INTERDEPENDENCY BETWEEN COMPLEXITY AND LONGEVITY THROUGH THE LENS OF THE DESIGNER

BY

SUNG SOO SHIN

DISSERTATION

Submitted in partial fulfillment of the requirements.
for the degree of Doctor of Philosophy in Informatics
in the Graduate College of the
University of Illinois Urbana–Champaign, 2023

Urbana, Illinois

Doctoral Committee:

Professor Stan Ruecker, Chair
Associate Professor Chang Dae Ham
Assistant Professor Juan Salamanca Garcia
Professor Megan Strickfaden, University of Alberta

ABSTRACT

In today's design landscape, the prevailing trend leans towards simplicity and minimalism. However, research by Berlyne (1971) stresses the importance of visual complexity in enhancing interest and preference. My research found that product samples incorporating a mixed design, integrating elements of both visual complexity and simplicity, received the highest ratings of odds ratios in terms of participants' willingness to keep them for ten years. This results in an inverted-U shape curve, which aligns with the inverted U-shaped curve of complexity by Berlyne. It illustrates that stimuli with moderate complexity are generally preferred and evoke higher levels of interest. Striking a balance between complexity and simplicity can result in visually captivating and enduring designs that resonate with users over time. The results of this study show that designers working toward that balance should consider the diverse preferences and cognitive capacities of individuals to create experiences that are visually engaging, intellectually stimulating, and capable of standing the test of time: one size, or level of complexity, does not fit all. According to this study, it was found that there is no absolute concept of pure complexity or pure simplicity in good design. The research indicated that approximately 84.66% simplicity can be present in products, even when the audience perceives them as having 0% complexity. Conversely, about 18.34% simplicity can be found in products, despite the audience perceiving them as being 100% complex. The study also shows that the frequency of interaction between users and products may have an impact on their longevity. Specifically, products that are used more frequently may have a higher chance of survival than those that are used less often. In addition, I introduce the CMYK Method, a unique approach to visual design analysis that provides designers with an effective way to evaluate design elements. This method employs specific colors to represent different aspects: cyan for complexity, magenta for simplicity, yellow for familiarity, and black for entropy. By quantitatively evaluating these elements, the CMYK Method formulates an objective and consistent means of analyzing designs. Combining the CMYK scores, supported by the CMYK Interpretation Chart, enables an overall perception of the design. It can be a valuable tool for designers, marketers, and other professionals who need to communicate the perception of a design quickly and effectively to others.

ACKNOWLEDGMENTS

I would like to convey my deepest emotions of gratitude and appreciation to all those who have supported and accompanied me throughout my remarkable journey in completing this Ph.D. dissertation. Words cannot adequately express the depth of my gratitude.

First and foremost, my heartfelt thanks go to my esteemed advisor, Dr. Ruecker. His unwavering support, exceptional guidance, and profound expertise have been the pillars that have sustained me. His invaluable insights, constructive feedback, and constant encouragement have not only shaped this research but also propelled me to reach new heights of excellence.

I would also like to extend my sincere appreciation to the esteemed members of my dissertation committee, Dr. Ham, Dr. Garcia, and Dr. Strickfaden. Their remarkable expertise, valuable input, and critical feedback have left an indelible mark on the quality and rigor of this dissertation. I am truly grateful for the time and effort they dedicated to reviewing and evaluating my work.

Moreover, my profound gratitude extends to my beloved wife, Hannah, whose unwavering support and unconditional love have been my rock throughout this arduous journey. Her presence has been a constant source of strength and inspiration, reminding me of the importance of perseverance and determination. I am equally grateful to my beautiful daughters, Estelle and Evelyn, whose radiant smiles and unwavering encouragement have filled my heart with joy and motivated me to overcome every challenge. Their belief in me has been a driving force that propelled me forward.

Thank you from the depths of my heart.

For those of you who are looking for simplicity…

TABLE OF CONTENTS

CHAPTER 1: INTRODUCTION

The concept of complexity has been studied and explored in various fields, such as physics, information science, mathematics, and psychology. In psychology, researchers have argued that complexity can enhance aesthetics, and I propose that complexity can also contribute to aesthetic longevity. Aesthetic longevity can be confused with enduring aesthetic (Ghim & Shin, 2021). The term “longevity” describes life span in biology or health psychology, which conveys three components – dynamism, mechanism, and tropism.

Aesthetic longevity extends beyond mere user satisfaction. It sustains a force keeping momentum (dynamism) by stimulating visual interest while embodying rationale (mechanism) behind its aesthetics and enticing (tropism) in users' emotional attributes. However, there is a common belief that simplicity is synonymous with longevity in aesthetics, although this notion may be context dependent. Since both complexity and simplicity in aesthetics can be subjective, I conducted a field experiment in which participants could physically hold, touch, and see product samples while answering survey questions. This approach aimed to provide participants with a direct experience of the physical products rather than relying solely on images from online sources. By using both quantitative and qualitative research methods, I sought to gain an objective understanding of the concepts of complexity and simplicity in aesthetics. In fact, comprehending complexity can lead to a deeper understanding of simplicity. Both complexity and simplicity exhibit an interconnected and complementary relationship. As a designer and researcher, I aim to delve into the relationship between visual complexity and aesthetic longevity, recognizing their interdependency.

Through their investigation, they seek to unravel how visual complexity contributes to aesthetic longevity. I believe that the interplay between visual complexity and aesthetic longevity is vital for creating captivating and long-lasting designs. By embracing complexity in a thoughtful and deliberate manner, designers can achieve designs that captivate and resonate with individuals over extended periods.

This study aims to address the research question, "What is the role of complexity in consumer products with long-lasting aesthetic longevity?" It is supported by five hypotheses that stem from research inquiries.

The first hypothesis posits that when visual complexity reaches 100%, participants perceive simplicity as 0%. For this hypothesis, a field experiment (2A) will be conducted using a set of thirty product images categorized as "best of best" award winners from the red dot design award. The experiment will evaluate factors such as visual complexity, visual simplicity, familiarity, and visual entropy. Data obtained from the field experiment will be analyzed using regression analysis and predictive modeling with the R package. The regression analysis will examine the relationship between visual complexity and visual simplicity. At the same time, the predictive model will generate an equation based on the regression results, providing numeric data to evaluate the hypotheses.

The second hypothesis examines the belief that complexity increases as visual entropy increases, which can also be evaluated using the same field experiment (2A) as the first hypothesis. However, there is a concern regarding participants' understanding of visual entropy. It is crucial to provide participants with a clear explanation of visual entropy to prevent misconceptions or incorrect interpretations. A regression analysis will be employed, and a predictive model will be generated to create an equation that yields numeric data for testing this hypothesis.

The third hypothesis explores the relationship between visual complexity and knowledge, memory, and familiarity. In the field experiment (1A), nine actual product samples will be provided to participants, who will answer survey questions incorporating the definitions of knowledge, memory, and familiarity defined by Geraci et al. (2009). The product samples will be categorized into three groups: speakers, wristwatches, and game controllers, each containing three products with varying levels of visual complexity. Data collected from the field experiment will be analyzed using multi-level modeling with the R package. This analysis will visualize the results, aiding in evaluating the hypothesis.

