2017 BMW 330i Sedan. This study also hypothesized that the typicality of a design and evaluation of aesthetic liking were positively related.

To examine this further, participants were to rank their favorite car designs in sequential order from one to nine (1 = Favorite, 9 = Least favorite). The responses ($n = 111$) revealed that the same vehicles rated as the most unique and aesthetically liked were also ranked as the top three favorites by participants. The Tesla Model 3 was ranked number one (*Mode* = 1, $M = 3.84$, $SD = 2.72$), the Mercedes-Benz C300 was ranked second (*Mode* = 2, $M = 3.54$, $SD = 2.15$), and the Tesla Model S was ranked third (*Mode* = 3, $M = 3.69$, $SD = 2.23$).

CHAPTER V

DISCUSSION & CONCLUSION

Theoretical Contributions

Overall, these findings are consistent with previous empirical studies suggesting that the typicality of a product's design influences consumer evaluations. Findings from both studies related to the *a priori* experimental hypotheses deduced from previous theoretical literature are described below.

The first hypothesis predicted that prototypicality would negatively affect processing fluency, or the amount of time that it would take to process a design. In other words, a more typical vehicle design would require less time to process because it was categorized by consumers quickly into pre-existing schemas. These constructs were found to be have a significantly positive relationship, which confirms this theoretical proposition and contributes empirical evidence to support the current understanding of visual information processing and categorization-schema theory as it relates to product design.

The second hypothesis predicted a negative relationship between the prototypicality of a product and how much visual information the product's design required participants to process. Total Dwell time was used to operationalize the entropy construct, and was found to have a significant positive relationship with prototypicality. In other words, participant total dwell time increased when a vehicle's design was reported to be more prototypical. This contradicts the current theoretical proposition that suggest typical designs should have lower visual entropy (i.e., less information) and, thus, are easier to cognitively process. This conclusion might be explained by the measure that was chosen to operationalize the visual entropy variable in the theoretical model. Although the most closely aligned eye tracking measure relative to entropy, future research should test other potential measures, such as individual scan paths, to examine the relationship further.

There was partial support for the third hypothesis, which stated that processing fluency would positively affect consumer evaluations, either measured by aesthetic linking (individual level, study 1) or total 2018 vehicle sales (car level, study 2). Although study 1 found that fluency was positively related to consumer evaluations of aesthetic liking, the effect was not significant. Study 2, however, found that fluency had a significant negative influence over 2018 vehicle sales, which suggests that vehicle designs processed with high fluency (i.e., more quickly processed) sold fewer total vehicles in 2018. Categorization-schema theory suggests that typical designs are more fluent to process because they are easier to understand and categorize into already existing schemas—the findings, however, suggest that designs that take longer to process actually lead to more sales. The limitation to this conclusion, however, is that the fluency construct was measured by the total average fluency rate of the sample from Study 1 (n = 111), which is not representative of U.S. consumers and suggests the need for additional research. Additionally, the experiment required participants to look only at the front of the vehicle on a 2D computer screen, which limits the ability to apply findings to consumers' vehicle purchases. However, despite the limitations of real world application of how consumers process a vehicle's design when shopping in a 3D environment like a showroom or car sales lot, the experiment does simulate the process of online car shopping research behavior.

The fourth hypothesis predicted that the visual entropy (total dwell time) of a vehicle's design would have a negative effect on consumer evaluations of aesthetic liking and annual vehicle sales. Relative to consumer evaluations of aesthetic liking, total dwell time had a positive influence, although the results were not significant. This suggests that designs with higher visual entropy resulted in higher ratings of aesthetic liking, which contradicts theoretical literature. Future research should include psychological constructs, such as need for cognition, to see if these have any mediating effects on the relationship between these variables. Annual sales, on the other hand, did have a negative relationship with the visual entropy of a vehicle's design. Designs with lower entropy, measured by Shannon's (1948) entropy and Montfoort et al.'s (2007) T_{50}, were discovered to have higher annual sales in 2018, although this relationship was not found to be significant. This is consistent with this study's predictions, as well as Shannon's (1948) theoretical propositions, which states that lower entropy stimuli (less information measured in bits) are more preferred by individuals because its gaze guiding qualities effectively aid in navigating the stimulus and cognitively understanding it.

The fifth hypothesis, which was examined post hoc and constructed from current visual processing theory literature, predicted that prototypicality had a direct positive relationship with both consumer evaluations and annual sales. This was tested *post hoc* because several of the relationships predicted were either found to be related in the opposite direction (negative rather than positive or vice versa) or not significant. It was, therefore of interest to see if prototypicality significantly influenced DVs (sales and aesthetic liking) without the moderators of fluency and entropy. Prototypicality was found to have a significant positive effect on aesthetic liking, which is consistent with the theoretical framework.

Prototypicality was also found to positively affect annual vehicle sales, but the relationship was not significant. This may be due to the objective prototypicality scores for each vehicle, which were generated by calculating the Euclidean distances and their difference relative to an averaged morph. The average morph only consisted of nine vehicles that were all sedans. Not only might the small sample of vehicles used to create these prototypicality scores have influenced this relationship, but the homogeneity of all the vehicles' shapes (e.g., sedan) might have also had an impact. Future research should use more car models with various forms (sports sedan, hatchback, etc.) to generate an average morph and ultimately prototypicality scores.

Processing fluency.

Fluency was also found to be positively related to aesthetic liking, but the results were not significant—suggesting that the measurement used for fluency (time to process image) did not account for the moderating effects fluency is theoretically proposed to have between the typicality and consumer evaluation of aesthetic liking. This is an important contribution to note for future empirical studies examining fluency as a moderating variable between a product's prototypicality and consumer evaluations, as many studies in the past have operationalized fluency with the same measure used in this study (time to evaluate) (Landwehr et al, 2013).

The findings contradict some of the categorization theory literature, which suggests that more familiar designs (high typicality) should result in highly fluent processing (high fluency). There are several potential explanations for this finding. The most probable reason for the negative correlation might be the control for branding, where each vehicle image was altered to not have any logos or branding on prominent features of the design. However, despite their removal, the designs of grilles, where logos are prominently displayed, were designed around the logo to further emphasize the brand and its recognition. Rather than distort the grille designs of cars, it was important to maintain the vehicle's true design as much as possible, but the absence of the logo was quite obvious for some vehicles. For example, although the Mercedes-Benz logo was removed from the grille, the circle in the middle of the grille that usually displays the familiar star symbol still remained. Therefore, because the star logo was absent from its typical grille location and the design of the grille was seemingly familiar, participants (on average) might have looked at familiar cars like this one longer to account for what was missing.

Furthermore, this effect might not have been as influential when evaluating unfamiliar or novel cars because the brand was unknown and therefore the absence of its logo did not affect how fluently the vehicle was processed. In other words, if a consumer is familiar with a brand and its products, then recognition and fluency should be easy and fast to process. However, if branding is removed from a product that consumers recognize, deeper cognitive processing occurs to verify that the product they're looking at is indeed from a particular brand. This could have an even stronger effect if the product design a consumer is looking at is one that they prefer or strongly aspire towards.

This brings up several other individual variables related to branding including conspicuous consumption, brand signaling and materialism—none of which were the primary focus of this paper, nor this specific study (which looked at variables on the car level, not individual). Mercedes-Benz, for example, is considered a luxury brand in the automotive market (aspirational brand), the car used in this study was classified as luxury compact and their brand dominance in the automotive industry is top ranked in the U.S. (Automotive News, 2018).

Prototypicality accounted for 6.68% of the fluency variance, which suggests that this variable has some influence on how fluently consumers process a vehicle's design.

Contributions to design literature.

The first objective was to determine which specific features consumers looked at most frequently and for the longest amount of time when evaluating a vehicle's design. The premise for understanding this was based on the theoretical proposition that areas where individuals spend most of their attention are areas that are most important to them. This was of particular interest when it comes to electric vehicles, whose functional needs no longer require the grille, which has been a prominent aesthetic consideration for companies to signal their brand to consumers. The question of interest here was: do consumers rely heavily on the grille when visually processing and evaluating an unfamiliar vehicle? If this was found to be true, how would removing the grille entirely from the vehicle's design impact consumer evaluations?

Attention as it relates to preference.

Attention was measured by fixation durations and total dwell time spent on each area of interest. As discussed in the literature review, the aDDM suggests that gaze fixation is the process by which individuals acquire information about each option prior to evaluation. Therefore, the more time spent on a stimulus or a specific feature within a stimulus the more evidence is accumulated in favor of the fixated alternative. Both studies contribute to this model in the following ways.

Post hoc exploratory analyses revealed that there was a common scan path amongst participants when looking at a vehicle with a grille and that the entropy, on average, was actually higher for models that had a grille. Vehicles that were completely missing a grille or had a less prominent grille area had a more consistent scan path and resulted in lower entropy. The grille was most commonly AOI looked at either first or second in all scan paths across vehicles, and findings revealed that grille entropy was, in fact, significantly correlated with sales in the predicted negative direction (t = -0.52, p = 0.00). This suggests that if a grille was less uncertain (lower entropy), sales are predicted to be higher. This is aligned with the theoretical proposition of categorization-schema theory that lower entropy leads to higher preference, but takes it a step further by identifying a specific design feature of a product. There were no other design elements of the vehicle that was significantly correlated with the dependent variable, annual sales.

Automotive executives should, therefore, pay particular attention to lowering the entropy of the grille design in new vehicles and can do so by designing all new vehicles with moderately unique grilles that are memorable, while also communicating brand consistency to establish recognizability. Although the logo is typically included in the grille, simply including the logo in the grille's design is not enough. The actual shape, texture and other design elements of the grille must be noteworthy enough to attract consumer attention and consistent throughout each new model extension a brand offers. This study took out the logos of each vehicle's grille and the grille still remained as the primary feature used by participants to guide their gaze during visual evaluations.

Findings from the 2017 Mercedes-Benz C300 grille design further revealed the effect that key features and their attention drawing power can have on consumer preference. Results indicated that fixations were clustered primarily around the empty circle in the center of the grille where the Mercedes-Benz star logo is typically located. Although all branding and logos were removed from vehicle images, the design of this particular grille was specifically created to emphasize the iconic star. The empty circle might have elicited a feeling of familiarity and at the same time, an increase in cognitive load—as measured by fixation duration (*M* = 0.42) and fixation count (*M* = 6.02)—because the logo was missing in this prominent position. In other words, the grille design itself guided participants to the most recognizable area and effectively signaled their desired brand information without the logo present. The 2017 Mercedes-Benz C300 was also rated as one of the top three most preferred vehicles overall and aesthetically (*M* = 5.31, *SD* = 1.28), and was also the most accurately categorized vehicle by its fuel type (*M* = 2.78, *SD* = 1.57).

The powerful attentional response elicited by the salient and familiar Mercedes-Benz grille makes it an exemplar for other companies to aspire towards when attempting to establish brand recognizability. Automotive companies should ensure that elements most relevant to consumers during the visual search process, are designed with a certain level of brand consistency so that these features effectively signal the brand and trigger brand recognition even when the logo in explicitly removed. The subtle circle in the center of the grille not only draws consumers attention directly to that area where the logo is usually placed, but its design also prompts brand schema recall. Because the vehicle's design looked familiar but was missing the explicit signal of the logo, participants fixated on this area longer and more frequently than any other design feature in order to resolve schema incongruity and identify the brand. Specifically, this moderately atypical key feature drew the most attention (measured by T_{50}) and increased cognitive load (measured by average fixation duration) as participants attempted to solve the puzzle of whether or not the car was the brand they recognized it to be.

The sense of familiarity elicited by this particular vehicle design could be explained by the mere exposure effect, based on previous exposures to other Mercedes-Benz branded vehicles with similar grille designs. However, mere exposure does not explain the increased cognitive load elicited in this example—mere exposure to a car model or brand does not necessarily lead to brand recognition, nor does it explain why specific features like the grille were used during the cognitive process to draw out important information about the car in order to make a decision. A more appropriate explanation might involve the concept of brand consistency, or aesthetic similarity across a brand's product extensions. In this example, the aesthetic similarity of grilles across other Mercedes-Benz models was done with such uniformity that it established brand consistency, which allowed consumers to use the grille as a useful feature to help locate the appropriate brand schema and identify the brand. Consistent with these arguments, other automotive companies have applied a similar design strategy and have seen great improvement in brand recognition. For example, Kia's latest redesigned models feature a consistent front shape with a unique "tiger-nose" grille (LeBlanc, 2012). Empirically, brand consistency has been found to improve brand recognition (Cruesen & Schoormans, 2005), increase sales (Liu et al, 2017), and overall market share (Landwehr et al., 2012). Consistent with these findings, this study also found that the Mercedes-Benz also had the third highest 2018 sales relative to the other nine vehicles ($60,409.00). This further emphasizes the monetary benefits that designing features with brand consistency can have long term.

Although brand schema was not the focus of the current examination, this explanation is consistent with categorization theory that suggests a higher level of brand consistency via aesthetic design can result in an easier transfer of brand information about a product (Liu et al., 2017; Bousch & Loken, 1991; Park, Milberg & Lawson, 1998; Sujan, 1985). However, while the above argument alludes to the positive effects that aesthetic brand consistency can have on a vehicle's desirability, there is a point where too much consistency can have a negative effect on consumer preference. As fluency research has suggested, if a product looks too much like others in the product category or brand category, it may be perceived as boring and unmemorable (Berlyne, 1971; Meyers-Levy & Tybout, 1989; Liu et al., 2017).

Findings related to the 2017 Tesla Model 3 signify the benefits that novel design strategies can have on consumer preference. The Tesla Model 3 was of particular interest because it was the only vehicle tested that did not have a grille. Interestingly, not only did it have the highest annual sales, but it was also ranked by participants as the most preferred vehicle of the nine examined. The Tesla Model 3 also had the lowest entropy score of all the vehicles examined as well, which suggests that eliminating the grille altogether does not necessarily decrease consumer preference as long as the rest of the vehicle is well designed.

Another exploratory objective of this research was to find the point at which the typicality of a product's design shifts from improving customer preference to harming vehicle preferences. Although typicality was found to be a significant predictor of aesthetic liking, participants most preferred the unique design of the 2018 Tesla Model 3, which was the only vehicle without a prominent grille area. These findings provide further confirmation of Mandler's hypothesis (1989) and suggest that consumer preference for the aesthetic design of a product is highest at a moderate level of typicality relative to its respective product category schema.

Contributions to information theory literature.

Another overarching objective was to determine whether or not there was a common scan path among consumers when strictly evaluating the aesthetics of a vehicle's design (e.g., pricing and branding was controlled). Similar to the findings observed from the T_{50} metric, entropy findings suggests that when a grille is present, attention is frequently guided toward this region. Entropy, however, tells us that in addition to its attention drawing power, that the grille is also centrally used by consumers to acquire information when ambiguity is visually present. As discussed previously, entropy is a measure of disorder in a system, and scan path entropy measures the how efficiently the arrangement of features in a stimulus are visually processed by comparing the number of diverging (or similar) scan paths that emerge during information acquisition. Higher scan path entropy, therefore, occurs when elements within a visual stimulus are noticeably different, which was certainly found to be the case with the grilles of vehicles. Not only does the design of the grille differ quite drastically between vehicles, but it is also the most distinctive element within a vehicle's design (e.g., hood, headlights). Therefore, findings from grille entropy in this study support the expected scan path behavior that diverse elements within a stimulus are suggested to produce in information theory's core entropy propositions.

The scan path entropy metric (Shannon, 1948) was significantly correlated with the prototypicality score of each vehicle model ($t = 0.38$, $p = 0.00$), however the relationship was positively correlated. This suggests that the less typical a design is relative to others observed, the lower its uncertainty is perceived to be. The T_{50} metric was also significantly correlated with the prototypicality score, and the relationship was found to be negative as predicted in the initial hypothesis ($t = -0.21$, $p = 0.00$). This not only affirms the statement made earlier that the temporal component of visual scanning is just as important to scan path entropy as the spatial component, but it also suggests that it may be more predictive when evaluating similar shaped products such as the vehicles examined in this study.

Although significant results were not found for every relationship in both Study 1 and Study 2, the strategy of different measures for the information entropy variable in each study (Study 1, total dwell time on the participant level vs. Study 2, scan path entropy on the car level) is important to note. While traditional eye movement metrics (e.g., fixation duration, saccadic amplitude, and dwell times) are relatively new in marketing literature, research suggests that the results of these measurements don't conflict with those from the entropy metric. Rather, the two metrics complement each other and confirm the same underlying structure of behavior from different perspectives. This study confirms previous research findings that have shown as dwell durations increase, more time is spent on less of the stimuli overall (per unit time). A decrease in saccadic amplitude means that consecutive fixations are closer together and that less of the overall is scanned. The behavioral complexity that the entropy metric illustrated by the combination of both the time element captured by dwell time, and the spatial position measured by saccadic amplitude. State-space transitions are directly guided by both saccade amplitude and total dwell time because each metric limits the maximum number of state-spaces that can be scanned.

Since the entropy metric is a composite metric, it has the potential to be more useful in the initial phases of data analysis prior to using more limited focused eye movement metrics. Dwell time and saccade size only measure a single characteristic, meaning that any changes outside of these measurements will not be captured. Entropy, conversely, includes both measures so that there an additional opportunity to observe an effect.

A composite score, however, can be disadvantageous, as it may suggest that some effects are smaller than they actually are. For example, should an effect occur entirely in one dimension, such as dwell time but not saccadic size, the measure of total dwell time would be more revealing and diagnostic than the entropy metric. Hence, the entropy and T_{50} measures were used in Study 2 as complements to the total dwell time metric used in Study 1 for the information entropy variable examined in this paper. Future research should continue testing the entropy metric to complement existing eye movement metrics as well, rather than a replacement.

Although significant findings were limited in the current study, the entropy and T_{50} measures have great potential for improving the exploratory strength in future studies by helping identify that an effect is demonstrated within a population. Once an effect has been found through this metric, researchers can identify which eye movement measures they should use to increase the granularity of data analysis within and between participants.

Limitations & Future Research

There are more mediating variables between Prototypicality and Fluency, as the results of hypothesis 1 were not found to be significant and the relationship's directionality was not supported. Findings from Study 1 suggest that the relationship between prototypicality and fluency was negative, while Study 2 results show a positive relationship. Landwehr et al. (2011), for example, found that the complexity of a vehicle's design had a significant mediating effect on the relationship between prototypicality and fluency. Future research should examine design variables, such as complexity, as well as psychological variables, such as need for cognition, to see if these independent variables can further explain how the prototypicality of a product impacts individual fluency rate.

There were no significant findings for hypothesis 4, which suggests that there are more mediating variables between Entropy to Consumer Preference. Future research should examine vehicle models accompanied by performance information such as fuel type, miles per fuel or electric charge (range), and cost of ownership to investigate whether utilitarian associations accompanying typicality changes might alter aesthetic liking of the vehicle. This would presumably increase entropy of the stimuli overall, but would allow researchers to explore various information affects the scan path, attention drawing power of vehicle design features, and ultimately consumer evaluations.

Further development of a measure for fluency using eye tracking methods should also be examined by future research. Hypothesis 1 and 3 used individual response times to measure fluency, which has frequently been used in other studies in the marketing and product design literature. However, the construct of fluency might be more complex than simply how much time someone looks at a stimulus, considering that eye movements are made up of saccades, gaze gists, fixations, and transitions—each of which can now be measured via eye tracking. An important note to make here is that both total number of fixations and total fixation duration were both tested as potential measurements for fluency during the data analysis. Neither measurement was significantly related to either prototypicality, nor consumer evaluations/sales.

An alternative approach to measuring fluency with response time that is promising for future examination is capturing the response rate when participants are actually evaluating the vehicle. This study measured the amount of time it took participants to simply look at the vehicle images entirely at the initial phase of the eye tracking experiment. This was not only a measure used in previous studies that produced significant findings, but it was also done due to the large sample size and amount of time required to individually edit and capture the response rate of each vehicle evaluation during each participant's experiment recordings (average experiment time recording was about 9 minutes).

Additionally, exposure effects were not controlled for in the recruitment of participants for this study. Other than asking their level of knowledge about electric vehicles in the demographic survey, participants were not asked whether or not they had experience with any of the vehicles examined. To control for this, future research should strategically select stimuli that participants have not been exposed in order to ensure that any sort of familiarity with the images tested does not bias the responses collected.

Although the relationships in Study 2's model were not significant, findings reveal that sales was significantly correlated in the predicted negative direction with the Shannon (1948) entropy metric (t = -0.45, p = 0.00), the T_{50} metric (t = -0.45, p = 0.00) and fluency (t = -0.78, p = 0.00). This suggests that although these variables do play some role in how many vehicles are sold, there are other significant variable that influenced total annual sales. Marketing variables such as price, brand strength, market share, and annual amount spent on advertising were controlled for in this experiment to specifically examine the effects that a vehicle's design has on annual sales. Although limited in scope, the findings here are relevant to both designers and marketing executives as they attempts to align new model designs with the expectations of consumers while also trying to stand out amongst competitors in a saturated market. Understanding which design features consumers use to make evaluations during the purchasing process is an important first step before launching a new vehicle model to the market.

Practical Implications

In addition to the affirming contributions to information theory literature, these findings offer several practical implications as well. One of the exploratory objective of this study was to find which vehicle features attract the most attention and are used to effectively acquire information during the cognitive process. The sections discussing findings of the scan path entropy and T_{50} measures related to a vehicle's grille underscore the importance of this specific design element from two key perspectives: 1) the grille is a salient feature that consumers rely heavily on when searching for information in the visual evaluation process, and 2) this area is a great opportunity for companies invest in a grille design that will effectively signal their brand message and aesthetics clearly. Iterations of new or existing grille designs can be tested prior to a new vehicle goes to market by conducting eye tracking experiments in addition to traditional consumer self-reported surveys, and then analyzed with entropy and T_{50} metrics.

Scan path entropy and T_{50} can be useful measures in test small physical design variations in new vehicles, large design alterations in radical designs such as concept cars, as well as marketing material such as online or print advertisements. Concept cars are created by companies to test radical new design ideas for possible use in future mass production models, but are very costly to build with little to no guaranteed return on the money invested. During the early stages and throughout the concept design process, however, novel design ideas can be repeatedly tested with these two entropy metrics through eye tracking experiments on either 2D concept sketches or actual 3D models. This could help designers understand which features attract consumer attention the most and whether or not the desired company message of highlighted innovations are effectively transferred to consumers. Additionally, elements that are displeasing, uncertain or confusing to consumers can be quickly identified and remedied before releasing the final concept car design to the public. This would allow companies to not only get critical and accurate feedback on novel designs and innovations displayed in the concept car, but it can also lower the high uncertainty that's associated with radical new concept cars and how it's received by consumers and the press.

This study supports the practical uses made by Hooge and Camps (2013), which suggest that if design enhancement is of interest to design practitioners, then both T_{50} and entropy can be helpful measures. Findings suggest that T_{50} does provide insight into the attention drawing power that specific AOIs elicit, such as the significant effects found with the grille in this study. The attention drawing power of the logo area within the grille's design, for example, can be further increased by either increasing its size, creating empty space around the logo area in the grille or designing the logo area with contrasting design features (e.g., lines, shapes, color, etc.) to make this area more conspicuous and recognizable (Hooge & Camps, 2013; Toet & Levi, 1992; Kooi, Toet, Tripathy & Levi, 1994).