The fourth hypothesis focuses on the significance of visual complexity as a factor in aesthetic longevity. In order to investigate this hypothesis, the same experiment (1A) can be utilized but with a different analysis approach. As the fourth hypothesis falls within a spectrum of statistical significance, the raw data will be processed using statistical methods with the R package. It is crucial to note that participants will physically evaluate the products and respond to survey questions in the field experiment (1A) rather than solely relying on online images. This tangible experience aims to minimize potential biases from exposure to product images alone. The findings will hold more significant meaning and validity by testing the hypothesis with participants engaging in real interactions with the product samples.

The fifth hypothesis delves into the impact of increased interaction and closer proximity on aesthetic longevity. In this scenario, participants will respond to a distinct set of survey questions within the same field experiment (1A). Valuable insights can be gained by analyzing the raw data obtained from the survey. The sample products employed in the experiment encompass a range of product usage and cater to diverse end users. Consequently, analyzing the survey data can show how these products are utilized based on user characteristics and product usage patterns. This exploration of user-product interactions and usage can provide valuable insights into the relationship between increased interaction, closer proximity, and aesthetic longevity.

By testing the five hypotheses and analyzing the raw data collected from the field experiment, it is possible to address the main research question effectively. In addition, the CMYK method offers a practical approach for visually analyzing designs within the categories of visual complexity, visual simplicity, familiarity, and visual entropy. The CMYK method involves examining and interpreting color variations based on the CMYK color model (Cyan represents complexity, Magenta represents simplicity, Yellow represents familiarity, and Black represents visual entropy). Applying this method makes it feasible to gain insights and understand the visual attributes and characteristics of the designs under investigation.

Furthermore, multi-dimensional scaling (MDS) can serve as an additional tool to validate the insights derived from the CMYK method. MDS is a statistical technique that maps data points or objects in a multi-dimensional space based on their similarities or dissimilarities. In this study, the x, y, and z axes are assigned visual complexity, visual simplicity, and familiarity, respectively. And I will add another dimension, the dot size, representing the visual entropy. By utilizing MDS, it is possible to visually represent and compare the relationships and distances between different designs based on criteria such as visual complexity, simplicity, familiarity, and entropy. This validation process helps to ensure the reliability and robustness of the obtained insights from the CMYK method.

By employing both the CMYK method and multi-dimensional scaling, I can gain a comprehensive understanding of the visual attributes of designs, validate their findings, and provide a solid basis for effectively answering the main research question.

CHAPTER 2: LITERATURE REVIEW

As technologies have advanced at an alarming rate, the amount of information we deal with now is much more significant than it used to be. As a result, our societies have become much more complex than ever, and we tend to look for simplicity. However, complexity exists everywhere and has been beloved for a long time, and we simply do not acknowledge that complexity could lead to longevity. It is meaningful and necessary for me to study how complexity, simplicity, and familiarity have been understood in various fields because I believe that the three subjects are directly and indirectly connected to longevity.

2.1 Complexity

"Order is a prerequisite of survival; therefore, the impulse to produce orderly arrangement is inbred by evolution." – Rudolf Arnheim 1971 –

Complexity: the word 'complex' originated from the Latin *complect*, meaning "to weave together" or "to entwine." As the root of a complex from Latin illustrates, the field of complexity itself is an entwining of many different areas (Mitchell, 2009). Complexity has been approached by many disciplines – information science, philosophy, mathematics, psychology, and thermodynamics – and defined within their boundaries. However, their concept of definition originated from thermodynamics and shared the same core concept with different interpretations. Besides mathematical and scientific research, researchers in visual perception have investigated complexity and used the concept of thermodynamics and entropy (Arnheim, 1974). This is not a place to discuss mathematical analysis, but it is worth examining the core foundation and high – level reasoning. Also, it is appropriate for me to extend the foundation of complexity to design and longevity. Among many researchers, Mitchell (2009) approaches and explains complexity in computational and scientific contexts, whereas Rescher (2020) illustrates complexity philosophically. While researchers were trying to define and understand complexity, Reason, and Goodwin (1999) propose six principles of complexity. Gell-Mann (2002) explains complexity in non-technical terms as "the length of a highly compressed description of the regularities of the entity under consideration." Gell-Mann stresses the term "compression," which is essential in defining complexity because the level of data compression (e.g., code, patterns, or information) is a method that many researchers and scientists use to describe the level of complexity. Mitchell embraces Gell-Mann's computational concepts and suggests seven (7) approaches to understanding complexity.

First, complexity as size: It is widely accepted that bigger entities have greater complexity than smaller ones because the conservation of larger systems entails the need for more significant input, output, or control mechanisms. Size and complexity are supposed to be positively correlated. When the size of a system increases or decreases, its complexity also does so (Bonner, 2004). However, Arnheim (1954) has a view that supports that complexity cannot be defined by size. Mitchell also argues that complexity cannot be defined as size. For example, the amoeba is 225 times more complex than yeast, and mustard plants have about the same number of genes that we do (Mitchell, 2009). Living things may not be persuasive because we, as human beings, have no control over those living things.

Second, complexity as entropy: The concept of entropy derives from the thermodynamic study of heat but has been used in many different disciplines without a clear definition. Entropy is not disorder or chaos but a measurement of disorder or unpredictability (Edell & Mitchell, 1978; Mitchell, 2009). The concept of entropy has been mistakenly used as a synonym for the disorder because its effect is ubiquitous. The field of psychology shares the same core view as thermodynamics since it is defined as "the quantitative measure of the degree of disorder in a system" (Arnheim, 1974). Mitchell concurs with Tame in that entropy is not a disorder, "[…] a highly ordered and very easy to describe sequence such as 'A A A A A…A' has entropy equal to zero. A completely random sequence has the maximum possible entropy" (Mitchell, 2009; Tame, 2019).

Third, complexity as algorithmic information content: Kolmogorov, Chaitin, Solomonoff, Levin, and Martin-Löf have been pioneering the mathematics of algorithmic complexity (Zenil, Kiani, & Tegnér, 2018, p. 7). Their contribution regarding complex objects is to provide an opportunity to analyze complex objects in an unbiased manner. They proposed algorithmic information content, defined as "the complexity of an object is the size of the shortest computer program that could generate a complete description of the object" (Mitchell, 2009, p. 98). Shannon emphasizes "the amount of information" and "the capacity to transmit information" rather than the information carrying a particular message. As a result, the word "information," in the sense of entropy and complexity, confuses information as a philosophical meaning that is one of the ways to communicate with others, and Shannon's information theory. Tame emphasized that it is critical to understand "information" in the correct context because "information may not mean what it is expected to mean in information theory" (Tame, 2019, p. 117).

Fourth, complexity as Logical Depth: Bennett formalized the definition of logical depth by incorporating the standard Turing machine that generates algorithmically random input. The standard Turing machine defined computation, computable function, and computational complexity and was invented by Alan Turing in 1936. Bennett indicated that depth from "logical depth" obeys a slow-growth law: "deep objects cannot be quickly produced from shallow ones by any deterministic process, nor with much probability by a probabilistic process, but can be produced slowly (Bennett, 1995)." Mitchell reiterates that the logical depth of an object is "a measure of how difficult that object is to construct" (Mitchell, 2009). Logical depth has reasonably theoretical properties that a general audience could accept with logic because it falls in with general intuitions. However, it is not a practical method to measure the complexity of living things because it is almost impossible to identify computable functions or computational complexity in living things.

Fifth, complexity as Thermodynamic Depth: Before thermodynamic depth was introduced, definitions of complexity – algorithm complexity, computational complexity, and logical depth – appeared in the literature. In 1988, Lloyd and Pagel proposed and defined the physical complexity of a dynamic system, and they called it depth. Lloyd and Pagel explain that thermodynamic depth has the intuitive property of complexity: "a system that appears simple at first glance may be complex on closer inspection" (Lloyd & Pagels, 1988). The depth was related to logical depth by Bennett: more complex objects are harder to construct. However, Lloyd and Pagel expressed their perspective toward complexity while proposing thermodynamic depth and emphasized that "complexity was a function of a process that brought the object into existence" (Lloyd & Pagels, 1988, p. 187).

Sixth, statistical Complexity: Over the last decade, statistical complexity has been a general indicator of structure or correlation (Feldman & Crutchfield, 1998a). It is too broad and general for non-scientific readers to understand fully. In other words, statistical complexity quantifies both randomness and the presence of a correlational structure (Rosso, De Micco, Larrondo, Martín, & Plastino, 2010). Crutchfield and Young proposed a definition of statistical complexity from the information perspective "as measuring the minimum amount of information about the past behavior of a system that is needed to optimally predict the statistical behavior of the system in the future" (Mitchell, 2009, p. 102). Berlyne introduces complexity in relation to interaction novelty and uses the term "the past behavior of a system" to define complexity (Berlyne, 1971). However, it is inseparable between the model's behavior statistically and the behavior of the system. For example, String A contains the message "ababab" and String B, "ababaa" does not have a message. String A has the model "repeat ab three times," whereas the model of String B could be "choose at random from a, d, e, or l." Both strings A and B have low statistical complexity because it is possible to define their models. However, B has a higher statistical complexity because identifying the correlational structure within its content is more complex than doing so within A's content.

Seventh, complexity as a fractal dimension: Hausdorff introduced the first concept of fractal dimension in 1919, which was used to measure small mathematically defined sets (Sandau & Kurz, 1997). Since the fractal dimension was introduced, more practical concepts – the Kolmogorov and Minkowski-Bouligand dimensions – were proposed. From the 1950s through the 1990s, measuring an image's mathematical and psychological complexity based on fractal dimension has been a significant approach (Forsythe, Nadal, Sheehy, Cela-Conde, & Sawey, 2011). It indicates that the fractal dimension has been widely applied in many fields, including art, architecture, environmental psychology, and biological science. The fractal dimension in perceptual and physiological can be described as "the fractal scaling relationship between the patterns at different magnifications" (Sandau & Kurz, 1997, p. 58). Regarding patterns and difference scaling, Mitchell uses coastlines as a classic example (Mitchell, 2009). Coastlines have patterns and scaling, which can be defined as similarity, whether viewed in close view, like looking at them in the car, or far away, like looking at them from an airplane.

Rescher (2020) also agrees that all disciplines agree on no definition of complexity. Rescher has philosophically approached complexity and suggested four (4) categories: *formulaic complexity, compositional complexity, structural complexity, and functional complexity*.

First, descriptive, generative, and computational complexity are under formulaic complexity. Let us look at two sequences: A 01010101010101 and B 123456123456123456. Sequence A is less complex than sequence B. Sequence A has only two components (0 and 1), whereas sequence B has six elements (1,2,3,4,5, and 6). Generative complexity was introduced by the Russian mathematician Andrei Kolmogorov, and it was to "measure generative complexity by the minimal length of an instruction program for generating sequence" (Newman, 1956; Rescher, 2020, p. 10). Based on generative complexity, the instructions for sequence A can be given as "repeat 0 and 1 six times" and sequence B as "repeat 1,2,3,4,5, and 6 three times." Rescher(2020) explains computational complexity by using a simple relationship between time and money and adds an information management aspect: C = P x t where Complexity (P) is a measure of the power of the information processor, and t is a required time to solve the problem. For example, solving 2x = 10 is much simpler than formulating a chess algorithm for a computer playing against the world champion chess player. Some people may not even take a minute to solve 2x = 10. However, it required computer scientists to use many powerful computers for many years to build algorithms for chess against humans.

Second, this consists of two complexities: constitutional complexity and taxonomical complexity. Constitutional complexity is the complexity required to perform expected operations or transactions. For example, it takes less than five (5) minutes to be ready to ride a bicycle: putting on a helmet and knee/elbow pads. However, it takes hours or days before commercial airliners are prepared to take off, and it takes a good half-hour for flight attendants to check inside cabins along with the captain's instructions. Rescher (2020) uses the term "artifice" to describe constitutional complexity. Rescher (2020) indicates that biologists tend to look at complexity as taxonomic complexity and uses. J.T. Bonner's example is that complexity can be expressed by measuring several different cell types in an organism. Complexity can be measured in loose terms; however, Rescher did not see the entire spectrum, including molecular biology. According to molecular biologists, humans are about 250 times more complex than yeasts, but if DNA base pairs are counted, we are only four (4) times more complex than yeasts (Mitchell, 2009). Surprisingly, mustard plants have as many genes as we, as humans, do.

Third, Rescher (2020) sees those two kinds of sub-complexity – organizational complexity and hierarchical complexity – make up structural complexity. He defines a complex system [as one] that embodies subsystems [which] can be organized either hierarchically or coordinately. It is a concept of fractal dimension or self-similarity. Mitchell (2009) and Rescher (2020) use coastlines to explain complexity as a self-similarity. Mitchell approaches it mathematically with an example of a Koch curve, and Rescher sees it as socio-economically with an example of the military structure. In organizational complexity, the subsystems can be functional and sustainable. However, subsystems in hierarchy complexity are not generally functional, although there are cases in that subsystems can be functional. The difference between organizational and hierarchy complexity is that organizational complexity is minimal, whereas hierarchy complexity can be endless, and subsystems in hierarchy complexity provide stability (Rescher, 2020).

Fourth, operational complexity and nomic complexity are housed under functional complexity. Operational complexity illustrates the relationship between movements and supports. For example, automobiles have two degrees of freedom – acceleration and X-Y axes of movement – whereas aircraft have three-dimensional freedom - speed and X, Y, and Z axes of movement. Adding another dimensional freedom (Z axis of movement) makes the difference in magnitude of intricacy between automobiles and aircraft significant. Of course, aircraft manufacturing processes are much more complicated than for automobiles, not to mention maintenance. Nomic complexity deals with "a timeless complexity in the working inter-relationship" among the elements (Rescher, 2020). Regarding inter-relationship, Rescher (2020) stresses that a simple operation can include a complex process. The shape of the knife is not typically complex; in fact, it is relatively simple. However, the knife blade had gone through several complex processes – thousands of hammering blows, dozens of quenching processes, and exquisite polishing processes – to produce a sharp and strong blade. Hartmanis and Hopcroft (1971) use a simple mathematical form to explain how a simple rule could change the magnitude of complexity:

"Add 1 to the number at hand and multiply the result by itself." This results “2, (2+1)2 = 9, (9+1)2 = 100, (100+1)2 = 10,201, ...”