Conclusion

The underlying notion that aesthetic design choices highlight the visual appeal of a new product and reflect its level of novelty to consumers was the focus of this examination. How unique a product's aesthetics is to an individual can determine the degree of schema incongruity one might encounter when visually interpreting new products. Findings revealed the significant effects that the design of a vehicle's grille can have on consumer preference. This suggests that the design of the grille itself is an important consideration for all car manufacturers, especially those launching new electric vehicle models that do not require functional use for a grille.

Respective to product designs, the results reveal that consumers consider moderately typical vehicle designs more aesthetically pleasing than typical vehicles, but designs that are too novel are less positively evaluated. The results for typicality are aligned with Mandler's (1982) hypothesis, which states that consumers prefer designs that are moderately incongruent with established product schemas. This is also in line with Heckler and Childers' (1992) theory that suggests solving a puzzle is rewarding. Expanding knowledge is perceived as pleasurable (Armstrong & Detweiler-Bedell, 2008; Blijlevens et al., 2012), which is then attributed to aesthetic appraisal of the product's design. However, if a design's level of novelty reaches a point that it is too difficult to assimilate into the existing knowledge schema system, then preserving the existing knowledge system, rather than adapting it with the extremely novel design, is more desirable. With this knowledge, firms can construct their new products with aesthetic design features that offer a way to resolve that product feature incongruity for consumers (Rindova & Petkova, 2007).

REFERENCES

Aaker, D. A., & Joachimsthaler, E. (2000). The brand relationship spectrum: The key to the brand architecture challenge. *California Management Review*, *42*(4), 8–23.

Abernathy, W. J., & Clark, K. B. (1985). Innovation: Mapping the winds of creative destruction. *Research Policy, 14*(1), 3–22.

Abernathy, W. J., & Utterback, J. M. (1978). Patterns of industrial innovation. *Technology Review, 80*(7), 40–47.

Armstrong, T., & Detweiler-Bedell, B. (2008). Beauty as an emotion: The exhilarating prospect of mastering a challenging world. *Review of general psychology*, *12*(4), 305–329.

Anderson, P., & Tuchman, M. L. (1990). Technological discontinuities and dominant designs: A cyclical model of technological change, *Administrative Science Quarterly, 35*, 604–633.

Arnold, U. (2000). New dimensions of outsourcing: A combination of transaction cost of and the core competencies concept. *European Journal of Purchasing & Supply, Management, 6*(1), 23–29.

Atalay, A. S., Bodur, H. O., & Rasolofoarison, D. (2012). Shining in the center: Central gaze cascade effect on product choice. *Journal of Consumer Research, 39*(4), 848–866.

Atuahene-Gima, K. (1995). An exploratory analysis of the impact of market orientation on new product performance: A contingency approach. *Journal of Product Innovation Management, 12*(4), 275–293.

Audrin, C., Brosch, T., Sander, D., & Chanal, J. (2018). More than meets the eye: The impact of materialism on information selection during luxury choices. *Frontiers in Behavioral Neuroscience, 12,* 172–184.

Automotive News. (2018). *Automotive News Market Data Book* [2017 Market Data]. Retrieved from https://www.autonews.com/data-lists

Automotive News. (2018). *Automotive News Market Data Book* [2018 U.S. Light-Vehicle Sales by Nameplate, YTD]. Retrieved from https://www.autonews.com/data-lists

Baldwin, C. Y., & Clark, K. B. (2000). *Design rules: The power of modularity* (Vol. 1). Cambridge, Massachusetts: The MIT Press.

Barden, P. (2013). *Decoded: The science behind why we buy*. West Sussex, United Kingdom: John Wiley & Sons.

Barksdale, H. C., & Darden, B. (1971). Marketers' attitudes toward the marketing concept. *Journal of Marketing*, *35*(4), 29–36.

Barron, J. (2007, August 1). To Ford, a disaster. To Edsel owners, love. *The New York Times.* Retrieved from http://www.nytimes.com/2007/08/01/nyregion/01edsel.html?_r=0

Barsalou, L. W. (1985). Ideals, central tendency, and frequency of instantiation as determinants of graded structure in categories. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *11*(4), 629–654.

Belk, R. W. (1988). Possessions and the extended self. *Journal of Consumer Research, 15*(2), 139–168.

Bergkvist, L., & Rossiter, J. R. (2007). The predictive validity of multiple-item versus single-item measures of the same constructs. *Journal of Marketing Research, 44*(2), 175–184.

Berlyne, D. E. (1971). *Aesthetics and psychobiology* (Vol. 336). New York, NY: Appleton-Century-Crofts.

Berntson, G. G., & Cacioppo, J. T. (Eds.). (2009). *Handbook of neuroscience for the behavioral sciences* (Vol. 2). West Sussex, United Kingdom: John Wiley & Sons.

Blijlevens, J., Carbon, C. C., Mugge, R., & Schoormans, J. P. (2012). Aesthetic appraisal of product designs: Independent effects of typicality and arousal. *British Journal of Psychology*, *103*(1), 44–57.

Bloch, P. H. (1995). Seeking the ideal form: Product design and consumer response. *Journal of Marketing*, 16–29.

Bloch, P. H. (2011). Product design and marketing: reflections after fifteen years. *Journal of Product Innovation Management*, *28*(3), 378–380.

Bloch, P. H., Brunel, F. F., & Arnold, T. J. (2003). Individual differences in the centrality of visual product aesthetics: Concept and measurement. *Journal of Consumer Research*, *29*(4), 551–565.

Bloch, P. H., & Richins, M. (1983). A theoretical model for the study of product importance perceptions. *Journal of Marketing*, *47*(3), 69–81

Bloomberg New Energy Finance. (2017). *Electric vehicle outlook 2017.* New York, NY: Bloomberg Finance L. P. Retrieved from https://data.bloomberglp.com/bnef/sites/14/2017/07/BNEF_EVO_2017_ExecutiveSummary.pdf

Blythe, J. (1999). Innovativeness and newness in high-tech consumer durables. *Journal of Product & Brand Management, 8*(5), 415–429.

Bojko, A. (2013). *Eye tracking the user experience: A practical guide to research.* Brooklyn, NY: Rosenfeld Media, LLC.

Bornstein, R. F. (1989). Exposure and affect: Overview and meta-analysis of research, 1968–1987. *Psychological Bulletin, 106*(2), 265–289.

Bosmans, A. (2006). Scents and sensibility: When do (in) congruent ambient scents influence product evaluations? *Journal of Marketing, 70*(3), 32–43.

Boztepe, S. (2007). User value: Competing theories and models. *International Journal of Design, 1*(2), 55–63.

Brady, J., & O'Mahony, M. (2011). Travel to work in Dublin. The potential impacts of electric vehicles on climate change and urban air quality. *Transportation Research Part D: Transport and Environment*, *16*(2), 188–193.

Campbell, M. C., & Goodstein, R. C. (2001). The moderating effect of perceived risk on consumers' evaluations of product incongruity: Preference for the norm. *Journal of Consumer Research*, *28*(3), 439–449.

Carpenter, G. S., & Nakamoto, K. (1990). Competitive strategies for late entry into a market with a dominant brand. *Management Science, 36*(10), 1268–1278.

Chae, S. W., & Lee, K. C. (2013). Exploring the effect of the human brand on consumers' decision quality in online shopping: An eye tracking approach. *Online Information Review, 37*(1), 83–100.

Chandon, P., Hutchinson, J. W., Bradlow, E. T., & Young, S. H. (2009). Does in-store marketing work? Effects of the number and position of shelf facings on brand attention and evaluation at the point of purchase. *Journal of Marketing, 73*(6), 1–17.

Chandon, P., & Wansink, B. (2007). The biasing health halos of fast-food restaurant health claims: Lower calorie estimates and higher side-dish consumption intentions. *Journal of Consumer Research, 34*(3), 301–314.

ChargePoint, Inc. (2017). *Charging forward report: All roads lead to e-mobility*. Retrieved from https://www.chargepoint.com/charging-forward-2017

Chaudhuri, A., Aboulnasr, K., & Ligas, M. (2010). Emotional responses on initial exposure to a hedonic or utilitarian description of a radical innovation. *Journal of Marketing Theory and Practice, 18*(4), 339–359.

Chitturi, R. (2009). Emotions by design: A consumer perspective. *International Journal of Design*, *3*(2), 7–17.

Chitturi, R., Raghunathan, R., & Mahajan, V. (2007). Form versus function: How the intensities of specific emotions evoked in functional versus hedonic trade-offs mediate product preferences. *Journal Of Marketing Research*, *44*(4), 702–714.

Chitturi, R., Raghunathan, R., & Mahajan, V. (2008). Delight by design: The role of hedonic versus utilitarian benefits. *Journal of Marketing*, *72*(3), 48–63.

Creusen, M. E. (2011). Research opportunities related to consumer response to product design. *Journal of Product Innovation Management*, *28*(3), 405–408.

Creusen, M. E., & Schoormans, J. P. (2005). The different roles of product appearance in consumer choice. *Journal of Product Innovation Management*, *22*(1), 63–81.

Crilly, N., Moultrie, J., & Clarkson, P. J. (2004). Seeing things: Consumer response to the visual domain in product design. *Design Studies*, *25*(6), 547–577.

Davvetas, V., & Diamantopoulos, A. (2016). How product category shapes preferences toward global and local brands: A schema theory perspective. *Journal of International Marketing*, *24*(4), 61–81.

Desmet, P., & Hekkert, P. (2007). Framework of product experience. *International Journal of Design*, *1*(1), 57–66.

Dhar, R. & Wertenbroch, K. (2000). Consumer choice between hedonic and utilitarian goods. *Journal of Marketing Research, 37*(1), 60–71.

Engel S. A., Rumelhart, D. E., Wandell, B. A., Lee A. T., Glover G. H., Chichilinsky E. J., Shadlen M. N. (1994). fMRI of human visual cortex. *Nature*, *370*, 106.

Feiereisen, S., Wong, V., & Broderick, A. J. (2008). Analogies and mental simulations in learning for really new products: The role of visual attention. *Journal of Product Innovation Management, 25*(6), 593–607.

Fiske, S. T. (1982). Schema-triggered affect: Applications to social perception. In M. S. Clark & S. T. Fiske (Eds.), *Affect and Cognition: The 17th Annual Carnegie Symposium (pp. 55–78*). Hillsdale, NJ: Lawrence Erlbaum Associates.

Fiske, S. T., & Taylor, S. E. (2013). *Social cognition: From brains to culture.* London, United Kingdom: Sage Publications Ltd.

Fredrickson, B. L. (1998). What good are positive emotions?. *Review of General Psychology, 2*(3), 300–319.

Garcia, R., & Calantone, R. (2002). A critical look at technological innovation typology and innovativeness terminology: A literature review. *Journal of Product Innovation Management*, *19*(2), 110–132.

Gatersleben, B. Niamh M., & Wokje A. (2014). Values, identity and pro-environmental behaviour. *Contemporary Social Science, 9*(4), 374–392.

Gerjets, P., & Scheiter, K. (2003). Goal configurations and processing strategies as moderators between instructional design and cognitive load: Evidence from hypertext-based instruction. *Educational Psychologist, 38*(1), 33–41.

Glaholt, M. G., & Reingold, E. M. (2011). Eye movement monitoring as a process tracing methodology in decision making research. *Journal of Neuroscience, Psychology, and Economics, 4*(2), 125–146.

Glöckner, A., & Herbold, A. K. (2011). An eye-tracking study on information processing in risky decisions: Evidence for compensatory strategies based on automatic processes. *Journal of Behavioral Decision Making, 24*(1), 71–98.

Gobeli, D. H., & Brown, D. J. (1987). Analyzing product innovations. *Research Management, 30*(4), 25–31.

Goldberg, J. H., & Kotval, X. P. (1999). Computer interface evaluation using eye movements: Methods and constructs. *International Journal of Industrial Ergonomics, 24*(6), 631–645.

Graf, L. K., & Landwehr, J. R. (2015). A dual-process perspective on fluency-based aesthetics: The pleasure-interest model of aesthetic liking. *Personality and Social Psychology Review, 19*(4), 395–410.

Graf, L. K., & Landwehr, J. R. (2017). Aesthetic pleasure versus aesthetic interest: The two routes to aesthetic liking. *Frontiers in Psychology, 8*, 15–30.

Graf, L. K., Mayer, S., & Landwehr, J. R. (2018). Measuring processing fluency: One versus five items. *Journal of Consumer Psychology, 28*(3), 393–411.

Graham, D. J., & Jeffery, R. W. (2011). Location, location, location: Eye tracking evidence that consumers preferentially view prominently positioned nutrition information. *Journal of the American Dietetic Association, 111*(11), 1704–1711.

Griffith, T. L. (1999). Technology features as triggers for sensemaking. *Academy of Management Review, 24*(3), 472–488.

Halkias, G. (2015). Mental representation of brands: A schema-based approach to consumers' organization of market knowledge. J*ournal of Product & Brand Management, 24*(5), 438–448.

Halkias, G., & Kokkinaki, F. (2014). The degree of ad–brand incongruity and the distinction between schema-driven and stimulus-driven attitudes. *Journal of Advertising, 43*(4), 397–409.

Hauser, J., Tellis, G. J., & Griffin, A. (2006). Research on innovation: A review and agenda for marketing science. *Marketing Science, 25*(6), 687–717.

Hawkins, T. R., Singh, B., Majeau-Bettez, G., & Strømman, A. H. (2013). Comparative environmental life cycle assessment of conventional and electric vehicles. *Journal of Industrial Ecology*, *17*(1), 53–64.

Hekkert, P. (2006). Design aesthetics: Principles of pleasure in design. *Psychology Science, 48*(2), 157–172.

Hekkert, P., Snelders, D., & Wieringen, P. C. (2003). Most advanced, yet acceptable: Typicality and novelty as joint predictors of aesthetic preference in industrial design. *British Journal of Psychology*, *94*(1), 111–124.

Hirschman, E. & Holbrook, M. (1982) Hedonic consumption: Emerging concepts, methods, and propositions. *Journal of Marketing, 46*, 92–101.

Hoeffler, S. (2003). Measuring preferences for really new products. *Journal of Marketing Research, 40*(4), 406–420.

Hoegg, J., Alba, J. W., & Dahl, D. W. (2010). The good, the bad, and the ugly: Influence of aesthetics on product feature judgments. *Journal of Consumer Psychology, 20*(4), 419–430.

Holbrook, M. B. (1980). Some preliminary notes on research in consumer esthetics. *ACR North American Advances*.

Hollins, B., & Pugh, S. (1990). *Successful product design: What to do and when.* London, United Kingdom: Butterworth-Heinemann.

Holmqvist, K., Nyström, M., Andersson, R., Dewhurst, R., Jarodzka, H., & Van de Weijer, J. (2011). *Eye tracking: A comprehensive guide to methods and measures.* Oxford, United Kingdom: Oxford University Press.

Hooge, I. T., & Camps, G. (2013). Scan path entropy and arrow plots: Capturing scanning behavior of multiple observers. *Frontiers in Psychology, 4*, 996–106.

Hoyer, W. D., & MacInnis, D. J. (2008). *Consumer Behavior.* Mason, OH: Cengage Learning.

Hutchinson, J. W., Lu, J., & Weingarten, E. (2017). Visual attention in consumer settings. In C. V. Jansson-Boyd & M. J. Zawisza (Eds.), *Routledge International Handbook of Consumer Psychology* (pp. 79–102). Oxon, United Kingdom: Routledge.

IEA. (2019). *Global EV Outlook 2019*. Paris, France: International Energy Agency. Retrieved from www.iea.org/publications/reports/globalevoutlook2019/.

Jacoby, L. L., & Dallas, M. (1981). On the relationship between autobiographical memory and perceptual learning. *Journal of Experimental Psychology: General*, *110*(3), 306.

Janiszewski, C. (1998). The influence of display characteristics on visual exploratory search behavior. *Journal of Consumer Research, 25*(3), 290–301.

Janiszewski, C., Andrew K., & Tavassoli, N. T. (2013). The influence of selective attention and inattention to products on subsequent choice. *Journal of Consumer Research, 39*(6), 1258–1274.

Jindal, R. P., Sarangee, K. R., Echambadi, R., & Lee, S. (2016). Designed to succeed: Dimensions of product design and their impact on market share. *Journal of Marketing*, *80*(4), 72–89.

Johannessen, J. A., Olsen, B., & Lumpkin, G. T. (2001). Innovation as newness: What is new, how new, and new to whom?. *European Journal of Innovation Management, 4*(1), 20–31.

Jordan, J., & Slater, M. (2009). An analysis of eye scanpath entropy in a progressively forming virtual environment. *Presence: Teleoperators and Virtual Environments, 18*(3), 185–199.

Kahn, B. E. (2017). Using visual design to improve customer perceptions of online assortments. *Journal of Retailing, 93*(1), 29–42.

Keaveney, S. M., Herrmann, A., Befurt, R., & Landwehr, J. R. (2012). The eyes have it: How a car's face influences consumer categorization and evaluation of product line extensions. *Psychology & Marketing*, *29*(1), 36–51.

Kelly Blue Book. (2018). *Average new-car prices rise nearly 4 percent for January 2018 on shifting sales mix, according to Kelley Blue Book.* Retrieved from https://mediaroom.kbb.com/2018-02-01-Average-New-Car-Prices-Rise-Nearly-4-Percent-For-January-2018-On-Shifting-Sales-Mix-According-To-Kelley-Blue-Book

Kooi, F. L., Toet, A., Tripathy, S. P., & Levi, D. M. (1994). The effect of similarity and duration on spatial interaction in peripheral vision. *Spatial Vision, 8*(2), 255–279.

Krajbich, I., & Rangel, A. (2011). Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions. *Proceedings of the National Academy of Sciences, 108*(33), 13852–13857.

Kreuzbauer, R., & Malter, A. J. (2005). Embodied cognition and new product design: Changing product form to influence brand categorization. *Journal of Product Innovation Management*, *22*(2), 165–176.

Labroo, A. A., & Lee, A. Y. (2006). Between two brands: A goal fluency account of brand evaluation. *Journal of Marketing Research, 43*(3), 374–385.

Lajos, J., Katona, Z., Chattopadhyay, A. & Sarvary, M. (2009). Category activation model: A spreading activation network model of subcategory positioning when categorization uncertainty is high. *Journal of Consumer Research, 31*(6), 122–136.

Landwehr, J. R., Labroo, A. A., & Herrmann, A. (2011). Gut liking for the ordinary: Incorporating design fluency improves automobile sales forecasts. *Marketing Science*, *30*(3), 416–429.

Landwehr, J. R., Wentzel, D., & Herrmann, A. (2012). The tipping point of design: How product design and brands interact to affect consumers' preferences. *Psychology & Marketing, 29*(6), 422–433.

Landwehr, J. R., Wentzel, D., & Herrmann, A. (2013). Product design for the long run: Consumer responses to typical and atypical designs at different stages of exposure. *Journal of Marketing, 77*(5), 92–107.

Leder, H., Belke, B., Oeberst, A., & Augustin, D. (2004). A model of aesthetic appreciation and aesthetic judgments. *British Journal of Psychology, 95*(4), 489–508.

Lee, A. Y. (2001). The mere exposure effect: An uncertainty reduction explanation revisited. *Personality and Social Psychology Bulletin, 27*(10), 1255–1266.

Lee, A. Y., & Aaker, J. L. (2004). Bringing the frame into focus: The influence of regulatory fit on processing fluency and persuasion. *Journal of Personality and Social Psychology, 86*(2), 205–218.

Lee, A. Y., & Labroo, A. A. (2004). The effect of conceptual and perceptual fluency on brand evaluation. *Journal of Marketing Research, 41*(2), 151–165.

Lessing, S., & Linge, L. (2002). *IICap? A new environment for eye tracking data analysis.* (Master's thesis). University of Lund, Sweden.

Levy, S. (1959). Symbols for sale. *Harvard Business Review, 37*(4), 117–124.

Lewalski, Z. M. (1988). *Product esthetics: An interpretation for designers.* Carson City, NV: Design & Development Engineering Press.

Liao, F., Molin, E., & van Wee, B. (2017). Consumer preferences for electric vehicles: A literature review. *Transport Reviews*, *37*(3), 252–275.

Liu, Y., Li, J., Chen, K., Haipeng, A., & Balachander, S. (2017). The effects of a product's aesthetic design on demand and marketing mix effectiveness: The role of segment prototypicality and brand consistency. *Journal of Marketing, 81*(1), 83–102.

Loken, B., Barsalou, L. W., & Joiner, C. (2008). Categorization theory and research in consumer psychology. In C. P. Haugtvedt, P. M. Herr, & F. R. Kardes (Eds.), *Handbook of Consumer Psychology* (pp. 133–165). Oxon, United Kingdom: Routledge.

Loken, B., & Ward, J. (1987). Measures of the attribute structure underlying product typicality. *ACR North American Advances, 14*, 22–26.

Loken, B., & Ward, J. (1990). Alternative approaches to understanding the determinants of typicality. *Journal of Consumer Research, 17*(2), 111–126.

Mandler, G. (1982). The structure of value: Accounting for taste. In M. S. Clark & S. T. Fiske (Eds.), *Affect and Cognition: The 17th Annual Carnegie Symposium (pp. 3–36*). Hillsdale, NJ: Lawrence Erlbaum Associates.

Mandler, G., Nakamura, Y., & Van Zandt, B. J. (1987). Nonspecific effects of exposure on stimuli that cannot be recognized. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 13*(4), 646–648.

Mayer, S., & Landwehr, J. R. (2018). Objective measures of design typicality. *Design Studies, 54*, 146–161.

McClelland, J. L., & Rumelhart, D. E. (1985). Distributed memory and the representation of general and specific information. *Journal of Experimental Psychology: General, 114*(2), 159–199.

Medin, D. L., & Schaffer, M. M. (1978). Context theory of classification learning. *Psychological Review, 85*(3), 207–238.

Mervis, C. B., & Rosch, E. (1981). Categorization of natural objects. *Annual Review of Psychology*, *32*(1), 89–115.

Meyers-Levy, J., & Tybout, A. M. (1989). Schema congruity as a basis for product evaluation. *Journal of Consumer Research, 16*(1), 39–54.

Mick, D., Burroughs, J., Hetzel, P., & Brannen, M. (2004). Pursuing the meaning of meaning in the commercial world: An international review of marketing and consumer research founded on semiotics. *Semiotics, 152*, 1–74.

Milosavljevic, M., & Cerf, M. (2008). First attention then intention: Insights from computational neuroscience of vision. *International Journal of Advertising, 27*(3), 381–398.

Milosavljevic, M., Navalpakkam, V., Koch, C., & Rangel, A. (2012). Relative visual saliency differences induce sizable bias in consumer choice. *Journal of Consumer Psychology, 22*(1), 67–74.

Moons, I., & De Pelsmacker, P. (2012). Emotions as determinants of electric car usage intention. *Journal of Marketing Management, 28*(3-4), 195–237.

Monö, R. (1997). *Design for product understanding: The aesthetics of design from a semiotic approach*. Stockholm: Liber.