Peter Reason and Brian Goodwin's six principles of complexity – rich interconnections, iteration, emergence, holism, fluctuation, and the edge of chaos – derive from various fields like mathematics and physics, which make the six principles more applicable to other areas (Reason & Goodwin, 1999).

First, Kauffman (1993) addresses a rich pattern of interconnection among components to explain a complex system. However, suppose the interconnection can be well defined by predictions or order due to simple or uniform interconnection. In that case, it may not be called complexity because, in a complex system, rich interconnections refer to the behavior of interconnections that is hard to predict due to insufficient knowledge of specific properties (Reason & Goodwin, 1999). Weather is a good example that shows rich interconnection among many elements – moisture, pressure, temperature, wind, etc. – and can be predicted, but it is hard to predict accurately. On the other hand, the behavior of a gas like helium can be well predicted based on gas law, and there is no complexity.

Second, iteration can be found in the fractal dimension, one of the approaches to understanding complexity. The term fractal originated from a French mathematician, Benoit Mandelbrot, who believed that the world is full of fractals – coastal lines, mountain ranges, snowflakes, trees, etc. (Mitchell, 2009). A Swedish mathematician, Niels Fabian Helge von Koch, displays complexity using fractal and iteration, which is well illustrated in Koch Curve. The Koch Curve can explain snowflakes with an iterative process. Reason & Goodwin(1999) address that iterative process and the emergent properties that result in a rich network by interacting among the elements.

Third, emergence is a consequence of interaction processes such as self-similarity or the Koch Curve. However, the emerging order is not predictable by simply knowing how the elements are interconnected and can be identified or observed by performing the iterative process. As an example of rich interconnections, emergence is well demonstrated by weather. Hurricanes/typhoons emerge by rich interconnections among many elements: winds, air temperature, air pressure, level of moisture, etc. In fact, those elements are enclosed in a dynamic system with iteration processes and develop emergence (Reason and Goodwin, 1999).

Fourth, the concept of holism was introduced in 1926 in the context of biology (Smuts, 1927). According to holism, the properties and behaviors of a system cannot be fully explained or understood by analyzing its separate parts in isolation. Instead, it emphasizes the interconnectedness and interdependence of elements within a system. Mittelstrass (2014) believes that holism plays a critical role in physics, philosophy, and biology. The word holism indicates that it illustrates holistic thinking. Function and structure are not separable because of their interaction, which is displayed in biology and social science. In social science, social relations can only be explained in terms of the social whole (Mittelstras, 2014). Reason and Goodwin (1999) believe that holism is one of the principles of complexity because rich interconnection can be well explained with holism. Reason and Goodwin (1999) share an example of propagating plants, which can be cut and grow a whole plant. In other words, a part can become whole. Mitchell (2009) provides a similar example with the amoeba, a single-celled microorganism while explaining complexity as size.

Fifth, Reason and Goodwin (1999) believe that fluctuations can be found during iteration and emergence from complexity. The dynamic system displays characteristics of complexity and is rather a non-linear system where a whole is different from the sum of parts (Mitchell, 2009). The linear system can be illustrated by mixing a cup of flour and a cup of sugar, which results in two cups of mixed flour and sugar. Mixing two cups of baking soda with a cup of vinegar, on the other hand, results in more than three cups of carbon dioxide. Reason and Goodwin (1999) explain that the fluctuations can be small and, sometimes, substantial, as in the example of a mixture of baking soda and vinegar.

Sixth, when it comes to complexity, generally, chaos accompanies it. Predictability can be a fine line to distinguish between complexity and chaos. In general, chaos indicates total randomness. However, some orders do exist in the universal property. A higher level of a chaotic system can be predictable, whereas it is impossible to predict detailed levels because of sensitive dependence on initial conditions (Mitchell, 2009). Carroll and Burton (2000) approach and illustrate the "edge of chaos" in organization theory as a natural system balanced by too complicated connections or too few connections that seem unstable. Researchers in the field of complexity refer to the "edge of chaos" as a transition between order and disorder, stability and chaos (Kauffman, 1993; Langton, Taylor, Farmer, & Rassmussen, 1992; Packard, 1988). The edge of chaos has a close relationship with fluctuation. Mixing baking soda and vinegar is a great example that illustrates a transition from stability to chaos, which expresses the emergent property of a whole system (Reason & Goodwin, 1999).

Each complexity principle – rich interconnections, iterations, emergence, holism, fluctuations, and the edge of chaos – has a relationship of interdependency. On a deeper level, complexity is connected to longevity. As chaos is frequently addressed with complexity, longevity is being addressed in the context of sustainability and durability. It is necessary to understand them better, which leads to understanding longevity correctly.

2.2 Simplicity

"*The universe exhibits a wonderful interplay of simplicity and complexity*."

– Murray Gell-Mann, Nobel Prize in Physics –

Skogen (2017) stresses the relationship between complexity and simplicity: "simplicity and complexity are deeply intertwined and dependent upon each other." In his paper, "*Consider a Spherical Cow: A course in environmental problem solving*," Harte (1985) counterintuitively describes the relationship between complexity and simplicity, pointing out that quantitative modeling requires simplification to render complex problems tractable. Paola and Leeder (2011) reiterate that "*simplification is essential if the goal is insight and models with few moving parts are easier to grasp and more clearly connect cause and effect."* The importance of simplification in complexity is not a strange idea at all. A study in cognitive psychology from Lombrozo (2007) states, "*complex hypotheses may fit observed data very closely, but generalize to novel data more* *poorly than simpler alternatives.*" However, simplicity is not the same as familiarity; simplicity in cognitive psychology shares a similar characteristic with familiarity in marketing. Heimbach, Johansson, and MacLachlan (1989), Wright (1975), and Schooler (1965) stress that consumers initiate a 'simplifying information process' when they are asked to undertake complex information. Lombrozo (2007) claims that the field of psychology generally agrees that simplicity is preferred because of the psychological reality of a preference. In other words, "simplifying the information process" can effectively extract insights and generalize complex information. Still, it can also establish biases and stereotypes because they are generally formed by stored knowledge and experience from the consumers.

Complexity and simplicity appear on opposite ends of the spectrum, like the North and South magnetic poles. This is because it is natural to think that the antonym of complexity is simplicity. This magnetic polarity has a similar relationship between complexity and simplicity in the field of visual perception, where complexity plays as North, and simplicity becomes South. They become attractive when complexity and simplicity are well balanced because simplicity is hard to define without addressing complexity. Although two magnetic poles (i.e., North and South) are being separated, a magnetic field influences magnetic forces and moves electric currents and magnetic materials. I theorize an abstract idea that there are elements between complexity and simplicity that work as magnetic fields between the North and South poles. The elements connect complexity and simplicity, influence or simplicity, and balance between complexity and simplicity. Van der Helm (2000) states that there are three elements – descriptive code, regularity, and simplicity – to quantify complexity. Regularity becomes a hidden ingredient to bridge between complexity and simplicity. It is characterized by an internal symmetrical, ordered, and harmonious arrangement. Simplistic designs are balanced in proportion, have little contrast in color, make use of pure and cold materials (Wallner, Magnier, & Mugge, 2020), and are still highly prototypical. They do not follow fast trend cycles.

Simplicity is a complicated concept in design, involving tension by nature. For example, a simplistic design risk being perceived as boring or uninteresting (Lidwell & Manacsa, 2011; Shelley, 2015), and it may negatively affect product longevity if it fails to satisfy the user. Simplicity for enduring aesthetics is not equal to minimalism; it is about finding an optimal point on a spectrum between opposite qualities. Though this approach of defining simplicity through (proto)typicality gives a clearer understanding of simplicity in design, typicality involves more complex matters due to an interplay between opposing forces, typicality, and novelty (Blijlevens, Carbon, Mugge, & Schoormans, 2012; Hekkert, Snelders, & Van Wieringen, 2003). According to Blijlevens et al., a slight deviation from the prototype maximizes aesthetic appraisal because atypicality expands knowledge (Armstrong & Detweiler-Bedell, 2008; Blijlevens et al., 2012). This deviation through novelty can make simplistic designs more interesting and enduring.
Piet Mondrian cannot be omitted when simplicity is discussed in the context of visual perception and aesthetics.

Interestingly, Jackson Pollock is often addressed while discussing artistic styles and how his art pieces are constructed. For example, the way Mondrian expressed and executed nature as "abstract plasticism" is at the opposite end of the spectrum from the way Pollock expressed nature as "abstract expressionism" (R. P. Taylor, Spehar, Wise, Clifford, Newell, & Martin, 2005). In general, Mondrian's works are known as "simplicity," "geometric," and "artificial," whereas Pollock's works are known as "complex," "natural," and "organic" (R. Taylor, Micolich, & Jonas, 2002). Both Mondrian's and Pollock's works are abstract and fractal. However, Pollock emphasizes, "my concerns are with the rhythm of nature" (Varnedoe & Karmel, 1998). Unlike Pollock's outcome of works, the processes of art pieces are "fast and spontaneous" (Varnedoe & Karmel, 1998) and "deceptively simple acts" (R. P. Taylor, Spehar, Wise, Clifford, Newell, & Martin, 2005) and "remarkably systematic" (R. Taylor et al., 2002). Mondrian, on the other hand, spent weeks executing the composition of his patterns (Deicher, 1999) with a "remarkably rigorous set of rules" (R. P. Taylor, Spehar, Wise, Clifford, Newell, Hagerhall, et al., 2005). Interestingly, fractal is an attribute of both Mondrian and Pollock and is frequently addressed in the context of "fractal dimension" in complexity theory. In other words, fractal carries attributes of both simplicity and complexity. It is necessary to understand the fractal while simplicity is addressed because the fractal frequently appears when complexity is discussed. Mathematician B.B. Mandelbrot introduced the term "fractal" in 1975 to describe a large class of irregular objects; it comes from the Latin *fractus*, meaning "broken" (Peitgen, Jürgens, Saupe, & Feigenbaum, 2004). To describe the fractal further, it is constructed by fine recurring patterns with a variation of contraction or dilution, resulting in shapes of complexity (Barnsley, 2014; Mandelbrot, 1982).

Falconer (2013) summaries the Von Koch Curve with the properties – fine structure, self-similarity, classical methods of geometry, inapplicable to mathematics, size, recursive construction, and natural appearance – and, interestingly, most of the Koch Curve's properties are aligned with Mondrian's and Pollock's works. Mondrian is well-known for its simple composition and its simplicity. His works can be perfectly described by using the term fractal, where fractal is a good example to explain complexity. Complexity conceals simplicity, but complexity conceives simplicity. The simplicity is manifested by the complexity.

2.3 Familiarity

The arousing effects of novelty can be curved or undone by introducing patterns that resemble what has been experienced before. – Daniel Berlyne 1971 –

Familiarity has been dominantly explored in the fields of psychology, advertising, and marketing. In advertising, familiarity plays a big role because familiarity can help users remember a product or brand. Johnson and Russo (1981) hypothesize that existing knowledge can help learn new information. Related research by Chase and Simon (1973) proved this theory by demonstrating that chess masters remember the chess positions better than novices. When the pieces were in random positions, however, chess masters remembered them no better than the novices.

Similarly, when consumers do not know enough about a certain situation or product, they try to find something familiar from previous experience or knowledge that can help them understand it. Familiarity can be affected depending on the type of product categories involved. Johnson and Russo believe that the different product categories require different information processing skills based on the particular categories (Johnson & Russo, 1984). However, familiarity plays a significant role in product selection and purchasing. For example, consumers with high familiarity with technical attributes have a better cognitive response to technical advertising than consumers without technical familiarity (Edell & Mitchell, 1978). Another study by Anderson and Jolson (1980) illustrates that technical advertising greatly increases purchase intention among consumers with considerable technical experience.

However, familiarity is a convoluted element in the field of consciousness and cognition. Although researchers in the field define "remember," "know," "familiarity," and "guess" based on how the researchers approach and interpret "familiarity" among those definitions, there has been inconsistency in how they interpret "familiarity," especially in relation to "remember" and "know." Besides the inconsistency of definition among these four words, another important issue is how participants understand and process them. Helen L Williams, Conway, and Moulin (2013) stress that there are two points to consider: firstly, participants may find it difficult to distinguish "*familiarity*" and "*certainty*,"; and secondly, participants can be confused between the "*underlying process of familiarity*" and "*a state of knowing."* (Donaldson, MAcKENZIE, & Underhill, 1996, p. 487) precisely state the issue:

> *Familiar* rather than *know* was used to indicate non-recollection because the word *know* carries a connotation of certainty inconsistent with a confidence rating indicating a lack of certainty. Participants find it hard to say that they are unsure that an item was there but that they know it was.

Geraci, McCabe, and Guillory (2009) recognize both issues – inconsistent definitions and the participants' misinterpretations – and believe that these can greatly impact theoretical implications. For example, Helen L. Williams and Moulin (2015) investigate well-regarded experiments and conclude that each experiment uses different definitions or emphasis. I recreated a table based on their findings (Table 2.1).