Montfoort, I., Frens, M. A., Hooge, I. T. C., Lagers-van Haselen, G. C., & Van der Geest, J. N. (2007). Visual search deficits in Williams-Beuren syndrome. *Neuropsychologia, 45*(5), 931–938.

Moran, P., & Ghoshal, S. (1999). Markets, firms, and the process of economic development. *Academy of Management Review, 24*(3), 390–412.

Moreau, C. P., Lehmann, D. R., & Markman, A. B. (2001). Entrenched knowledge structures and consumer response to new products. *Journal of Marketing Research, 38*(1), 14–29.

Mugge, R., & Dahl, D. W. (2013). Seeking the ideal level of design newness: Consumer response to radical and incremental product design. *Journal of Product Innovation Management*, *30*, 34–47.

Noseworthy, T. J., Murray, K. B., & Di Muro, F. (2017). When two wrongs make a right: Using conjunctive enablers to enhance evaluations for extremely incongruent new products. *Journal of Consumer Research*, *44*(6), 1379–1396.

Noseworthy, T. J., & Trudel, R. (2011). Looks interesting, but what does it do? Evaluation of incongruent product form depends on positioning. *Journal of Marketing Research, 48*(6), 1008–1019.

Noton, D., & Stark, L. (1971a). Eye movements and visual perception. *Scientific American, 224*, 34–43.

Noton, D., & Stark, L. (1971b). Scanpaths in eye movements during pattern perception. *Science, 171*(3968), 308–311.

Noton, D., & Stark, L. (1971c). Scanpaths in saccadic eye movements while viewing and recognizing patterns. *Vision Research, 11,* 929–942.

Novemsky, N., Dhar, R., Schwarz, N., & Simonson, I. (2007). Preference fluency in choice. *Journal of Marketing Research, 44*(3), 347–356.

Ogawa, S., & Piller, F. T. (2006). Reducing the risks of new product development. *MIT Sloan Management Review*, *47*(2), 65.

Orquin, J. L., & Loose, S. M. (2013). Attention and choice: A review on eye movements in decision making. *Acta Psychologica, 144*(1), 190–206.

Orth, U. R., & Malkewitz, K. (2008). Holistic package design and consumer brand impressions. *Journal of Marketing*, *72*(3), 64–81.

Paas, F., Renkl, A., & Sweller, J. (2004). Cognitive load theory: Instructional implications of the interaction between information structures and cognitive architecture. *Instructional Science, 32*(1-2), 1–8.

Park, C. W., Milberg, S., & Lawson, R. (1991). Evaluation of brand extensions: The role of product feature similarity and brand concept consistency. *Journal of Consumer Research, 18*(2), 185–193.

Peck, J., & Childers, T. L. (2003). To have and to hold: The influence of haptic information on product judgments. *Journal of Marketing, 67*(2), 35–48.

Petruzzellis, L. (2010). Mobile phone choice: Technology versus marketing. The brand effect in the Italian market. *European Journal of Marketing, 44*(5), 610–634.

Pieters, R., Rosbergen, E., & Wedel, M. (1999). Visual attention to repeated print advertising: A test of scanpath theory. *Journal of Marketing Research*, 424–438.

Pieters, R., & Wedel, M. (2004). Attention capture and transfer in advertising: Brand, pictorial, and text-size effects. *Journal of Marketing, 68*(2), 36–50.

Pieters, R., Wedel, M., & Batra, R. (2010). The stopping power of advertising: Measures and effects of visual complexity. *Journal of Marketing, 74*(5), 48–60.

Pinch, T. J., & Bijker, W. E. (1987). The social construction of facts and artifacts: Or how the sociology of. *The social constructions of technological systems: New directions in the Sociology and History of Technology, 17*, 1–6.

Pocheptsova, A., Labroo, A. A., & Dhar, R. (2010). Making products feel special: When metacognitive difficulty enhances evaluation. *Journal of Marketing Research*, *47*(6), 1059–1069.

Priem, R. L. (2002). A consumer perspective on value creation. *Academy of Management Review, 32*(1), 219–235.

Radford, S. K., & Bloch, P. H. (2011). Linking innovation to design: Consumer responses to visual product newness. *Journal of Product Innovation Management, 28*(1), 208–220.

Radford, S. K. (2007). *Have you seen the new model? Visual design and product newness* (Doctoral Dissertation, University of Missouri—Columbia). Retrieved from https://mospace.umsystem.edu/xmlui/bitstream/handle/10355/4654/research.pdf

Ravens, S. (2017). *Charging ahead with EV analytics: Adopting a flexible approach to IoT infrastructure for EV integration*. Boulder, CO: Navigant Consulting, Inc. Retrieved from https://www.navigantresearch.com/reports/charging-ahead-with-ev-analytics

Rayner, K. (1998). Eye movements in reading and information processing: 20 years of research. *Psychological Bulletin, 124*(3), 372–422.

Reber, R., Winkielman, P., & Schwarz, N. (1998). Effects of perceptual fluency on affective judgments. *Psychological Science, 9*(1), 45–48.

Reber, R., Schwarz, N., & Winkielman, P. (2004). Processing fluency and aesthetic pleasure: Is beauty in the perceiver's processing experience?. *Personality and Social Psychology Review, 8*(4), 364–382.

Rindova, V. P., & Petkova, A. P. (2007). When is a new thing a good thing? Technological change, product form design, and perceptions of value for product innovations. *Organization Science, 18*(2), 217–232.

Rogers, E. M. (1995). Lessons for guidelines from the diffusion of innovations. *Joint Commission Journal on Quality and Patient Safety, 21*(7), 324–328.

Rogers, E. M. (2003). *The diffusion of innovation* (5th ed.). New York, NY: Free Press.

Rosa, J. A., Porac, J. F., Runser-Spanjol, J., & Saxon, M. S. (1999). Sociocognitive dynamics in a product market. *Journal of Marketing*, 64–77.

Rosch, E., & Mervis, C. B. (1975). Family resemblances: Studies in the internal structure of categories. *Cognitive Psychology, 7*(4), 573–605.

Rosch, E., Mervis, C. B., Gray, W. D., Johnson, D. M., & Boyes-Braem, P. (1976). Basic objects in natural categories. *Cognitive Psychology, 8*(3), 382–439.

Rosch, E., Simpson, C., & Miller, R. S. (1976). Structural bases of typicality effects. *Journal Of Experimental Psychology: Human Perception And Performance, 2*(4), 491–502.

Rosch, E., & Lloyd, B. B. (1978). *Cognition and categorization*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Rosch, E. (1999). Principles of categorization. In E. Margolis & S. Lawrence (Eds.), *Concepts: Core readings* (pp. 189–206). Cambridge, Massachusetts: The MIT Press.

Russo, J. E. (1978). Eye fixations can save the world: A critical evaluation and a comparison between eye fixations and other information processing methodologies. *Advances in Consumer Research, 5*, 561–570.

Schwarz, N. (2004). Metacognitive experiences in consumer judgment and decision making. *Journal of Consumer Psychology, 14*(4), 332–348.

Schwarz, N. (2015). Which mission? Thoughts about the past and future of BDT. *Journal of Marketing Behavior, 1*(1), 53–58.

Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal, 27*(3), 379–423.

Shic, F., Chawarska, K., & Scassellati, B. (2008). The amorphous fixation measure revisited: With applications to autism. *Proceedings of the Cognitive Science Society 30*, 1–6.

Shimojo, S., Simion, C., Shimojo, E., & Scheier, C. (2003). Gaze bias both reflects and influences preference. *Nature Neuroscience, 6*(12), 1317–1322.

Smith, L. B. (1989). From global similarities to kinds of similarities: The construction of dimensions in development. In S. Vosniadou, & A. Ortoney (Eds.), *Similarity and Analogical Reasoning* (pp. 147–177). Cambridge: Cambridge University Press.

Solomon, M. R. (1983). The role of products as social stimuli: A symbolic interactionism perspective. *Journal of Consumer Research*, *10*(3), 319–329.

Solomon, M. R. (2010). *Consumer behaviour: A European perspective* (4th ed.). Harlow, United Kingdom; New York, NY: Prentice Hall/Financial Times.

Stanton, S. J., Townsend, J. D., & Kang, W. (2016). Aesthetic responses to prototypicality and uniqueness of product design. *Marketing Letters, 27*(2), 235–246.

Sujan, M. (1985). Consumer knowledge: Effects on evaluation strategies mediating consumer judgements. *Journal of Consumer Research, 12*(1), 31–46.

Sujan, M., & Bettman, J. R. (1989). The effects of brand positioning strategies on consumers' brand and category perceptions: Some insights from schema research. *Journal of Marketing Research,* 454–467.

Sujan, M., & Dekleva, C. (1987). Product categorization and inference making: Some implications for comparative advertising. *Journal of Consumer Research, 14*(3), 372–378.

Sweller, J. (1994). Cognitive load theory, learning difficulty, and instructional design. *Learning and Instruction, 4*(4), 295–312.

Tobii. (2016). Tobii Technology: Tobii Pro Lab Studio Software (Version 1.73).

Todd, J., Chen, J., & Clogston, F. (2013). *Creating the clean energy economy: Analysis of the electric vehicle industry.* Washington, DC: International Economic Development Council.

Toet, A. & Levi, D. M. (1992). The two-dimensional shape of spatial interaction zones in the parafovea. *Vision Research, 32*(7)*,* 1349–1357.

Tushman, M. L., & Anderson, P. (1986). Technological discontinuities and organizational environments. *Administrative Science Quarterly*, 439–465.

Van Rompay, T., Pruyn, T. H. & Tieke, P. (2009). Symbolic meaning integration in design and its influence on product and brand evaluation. *International Journal of Design, 3*(2).

Veryzer, R. W. (1999). A nonconscious processing explanation of consumer response to product design. *Psychology & Marketing*, *16*(6), 497–522.

Veryzer, R. W., & Hutchinson, J. W. (1998). The influence of unity and prototypicality on aesthetic responses to new product designs. *Journal of Consumer Research*, *24*(4), 374–394.

Viswanathan, M., & Childers, T. L. (1999). Understanding how product attributes influence product categorization: Development and validation of fuzzy set-based measures of gradedness in product categories. *Journal of Marketing Research,* 75–94.

Voss, K. E., Spangenberg, E. R., & Grohmann, B. (2003). Measuring the hedonic and utilitarian dimensions of consumer attitude. *Journal of Marketing Research, 40*(3), 310–320.

Wedel, M., & Pieters, R. (2008). A review of eye tracking research in marketing. *Review of Marketing Research*, *4*, 123–147.

Wedel, M., Pieters, R., & Liechty, J. (2008). Attention switching during scene perception: How goals influence the time course of eye movements across advertisements. *Journal of Experimental Psychology: Applied, 14*(2), 129–138.

Wedel, M., & Pieters, R. (Eds.). (2012). *Visual marketing: From attention to action.* London, United Kingdom: Psychology Press.

Whittlesea, B. W. (1993). Illusions of familiarity. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 19*(6), 1235–1253.

Willemsen, L. M., Neijens, P. C., Bronner, F., & De Ridder, J. A. (2011). Highly recommended! The content characteristics and perceived usefulness of online consumer reviews. *Journal of Computer-Mediated Communication, 17*(1), 19–38.

Winkielman, P., & Cacioppo, J. T. (2001). Mind at ease puts a smile on the face: psychophysiological evidence that processing facilitation elicits positive affect. *Journal Of Personality And Social Psychology, 81*(6), 989–1000.

Winkielman, P., Halberstadt, J., Fazendeiro, T., & Catty, S. (2006). Prototypes are attractive because they are easy on the mind. *Psychological Science, 17*(9), 799–806.