Table 2.1: Criteria of usage for remember, know, guess based on the field or area

Author(s)	Title	Field or Area	Elements	Criteria
Gardiner and Java (1990)	Recollective experience in word and nonword recognition.	Memory & Cognition	Remember, Know	"Standard definitions"
Rajaram (1993)	Remembering and knowing: Two means of access to the personal past.	Memory & Cognition	Remember, Know	"Standard definitions"/ definitions that emphasize confidence
Gardiner, Java, and Richardson-Klavehn (1996)	How does the level of processing really influence awareness in recognition memory?	Experimental Psychology	Remember, Know, Guess	Definitions that emphasize both familiarity and confidence
Donaldson, MacKenzie, and Underhill (1996)	A comparison of recollective memory and source monitoring.	Psychonomic	Remember, Familiar	Justifications for using "Familiar" instead of "Know."
Kelley and Jacoby (1998)	Subjective reports and process dissociation: Fluency, knowing, and feeling. Acta Psychologica	Learning and memory	Remember, Know	Definitions that emphasize both familiarity and confidence
Dewhurst and Anderson (1999)	Cognitive effort and recollective experience in recognition	Memory	Remember, Know, Guess	Definitions that emphasize familiarity
Bastin and Van der Linden (2003)	The contribution of recollection and familiarity to recognition memory: A study of the effects of the test format and aging	Neuropsychology	Remember, Know, Guess	Definitions that emphasize both familiarity and confidence
Geraci et al. (2009)	On interpreting the relationship between remember–know judgments and confidence: The role of instructions.	Consciousness and Cognition	Remember, Know	Definitions that emphasize confidence
Harlow, MacKenzie, and Donaldson (2010)	Familiarity with associations? A test of the domain dichotomy theory.	Experimental Psychology: Learning, Memory, and Cognition	Recollect, Familiar	Justifications for using "Familiar" instead of "Know."
Ingram, Mickes, and Wixted (2011)	Recollection can be weak, and familiarity can be strong.	Experimental Psychology: Learning, Memory, and Cognition	Remember, Familiar	Justifications for using "Familiar" instead of "Know."

To produce consistent definitions and prevent misinterpretations from participants, Geraci et al. (2009) advocate and include definitions for Remember, Know, Familiar, and Guess, which are accompanied by a real-world example of the subjective experience (see Table 2).

Table 2.2: Definitions of remember, know, familiar, and guess (Geraci et al., 2009)

Subjective experience	Definition
Remember	For this item, participants had an experience of Remembering. This could include seeing the word in their mind's eye, remembering what they thought or pictured when they saw the word on the original list, and/or having a sense of themselves in the past. For example, if you see someone on the street, you may think, "Who is that? Oh yes, I remember, I was in the chemist's shop, it is the person I saw in the queue at the chemist's. I remember thinking what a funny hat they had on. . ."
Know	For this item, participants simply Know the word without any other feelings associated with vividly remembering that they had seen it before. For example, if you see someone on the street, you may think, "Who is that? Oh yes, it is my friend George, and I know him really well. . ."
Familiar	This word the participant had a feeling of familiarity with the word, and because of this, they thought that the word was on the previous list. For example, if you see someone on the street, you may think, "Who is that? They look very familiar. . . I do not know where I know them from, but they are definitely familiar. . ."
Guess	For this word, the participant had no feeling of familiarity or any other memories associated with the word and simply Guessed that the word was on the previous list

Based on the three experiments, Geraci et al. (2009) concluded that Remember holds a confidence level of "Very High"; Know holds a "High" confidence level; Familiar holds a confidence level of "Medium"; and Guess holds a "Low" confidence level.

Regarding product selections, "familiarity" has a different approach based on psychology. Heimbach et al. (1989), for example, illustrate "familiarity" as "the role of product familiarity" in the context of country-of-origin cues. Heimbach et al. (1989) developed their theoretical rationale based on an individual's product familiarity accompanied by the country of origin. This can be explained by recognizing the country-of-origin cues to establish "a heuristic or proxy" for intrinsic product attributes and adopting a "simplifying information processing." Wright (1975) explains that consumers look for simplifying information processing when complex information needs to be processed, and the consumers are not motivated. Heimbach et al. (1989) describe it as a mental "shortcut" where the consumers look for simple cues that summarize complex information. Further, in another study by Heimbach et al. (1989), familiarity is key to initiating the simplifying information process against the complex information that needs to be undertaken.

The study of simplifying information processing is an extension of work by Schooler (1965), who established the first "country-of-origin effect" study. It explains that product familiarity triggers assumptions when there are not enough attributes available to evaluate the products, where biases are formed. In other words, consumers have to rely on previous experience or knowledge, which will likely utilize their stored stereotypes and biases formed by their product familiarity.

One thing remains to be addressed in the study of the "country-of-origin effect." The experiments conducted by Geraci et al. (2009) focused on advertising and Latin words, employing 2D stimuli. In contrast, I prepared a field experiment that involved 3D stimuli that participants could visually perceive and physically interact with. Due to these fundamental differences in stimuli and experimental aims, I do not anticipate achieving an equivalent level of confidence as the study conducted by Geraci et al. (2009).

2.4 Longevity

"*Major dimensions of personality could predict longevity across the lifespan*."

– Friedman et al. 1993 –

There have been several approaches to studying products that have lasted longer than several decades, and each approach has a different background. While researching long-lasting products, several terminologies – sustainability, durability, and longevity – have appeared in the research context and users' everyday conversations. The terms - sustainability, durability, and longevity - may appear to have similar meanings. The goals for sustainability, durability, and longevity could be in the same direction, and the three share some of the same core philosophies. However, each term has a different background, approach to determining the research method, and objectives. Because these three terms appear to be pursuing the same goal, even designers have been using those terms without understanding the context, and sometimes, terms have been misused or mixed up with other terms. Therefore, researchers and designers must understand the terms and their backgrounds correctly to apply research methods to achieve the goal.

There have been two main streams for the subject, "lasting long product." The first is in the context of sustainability. Cooper (2012) explains that the term "sustainability" or "sustainable development" had been recognized and addressed when environmental threats were brought up in society. Also, Fibuch and Van Way III (2012) state that sustainability has had a strong relationship with products since the environmental movement was first actively addressed twenty (20) years ago. Faber, Jorna, and Van Engelen (2010) claim that the characteristics of sustainability can be explained as an interaction between artifacts and the environment. They point out that sustainability is a complex and confusing concept because about fifty (50) definitions and circumscriptions of sustainability exist. For example, ecologists, economists, sociologists, and biologists each have their definition of sustainability. Cooper (2012) has used the term "sustainability" in design to increase product longevity. Cooper has a background in economics, and his research for product longevity has focused on sustainability in the context of circular economy and policy.

Consumers had started believing sustainability could be the answer to environmental issues. The issue of environmental impact has brought an opportunity to discuss sustainability in the context of sustainable design (Burall, 1991; Charter & Tischner, 2001; Fiksel, 1996; Lewis, Gertsakis, Grant, Morelli, & Sweatman, 2001), the utilization of products (Barbiroli, 2008; Mont, 2008; W. Stahel, 2010; W. R. Stahel & Jackson, 1993; Weaver, 2008), and waste reduction (Braathen, 2004; Coggins, 2001; De Young et al., 1993; Eunomia & Consulting, 2007; King, Burgess, Ijomah, & McMahon, 2006; Runkel, 2003). In other words, sustainability has been focused on addressing environmental impacts like waste reductions and product utilization. While product utilization has received great attention, the term "durability" has been addressed. Cooper (1994 b), for example, defines durability as "the ability of a product to perform its required function over a lengthy period under normal conditions of use without excessive expenditure on maintenance or repair' (Cooper, 1994 a, p. 5).