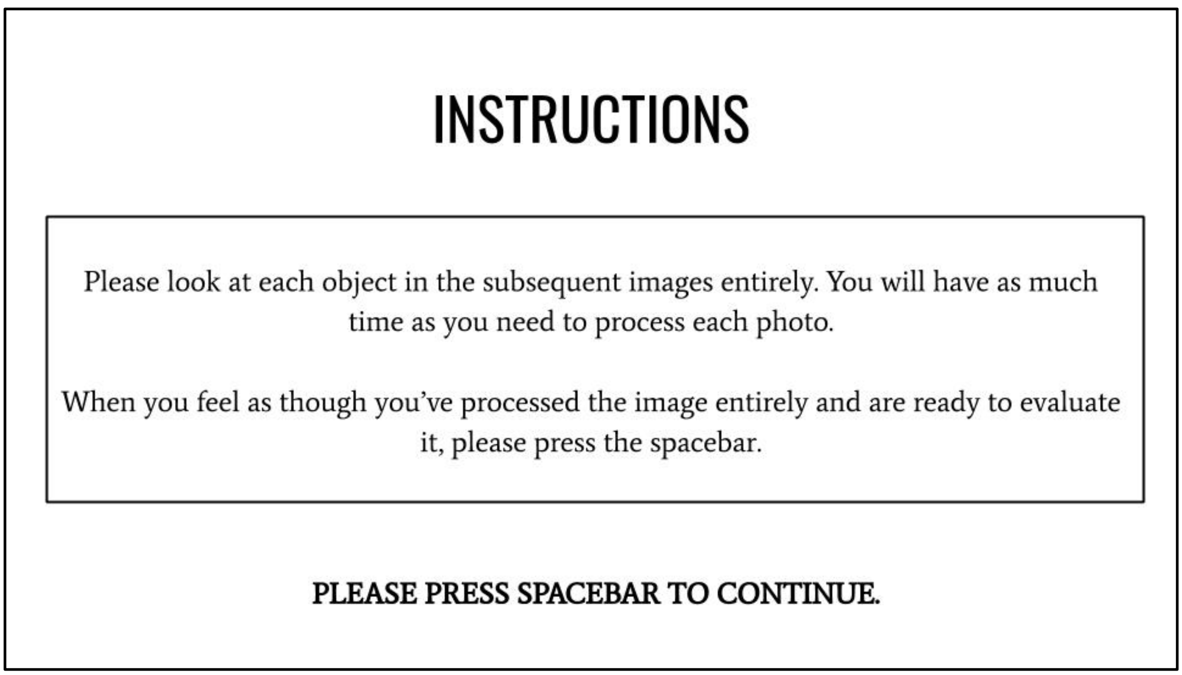
Winkielman, P., Schwarz, N., Fazendeiro, T., & Reber, R. (2003). The hedonic marking of processing fluency: Implications for evaluative judgment. *The Psychology Of Evaluation: Affective Processes In Cognition And Emotion*, 189–217.

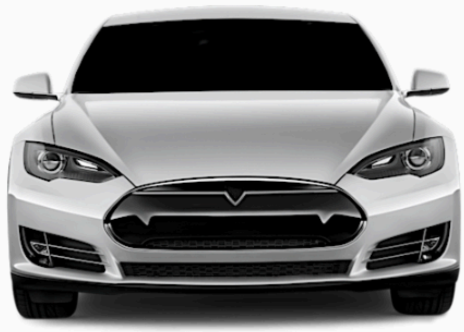
Xiao, Y. J., & Van Bavel, J. J. (2012). See your friends close and your enemies closer: Social identity and identity threat shape the representation of physical distance. *Personality and Social Psychology Bulletin, 38*(7), 959–972.

Zajonc, R. (1998). Emotions. In D. Gilbert, S. Fiske, & G. Lindzey (Eds.), *Handbook of Social Psychology* (pp. 591–632). Oxford, United Kingdom: Oxford University Press.

APPENDICES

Appendix A: Experiment and Survey Stimuli Flow





How well does the design of this car match your expectations for cars in general?

Not well at all 1	2	3	4	5	6	Very well 7
○	○	○	○	○	○	○

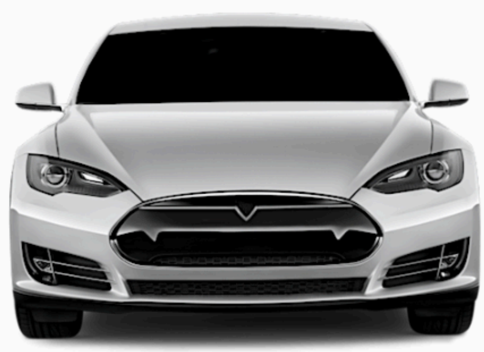
How much do you like this car's design overall?

I don't like it 1	2	3	4	5	6	I like it very much 7
○	○	○	○	○	○	○

How unique is the design of this car, in your opinion?

Not at all unique 1	2	3	4	5	6	Extremely unique 7
○	○	○	○	○	○	○

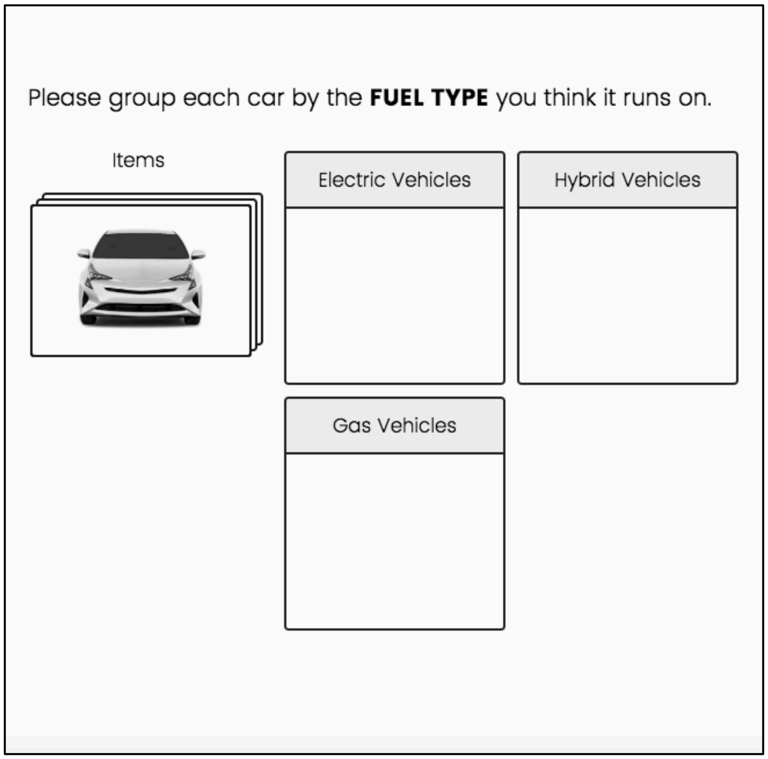
→

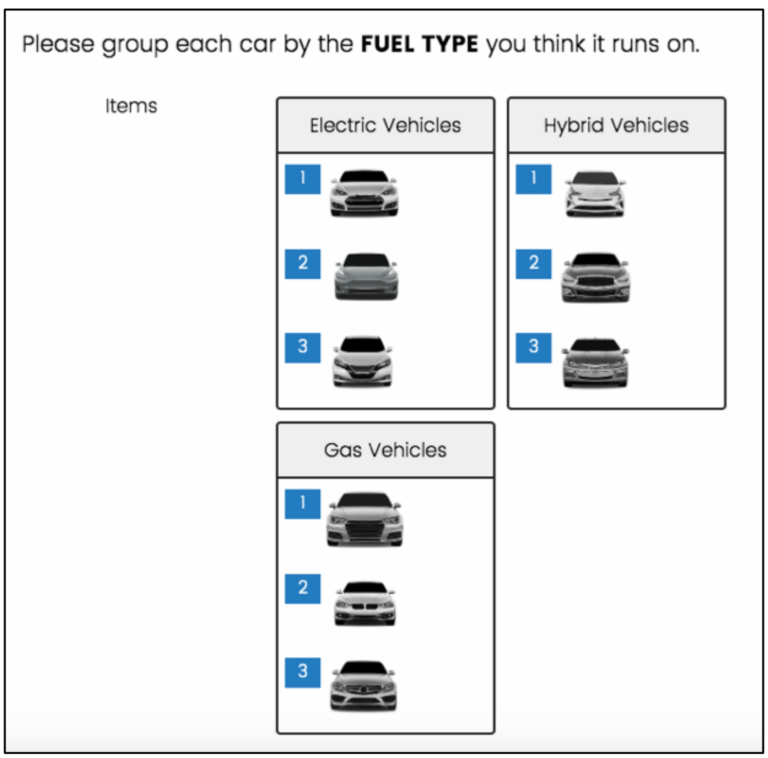


How likely is this car an electric vehicle, in your opinion?

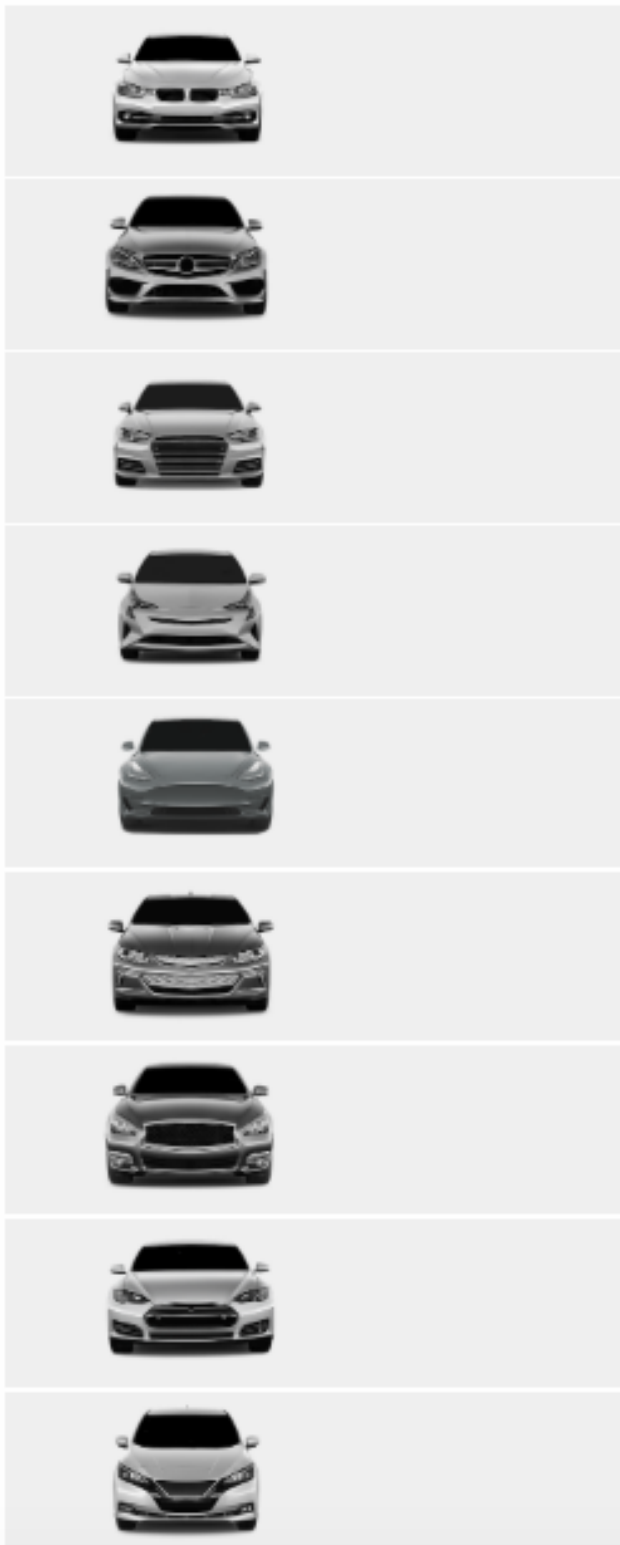
Very unlikely 1	2	3	4	5	6	Very likely 7
○	○	○	○	○	○	○

→


Please group each car by the **FUEL TYPE** you think it runs on.
Items
Electric Vehicles
Hybrid Vehicles
Gas Vehicles

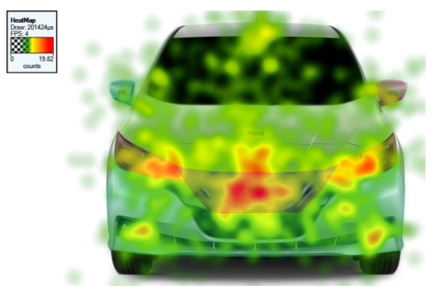
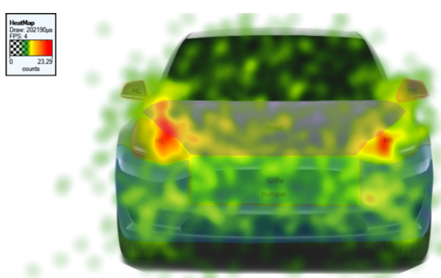
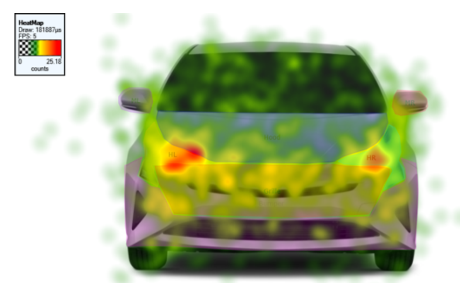

Please group each car by the **FUEL TYPE** you think it runs on.
Items
Electric Vehicles
1
2
3
Hybrid Vehicles
1
2
3
Gas Vehicles
1
2
3

Rank your **FAVORITE CAR DESIGNS** by dragging each image in sequential order from top to bottom (1 = Most Favorite/Top, 10 = Least Favorite/Bottom).



Appendix B: Additional Figures

Figure B1. *Stimuli Heatmaps*

Electric	Combustion	Hybrid
 2015 Tesla Model S	 2017 Audi A4	 2017 Chevrolet Volt
 2017 Nissan Leaf	 2017 BMW 300i	 2017 INFINITI Q70
 2017 Tesla Model 3	 2017 Mercedes-Benz C300	 2017 Toyota Prius Two

Appendix C: Additional Tables

Table C1.
Correlation Matrices

Study 1: Correlations Matrix of Model Variables (n = 111)					
	Evaluation	Typicality	Uniqueness	Fluency	Total Dwell
Evaluation	1.0000				
p-value					
Typicality	0.7591***	1.0000			
p-value	0.0000				
Uniqueness	0.5348***	0.4145***	1.0000		
p-value	0.0000	0.0000			
Fluency		0.0797**	0.0777**	1.0000	
p-value		0.0118	0.014		
Total Dwell		0.0978***	0.0794**	0.9235***	1.0000
p-value		0.002	0.0121	0.0000	

Study 2: Correlations Matrix of Model Variables (n = 9)					
	Sales	Typicality	Shannon Entropy	T_{50}	Fluency
Sales	1.0000				
p-value					
Typicality	0.1546***	1.0000			
p-value	0.0000				
Shannon Entropy	-0.4484***	0.3804***	1.0000		
p-value	0.0000	0.0000			
T_{50}	-0.4454***	-0.2083***	0.2288***	1.0000	
p-value	0.0000	0.0000	0.0000		
Fluency	-0.7781***	-0.4283***	0.3071***	0.1510***	1.0000
p-value	0.0000	0.0000	0.0000	0.0000	

Note.
*$p < 0.1$
**$p < 0.05$
***$p < 0.01$

Table C2.
Entropy Calculations Between Car Model AOIs

Car Model	AOI	2015 Tesla Model S	2017 Nissan Leaf	2017 Tesla Model 3	2017 Audi A4	2017 BMW 330i	2017 Mercedes-Benz C300	2017 Chevrolet Volt	2017 Infiniti Q70	2017 Toyota Prius Two
2015 Tesla Model S	Bumper (B)		-0.01	0.00	0.00	-0.01	0.01	-0.01	0.00	-0.01
	Grille (G)		0.01	0.01	0.01	0.02	0.01	0.00	0.00	0.01
	Hood (H)		0.03	-0.04	-0.02	0.01	0.02	0.01	-0.03	-0.02
	Headlight Left (HL)		0.01	0.00	0.00	0.00	-0.01	0.00	0.00	0.00
	Headlight Right (HR)		0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.00
	Mirror Left (ML)		0.01	-0.02	0.00	-0.01	0.01	0.00	-0.01	-0.02
	Mirror Right (MR)		-0.06	-0.06	-0.05	-0.03	-0.07	-0.06	-0.05	-0.07
2017 Nissan Leaf	Bumper (B)	0.01		0.02	0.01	0.00	0.02	0.00	0.01	0.01
	Grille (G)	-0.01		0.00	0.01	0.01	0.00	-0.01	-0.01	0.00
	Hood (H)	-0.03		-0.07	-0.04	-0.02	-0.01	-0.02	-0.05	-0.05
	Headlight Left (HL)	-0.01		0.00	-0.01	-0.01	-0.01	0.00	-0.01	-0.01
	Headlight Right (HR)	0.00		0.01	0.00	0.00	0.00	0.00	0.00	0.00
	Mirror Left (ML)	-0.01		-0.03	-0.01	-0.03	0.00	-0.02	-0.02	-0.03
	Mirror Right (MR)	0.06		0.00	0.01	0.03	0.00	0.00	0.01	-0.01
	Bumper (B)	0.00	-0.02		0.00	-0.01	0.01	-0.01	0.00	-0.01

2017 Tesla Model 3	Grille (G)	-0.01	0.00		0.00	0.01	-0.01	-0.01	-0.01	0.00
	Hood (H)	0.04	0.07		0.02	0.05	0.06	0.05	0.01	0.02
	Headlight Left (HL)	0.00	0.00		-0.01	-0.01	-0.01	0.00	-0.01	-0.01
	Headlight Right (HR)	-0.01	-0.01		-0.02	-0.01	-0.01	-0.01	-0.01	-0.01
	Mirror Left (ML)	0.02	0.03		0.02	0.00	0.03	0.01	0.01	0.00
	Mirror Right (MR)	0.06	0.00		0.01	0.02	-0.01	0.00	0.01	-0.01
2017 Audi A4	Bumper (B)	0.00	-0.01	0.00		-0.01	0.01	-0.01	0.00	-0.01
	Grille (G)	-0.01	-0.01	0.00		0.01	-0.01	-0.02	-0.01	-0.01
	Hood (H)	0.02	0.04	-0.02		0.02	0.04	0.03	-0.01	0.00
	Headlight Left (HL)	0.00	0.01	0.01		0.00	0.00	0.00	0.00	0.00
	Headlight Right (HR)	0.00	0.00	0.02		0.01	0.00	0.00	0.01	0.00
	Mirror Left (ML)	0.00	0.01	-0.02		-0.01	0.01	0.00	-0.01	-0.02
	Mirror Right (MR)	0.05	-0.01	-0.01		0.02	-0.02	-0.01	0.00	-0.02
2017 BMW 330i	Bumper (B)	0.01	0.00	0.01	0.01		0.02	0.00	0.01	0.00
	Grille (G)	-0.02	-0.01	-0.01	-0.01		-0.01	-0.02	-0.02	-0.01
	Hood (H)	-0.01	0.02	-0.05	-0.02		0.01	0.00	-0.03	-0.03
	Headlight Left (HL)	0.00	0.01	0.01	0.00		0.00	0.01	0.00	0.00
	Headlight Right (HR)	0.00	0.00	0.01	-0.01		0.00	0.00	0.00	0.00

	Mirror Left (ML)	0.01	0.03	0.00	0.01		0.03	0.01	0.01	-0.01
	Mirror Right (MR)	0.03	-0.03	-0.02	-0.02		-0.03	-0.03	-0.02	-0.03
2017 Mercedes-Benz C300	Bumper (B)	-0.01	-0.02	-0.01	-0.01	-0.02		-0.02	-0.01	-0.02
	Grille (G)	-0.01	0.00	0.01	0.01	0.01		-0.01	0.00	0.00
	Hood (H)	-0.02	0.01	-0.06	-0.04	-0.01		-0.01	-0.05	-0.04
	Headlight Left (HL)	0.01	0.01	0.01	0.00	0.00		0.01	0.00	0.00
	Headlight Right (HR)	0.00	0.00	0.01	0.00	0.00		0.00	0.01	0.00
	Mirror Left (ML)	-0.01	0.00	-0.03	-0.01	-0.03		-0.02	-0.02	-0.03
	Mirror Right (MR)	0.07	0.00	0.01	0.02	0.03		0.01	0.02	0.00
2017 Chevrolet Volt	Bumper (B)	0.01	0.00	0.01	0.01	0.00	0.02		0.01	0.00
	Grille (G)	0.00	0.01	0.01	0.02	0.02	0.01		0.00	0.01
	Hood (H)	-0.01	0.02	-0.05	-0.03	0.00	0.01		-0.04	-0.03
	Headlight Left (HL)	0.00	0.00	0.00	0.00	-0.01	-0.01		0.00	0.00
	Headlight Right (HR)	0.00	0.00	0.01	0.00	0.00	0.00		0.01	0.00
	Mirror Left (ML)	0.00	0.02	-0.01	0.00	-0.01	0.02		0.00	-0.01
	Mirror Right (MR)	0.06	0.00	0.00	0.01	0.03	-0.01		0.01	-0.01
2017 Infiniti Q70 Hybrid	Bumper (B)	0.00	-0.01	0.00	0.00	-0.01	0.01	-0.01		-0.01
	Grille (G)	0.00	0.01	0.01	0.01	0.02	0.00	0.00		0.01

	Hood (H)	0.03	0.05	-0.01	0.01	0.03	0.05	0.04		0.01
	Headlight Left (HL)	0.00	0.01	0.01	0.00	0.00	0.00	0.00		0.00
	Headlight Right (HR)	-0.01	0.00	0.01	-0.01	0.00	-0.01	-0.01		-0.01
	Mirror Left (ML)	0.01	0.02	-0.01	0.01	-0.01	0.02	0.00		-0.01
	Mirror Right (MR)	0.05	-0.01	-0.01	0.00	0.02	-0.02	-0.01		-0.02
2017 Toyota Prius Two	Bumper (B)	0.01	-0.01	0.01	0.01	0.00	0.02	0.00	0.01	
	Grille (G)	-0.01	0.00	0.00	0.01	0.01	0.00	-0.01	-0.01	
	Hood (H)	0.02	0.05	-0.02	0.00	0.03	0.04	0.03	-0.01	
	Headlight Left (HL)	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	
	Headlight Right (HR)	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	
	Mirror Left (ML)	0.02	0.03	0.00	0.02	0.01	0.03	0.01	0.01	
	Mirror Right (MR)	0.07	0.01	0.01	0.02	0.03	0.00	0.01	0.02	

Appendix D: IRB Documents

IRB Approval Letter

Oklahoma State University Institutional Review Board

Date:	02/25/2019
Application Number:	HS-19-12
Proposal Title:	THE INFLUENCE OF EXTERIOR DESIGN ATTRIBUTES ON CONSUMER PREFERENCE FOR ELECTRIC VEHICLES
Principal Investigator:	Quinn Vandenberg
Co-Investigator(s):	
Faculty Adviser:	Greg Clare
Project Coordinator:	
Research Assistant(s):	
Processed as:	Expedited
Expedited Category:	

Status Recommended by Reviewer(s): Approved
Approval Date: 02/21/2019

The IRB application referenced above has been approved. It is the judgment of the reviewers that the rights and welfare of individuals who may be asked to participate in this study will be respected, and that the research will be conducted in a manner consistent with the IRB requirements as outlined in section 45 CFR 46.