Second, Chapman (2009) introduces a design for durability to extend product life. It focuses on emotional durability, where he suggests a six-point experiential framework: narrative, detachment, surface, attachment, enchantment, and consciousness. Chapman believes the six-point framework can trigger emotional durability between the product and the user. Certainly, emotional durability can be one of the methods to achieve product longevity and uses mainly psychological mechanisms between its user and the product. It approaches a personal level, whereas Cooper tends to address policy. In other words, Chapman addresses product longevity at the micro level, and Cooper approaches product longevity at the macro level. The term longevity has been used as product longevity in both micro and macro approaches. It is not difficult for users and designers to understand the general meaning of product longevity. However, sustainability is not appropriate to replace product longevity, although it may aim for the same goal. Longevity can be replaced with a life span. The term is frequently used in health care, biology, and psychology regarding longevity or life span. (Aldwin, Park, & Spiro, 2007) state that conscientiousness is critical for health and longevity. As longevity is frequently addressed in health psychology, longevity has a strong emotional component (Aldwin et al., 2007).

According to health psychology research, three (3) personality measures – dynamism, mechanism, and tropism – can influence longevity (Aldwin et al., 2007). First, dynamism is a concept of force (Kuznetsov, 1987). Depending on the types of force, some researchers argue that the origin of dynamism is Newton, and some suggest that Leibniz is the origin of dynamism. This is not an appropriate place to argue who the origin is. Kuznetsov (1987) illustrates dynamism thoroughly. In general, there is no argument that dynamism is about force. The difference between Newton's concept and Leibniz's concept is the types of force. Newton discusses dynamism in physics, whereas Leibniz approaches dynamism in metaphysics. In other words, Leibniz's metaphysic was transformed from Newton's phenomenological force

(Kuznetsov, 1987) and frequently addresses a term, extension, to explain the force that physics cannot explain. Leibniz says, "I still agree that naturally everybody is extended and that there is no extension without a body" Kuznetsov (1987, p. 248).

Complexity theory opens up many possibilities for various disciplines to explore, and Wahl (2006) uses complexity theory to untangle nature's scale-linking properties. Complexity is one of the ingredients that can be utilized to approach longevity. The simplest way to express a complex system is that any system with more than three attributes interacts with each other (Wahl, 2006). I believe that embracing these three elements, from health psychology to product longevity, will lead to meaningful design research, and it is worth re-interpreting them through a design researcher's lens.

First, dynamism deals with forces in physics, and health psychology sees them as influences. Influences can break down into three intrapersonal forces – object relations, dependency, and attachment – in the context of psychoanalytic and social learning theory. These three forces appear to be overlapped, especially with dependency and attachment, and people misuse them frequently. Leibniz defines dynamism in metaphysics as forces that could be extended; health psychologists embrace Leibniz's dynamism concept as one of the elements influencing longevity in the health field. Aldwin et al. (2007) suggest that children who have been abused are likely to have greater chances of suffering from mental issues when they become adults. When children are exposed to negative external forces, the experience can get extended to adulthood and cause issues. Designers could adopt the concept of dynamism in health psychology to investigate the external forces that could influence longevity.

Second, psychophysiological and behavioral researchers see mechanisms as brain functions controlling aggression and impulse. Without reason and order, functions and control may not be established, and Norman (2016) argues that complexity carries reason and order. Without Reasons and orders, complexity becomes chaos. Complexity can influence longevity and be reasonable research further. Mitchell (2007) introduces seven (7) approaches or perspectives to understand complexity, and it is worth investigating the seven approaches from a design research perspective. Mechanisms are emerging evidence that influences longevity (Aldwin et al. 2007). Friedman (2000) indicates that mechanisms are a "mediator" between personality and health. Aldwin et al. (2007) state that there are two types of mechanisms: psychophysiological and behavioral mechanisms. R. Williams et al. (2004) argue that the serotonin function hints at aggression and impulse control and associates it with healthy behavior. Bogg and Roberts (2013) believe conscientiousness is connected to psychophysiological mechanisms, health-related behaviors, and social-environmental factors. In contrast, Bogg and Roberts (2013) explain that psychophysiological mechanisms are known to contribute to health processes. The behavioral mechanism is also connected to conscientiousness, one of the key factors for longevity in health. Bogg and Roberts (2004) indicate that tobacco use, alcohol abuse, drug abuse, etc., are related to the behavioral mechanism influencing longevity.

Third, tropism is often addressed in biology and described as a phenomenon of plants moving toward the light source. Both Aldwin et al. (2007) and Friedman (2000) see tropism from the perspective of the environment to understand longevity. Longevity can be significantly varied depending on the environment that the objects/products belong to because the environment exerts dynamism. Another approach to tropism in the context of design is that aesthetic longevity can be viewed as part of tropism because a good aesthetic attracts the users just like the light source affects the plants to move toward the light source. The users' environment influences longevity. Tropisms influence longevity. Friedman (2000) also thinks that tropisms are related to longevity. Also, Aldwin et al. (2007) and Friedman (2000) believe conscientiousness is important in increasing longevity. Both Aldwin et al. (2007) and Friedman (2000) explain tropisms in the context of an environment. Generally, tropisms are introduced in biology, and plants move toward a source of light. Friedman sees tropisms from the perspective of health psychology, where some people seek out more positive, fulfilling, and health-promoting environments. In contrast, others tend to stay in dark, negative, health-threatening environments (Friedman, 2000). In other words, the environment or certain affiliations can explain the consequences of health and longevity. Jessor (1998) and Tinsley (1992) address that children's health behaviors – habits, models, and emotional climate – can be influenced by children's adult family members. It is the same true that product longevity can be varied depending on the environment that the product is being used in or the type of users for the products.

Lastly, Sigaki, Perc, and Ribeiro (2018) have a meaningful study investigating entropy and complexity for painting in physics. Statistical complexity provides a measure of the regularity in an object Feldman and Crutchfield (1998b), whereas deterministic complexities dominate by the random components in an object(Cover, 1999). Bandt and Pompe (2002) believe that permutation entropy is a type of "*complexity parameters for time series based on comparison of neighboring values*." The study(Sigaki et al., 2018)investigates almost 140,000 paintings based on local spatial patterns, which can be analyzed by statistical complexity and permutation entropy. The author believes that Sigaki et al. (2018)study is meaningful for this research because the masterpieces that we highly value and hope to last long were investigated through the lens of entropy and complexity.

2.5 Affordance

"*When Koffka asserted that 'each thing says what it is,' he failed to mention that it may lie. More exactly, a thing may not look like what it is."* – James J. Gibson 1986 –

Gibson initially introduced the term "affordance" in 1979, and he was mainly concerned with the relation between physics and physical optics, which is a limited approach. Since then, much ecological psychology, human-computer interaction (HCI), design, neuroscience, and robotics have started interpreting the concept of affordances through their lenses. Norman (2016) stresses the importance of affordance in the context of complexity and states in his book, "…[affordances] are important, for they are part of the world that makes action possible" (Norman, 2016, p. 229). Norman explains further that good design makes complex systems appear simple, which Norman believes is an indication that good designs have good affordances. In other words, affordance can influence complexity, simplicity, and longevity. It has a similar path in that complexity has been approached and defined in many different fields, even though it originated from thermodynamics. Also, affordance has been viewed from a circular economy where material affordance is focused on what the materials enable and prevent (Babri, Corvellec, & Stål, 2021). With proper material affordances, such as normalization of secondary material sourcing and product design geared toward recyclability, Babri et al. (2021) believe in improving circular economy and product longevity from the proper material selection. Although ecological psychologists believe that affordance has been poorly defined (Scarantino, 2003), Gibson's affordance has impacted and contributed to many fields, and many notions of affordance have emerged and evolved.