This study meets criteria in the Revised Common Rule, as well as, one or more of the circumstances for which <u>continuing review is not required.</u> As Principal Investigator of this research, you will be required to submit a status report to the IRB triennially.

The final versions of any recruitment, consent, and assent documents bearing the IRB approval stamp are available for download from IRBManager. These are the versions that must be used during the study.

As Principal Investigator, it is your responsibility to do the following:

1. Conduct this study exactly as it has been approved. Any modifications to the research protocol must be approved by the IRB. Protocol modifications requiring approval may include changes to the title, PI, adviser, other research personnel, funding status or sponsor, subject population composition or size, recruitment, inclusion/exclusion criteria, research site, research procedures and consent/assent process or forms.
2. Submit a status report to the IRB when requested
3. Promptly report to the IRB any harm experienced by a participant that is both unanticipated and related per IRB policy.
4. Maintain accurate and complete study records for evaluation by the OSU IRB and, if applicable, inspection by regulatory agencies and/or the study sponsor.
5. Notify the IRB office when your research project is complete or when you are no longer affiliated with Oklahoma State University.

If you have questions about the IRB procedures or need any assistance from the Board, please contact the IRB Office at 405-744-3377 or irb@okstate.edu.

Sincerely,
Oklahoma State University IRB

Participant Consent Form

Information Sheet of Consent

Thank you for participating in this study. The following contains information about this study and your rights as a research participant.

Project Title: The Influence Of Exterior Design Attributes On Consumer Preference For Electric Vehicles

Principle Investigator: Quinn Vandenberg, Ph.D. Candidate
Design, Housing, & Merchandising
Oklahoma State University
quinnv@okstate.edu, (831) 917-6634

Faculty Advisor: Dr. Greg Clare, Ph.D.
Design, Housing, & Merchandising
Oklahoma State University
greg.clare@okstate.edu

Purpose: The purpose of this research is to use a special technique called eye-tracking to measure your eye movements. Your participation will help us gain knowledge about human responses to new product designs.

Procedures: I will schedule a day and time with you to come to the Mixed Reality Lab in Room 463 of the Human Sciences Building. On the day of your scheduled visit, I will set you up in front of a computer screen with the eye tracking hardware attached to the monitor and explain the eye tracking experiment and calibration process. Once we go over the instructions and calibration process, you can begin the experiment whenever you are ready.

You will initially be asked to complete a brief survey through the eye tracking system.

When done with the survey, you will begin looking a series of product images. You will have as much time as you need to process each photo. When you feel as though you are ready to evaluate an image, you will then be asked to respond to a four question survey about each photo. The eye tracking system will only be recording your eye movements—there will be no audio or video recording of you at anytime.

Your participation is expected to take a total of 10-15 minutes, and involve only one visit.

Approved: 02/21/2019
Protocol #: HS-19-12

Risks of Participation: There are no known risks associated with this project which are greater than those ordinarily encountered in daily life. Moreover, you may stop the experiment at any time.

Benefits: Potential benefits are a greater understanding of how eye movements occur during novel and repeated exposure to new product image stimuli.

Confidentiality: At no point during the survey nor eye tracking experiment will your name be recorded. Your survey responses and eye tracking data are initially coded by participant number (e.g., Participant #1) to ensure that all responses are accurately connected to each participant without ever recording names. Demographic data will be limited and used only in aggregate. Your participation in this study will remain confidential. Servers and computers where the data and images are stored are password protected. Only people authorized by the Principal Investigator will be granted access to the data.

Contacts: If you have any questions or concerns about this project, please contact the Principal Investigator, Quinn Vandenberg at 831-917-6634 or quinnv@okstate.edu. Additionally, you may also contact Dr. Greg Clare, the Advisor of this research, at 405-744-4312 or greg.clare@okstate.edu. If you have questions about your rights as a research volunteer, you may contact the IRB Office at 223 Scott Hall, Stillwater, OK 74078, 405-744-3377 or irb@okstate.edu.

Participant Rights: Your participation in this research is voluntary. If, for any reason, you become uncomfortable, you may quit the experiment with no repercussions.

Approved: 02/21/2019
Protocol #: HS-19-12

Participant Recruitment Letter

SUBJECT: Participants Needed for Eye Tracking Experiment

Dear [Name]:

My name is Quinn Vandenberg, I am a Ph.D. Candidate in Human Sciences at Oklahoma State University. I am emailing you to see if you might be interested in participating in my dissertation study, which includes new eye tracking technology.

My dissertation examines consumer responses to new vehicle designs using eye tracking technology, which captures the eye movements of each participant when looking at various vehicle models. The purpose of my experiment is to understand how the design of a vehicle influences consumer preference.

Your participation would be greatly appreciated, as it will contribute towards helping me complete my dissertation and finish my doctoral program.

Please let me know if you are interested in participating by responding to this email and I will schedule a time with you, at your convenience, for you to come into the Mixed Reality Lab. If you have any questions or concerns, please feel free to reach out to me at any time. My email address is quinnv@okstate.edu and my phone number is (831)917-6634.

Thank you for your time and consideration. I look forward to hearing from you soon!

Sincerely,
Quinn

Ph.D. Candidate
Human Sciences
Oklahoma State University

Approved: 02/21/2019
Protocol #: HS-19-12

Participant Recruitment Flyer

Eye Tracking Participants Needed for Dissertation!

WANT TO PARTICIPATE IN AN EYE TRACKING STUDY ABOUT NEW CARS?

.The purpose of my experiment is to understand how the design of a vehicle influences consumer preference with eye tracking technology, which captures participant eye movements when looking at various models.

INTERESTED?
CONTACT QUINN VANDENBERG AT QUINNV@OKSTAT U FOR MORE INFORMATION.

SBE Supporting Material

Demographic survey questions.

1. What is your age?

   18-20

   21-23

   24-27

   27-29

   30–35

   35+

2. What is your gender?

   Male

   Female

3. What is your highest level of education?

   High School

   Some College

   Bachelor's Degree

   Master's Degree

   Ph.D., J.D. (or other advanced degree)

   Other (please specify) _________

4. Do you have a car at your disposal on a daily basis?

   Yes

   No

5. What type of fuel does your current car take?

   Gasoline

   Diesel

   Ethanol

   Gasoline/electric hybrid

   Bio and natural gas

   Electric (no fuel)

6. Do you have any experience with electric vehicles?

   No experience at all

   Very little experience

   Some experience

   A great deal of experience

Eye tracking survey measures.

Evaluation of Aesthetic Liking - (Landwehr et al., 2013)

Measured on a 7-point Likert scale (1 = I don't like it, 7 = I like it very much).

Scale item:

1. "How much do you like the car's design?"

Subjective Prototypicality Measure (Landwehr, Labroo & Herrmann, 2011)

Measured on 7-point Likert scale (1 = novel, unique; 7 familiar, typical).

Scale items:

1. "How novel is this product?"
2. "How well does this car model match your expectations for cars in general?"
3. "How likely is it that this car is electric?" (Campbell & Goodstein, 2001).

Appendix E: Eye movement Measures & Definitions

Absolute Saccadic Direction: The offset in degrees between the horizontal axis and the current fixation location; where the previous fixation location is the origin in the coordinate system (Holmqvist et al., 2011).

Drifts: Slow movements that take the eye away from the center of fixation (Holmqvist et al., 2011; Bojko, A., 2013).

Dwell: A dwell is defined as one visit in an AOI, from entry to exit (Holmqvist et al., 2011; Bojko, A., 2013).

Dwell Time: The sum of all fixation durations during a dwell in an AOI. Raw data dwell time measure includes the durations of non-fixations such as blinks, saccades, and glissades, as well as fixations shorter than the minimum fixation duration criteria (Holmqvist et al., 2011; Bojko, A., 2013).

First Fixation Duration (seconds): This metric measures the duration of the first fixation on an AOI or an AOI group (Tobii, 2016; Bojko, A., 2013).

Fixation Duration (seconds): Measures the duration of each individual fixation within an AOI, or within all AOIs belonging to an AOI group (Tobii, 2016; Bojko, A., 2013).

Fixation Count: Number of times the participant fixates on an AOI or AOI group (Tobii, 2016).

Latency Measures: Expressed the duration of the onset of one event to the onset of a second event. Measures of this type also appear in the form of spatial distances (Holmqvist et al., 2011; Bojko, A., 2013).

Movement Measures: Concerned with the whole variety of eye movements through space and the properties of these movements of has not been looking, and the properties of eye movements at spatial locations. (Holmqvist et al., 2011; Bojko, A., 2013).

Micro Saccades: Movements that quickly bring the eye back to its original position (Holmqvist et al., 2011; Bojko, A., 2013).

Numerosity Measures: Pertain to the number, proportion, or rate of any countable eye movement event (Holmqvist et al., 2011).

Percentage Fixated (%): This metric measures the number of recordings in which participants have fixated at least once within an AOI or AOI groups, expressed as a fraction of the total number of recordings (Holmqvist et al., 2011).

Saccadic Amplitude: Saccadic measures are calculated based on the fixation locations as defined by the fixation filter and not from the saccades themselves (Holmqvist et al., 2011).

Time to First Fixation (seconds): Measures how long it takes before a test participant fixates on an active AOI for the first time (Tobii, 2016; Bojko, A., 2013).

Total Dwell Time: The sum of all dwell times in the one and same AOI over a trial (i.e., total fixation time, gaze duration, etc.) (Holmqvist et al., 2011; Bojko, A., 2013).

Total Fixation Duration (seconds): Duration of all fixations within an AOI. This metric measures the sum duration for all fixations within an AOI (Tobii, 2016; Bojko, A., 2013).

Total Visit Duration (seconds): Duration of all visits within an AOI or AOI group. Total Visit Duration is defined as the sum of visit durations of an active AOI. An individual visit is defined as the time interval between the first fixation on the active AOI and the end of the last fixation within the same active AOI where there have been no fixations outside of the AOI (Tobii, 2016).

Visit: A visit is defined as the interval of time between the first fixation on the AOI and the next fixation outside the AOI (Tobii, 2016).

Visit Count: Number of visits within an AOI or AOI group (Tobii, 2016).

Visit Duration (seconds): This metric measures the duration of each individual visit within an AOI (or AOI group) (Tobii, 2016).

VITA

Quinn Elise Button

Candidate for the Degree of

Doctor of Philosophy

Dissertation: THE INFLUENCE OF EXTERIOR DESIGN ATTRIBUTES ON CONSUMER PREFERENCE FOR ELECTRIC VEHICLES

Major Field: Human Sciences

Biographical:

Education:

Completed the requirements for the Doctor of Philosophy in Human Sciences at Oklahoma State University, Stillwater, Oklahoma in July, 2019

Completed the requirements for the Masters of Science in Entrepreneurship at Oklahoma State University, Stillwater, Oklahoma in June, 2016

Completed the requirements for the Bachelor of Science in Textiles & Clothing, Marketing & Management at University of California, Davis, California in June, 2009

Experience:

Instructor of Record for Design Theory & Principles at Oklahoma State University

Digital Media & Marketing Consultant at Pebble Beach, California

Co-Founder of Life Out of the Box at Stillwater, Oklahoma

President of Graduate Students of Human Sciences

Resident of Riata Center of Entrepreneurship & OSUAccelerate Student Incubator

TedxOSU Presenter – How Business Can Change the World