By Gibson- Ecological Psychology (1979) Gibson uses the environment to define and explain affordance. "The affordances of the environment are what it offers the animal, what it provides" (Gibson, 1979). "Offers" and "provides" are explicit interpretations in both environment and animals. There is no need to mentally understand the situation, which heavily relies on physical optics. Although "offer" may seem to sit on the opposite spectrum of "provide," they are in a "complementarity" relationship between animals and the environment (Scarantino, 2003), where Gibson uses the term "valence," "invitation," and " demand." Gibson suggests that affordance is invariant, but the need can change depending on the observer. In other words, the "value" of affordance does not change. However, the observer can change the "meaning" of affordance. Gestalt psychologists also address that the meaning and value can be recognized directly as affordance stemming from Gestalt psychology. Both gestalt psychology and affordance suggest that value and meaning are directly recognized, as Gibson emphasizes that "value" and "meaning" in the environment can be directly observed. Bodily sense can be explained by them (Gibson, 1979). However, Gibson takes affordance in the lens of phenomenology and elevates it further (Scarantino, 2003), which meaning and value for affordance "explain as a pale of the context of memory images or unconscious set of response tendencies" (Gibson, 1979, p. 138). In contrast, gestalt psychology sees meaning and value as "physiognomic quality" that can be noted in the observer's face. Interestingly, complexity can also be approached with Gibson's notion.

The value of complexity does not change, but the meaning of complexity can be changed based on the context of the complexity lies in. There is another element, information, which is a core concept for both affordance and complexity, however, ‘information’ has addressed and sits on the opposite spectrum, “explicit” and “implicit”. Gibson believes that information needs to be perceived “directly” and “immediately” in the ambient light whereas one of aspects to understand complexity is to evaluate if the information has been compressed.

By Norman- Design (1988): Norman acknowledges that affordance is derived from Gibson’s definition and re-iterates that affordance results from the perception created by an observer’s past knowledge and experience. However, Norman believes that affordance is heavily tied to the observer’s past knowledge and experience, whereas Gibson states that affordance itself is independent of the observer’s past knowledge and experience (McGrenere & Ho, 2000) due to the value of affordance does not change, but the meaning is changed. In the field of HCI and Design, Norman’s affordance has been widely accepted and utilized in Norman’s interpretation, where affordances “provide strong clues to the operations of things” (Norman, 1988, p. 8). Norman stresses perceived affordance through the lens of designers and differentiates between real affordance and perceived affordance, where users deal with affordance in screen–based products. Another notion from Norman is that physical affordance and perceived affordance don’t have to exist at the same time as physical products (Norman, 1999). Unlike Gibson, who stresses value, meaning, and sense, Norman emphasizes three kinds of behavioral constraints: physical, logical, and cultural, and he uses examples in the field of HCI. Physical constraints are real affordance, like a physical boundary on the screen. Users can not move the cursor outside the screen, and it has “physiognomic quality” from the gestalt. Also, when the cursor carries meaning as physical location, for example, closing the window, it is physical affordance. Logical and cultural constraints are where past knowledge and experience are needed and share one common aspect. Logical constraints can guide users logically, and the users can expect how they take action to the next step, for example, page numbers for the book. Cultural constraints are conventions established within a cultural group. The convention constraints can encourage users to perform a certain action and discourage them, users, from avoiding a certain task. The cultural constraints can be emerged and be abandoned by the group based on the needs or cultural movements. Logical and cultural constraints are soft boundaries, but the boundaries can help navigate an unknown environment (Norman, 1999). Both Gibson and Norman address the affordance that action possibilities should be visible, but Norman stresses more users' perspective, which indicates that action possibilities make visible to the users (McGrenere & Ho, 2000).

By Turvey – Ontology & Metaphysics (1992): Turvey approaches and construes affordance in the field of ontology and metaphysics and broads the spectrum of the definition of affordance. However, Stoffregen argues and disagrees with Turvey's affordance view and definition. Turvey brings two important concepts: perspective control (PC) and disposition. He states that "PC controls concerned with future events, interpretable as goals to be realized" (Turvey, 1992, p. 174). Turvey sees that prospective control exists in the ecological approach where it investigates law because prospective control concerns the real possibilities aligned with the law. Still, Turvey asserts, "the real possibilities in question are affordances" (Turvey, 1992, p. 178). From an ontological perspective, affordance is rooted in dispositional properties, where Turvey (1992, p.

178) defines disposition as the "Property of a thing that is potential or possible" and has three fundamental characteristics.

First, the disposition to do Y is prior to doing Y. Sugar is soluble in a liquid such as coffee. Whether the sugar is exposed to coffee, sugar is even soluble prior to being exposed to coffee. Second, dispositional come in pairs. Sugar is soluble, and coffee can play as a solvent. The disposition has two complementary sides, which Turvey addresses as affordance and effectivity. Depending on the point of view, coffee's propensity to play as a solvent to certain materials like sugar can be a disposition or effectivity of the disposition of sugar to dissolve.

Third, dispositional never fails to be actualized when conjoined with relevant circumstances. Turvey asserts that actualization always occurs when affordance meets effectivity, where actualization can be viewed as an event.

There is another important concept, effectiveness, while explaining affordance as a compliment. Shaw et al. propose that effectivity complements affordance (Shaw, Turvey, & Mace, 1982). While affordance and effectivity are complemented each other, Cutting adds that affordances are directional from the environment to the animal, and effectivity is directional from the animal to the environment (Cutting, 1982). Effectivity can be understood in the context of affordance as complementation of affordance and having the characteristic of directional. Neither Turvey nor Shaw was successful in defining effectivity clearly. However, Sanders explains effectivity in the context of Stoffregen's affordance view, whereas "effectivity is held to be the necessary subject-side counterpart to an affordance" (Sanders, 1997, p. 103). Sanders (1997) explains further by taking Turvey, Shaw, and Stoffregen's views. Effectivity is prediction and disposition, while affordance takes the position of an opportunity for action in the environment.

By Stoffregen - Kinesiology (2003): Stoffregen approaches affordance in the sense of holism because he addresses affordance in a larger context of the ecological approach to perception and action. Turvey sees affordances as separate entities. Stoffregen clearly states that “affordances are properties of the animal–environment system, that is, that they are emergent properties that do not inhere in either the environment or the animal” (Stoffregen, 2003). In contrast, Turvey proposes that affordances are properties of the environment (Turvey, 1992). An emergent property is where individual component properties converge to one system property, which becomes a whole. Stoffregen’s research background is in kinesiology, and it is natural that his approach to affordance is different from Turvey's. Stoffregen decides to use the term “opportunity for action” rather than affordance because the word “affordance” can be interpreted in several ways and be confused by readers depending on where the readers come from. In order to understand the opportunity for action, he brings an important ecological concept of “event, “which can be categorized as animate events and inanimate events. An event is an actualization between certain properties of animals and the properties of the environment. The event that voluntarily occurred is an animate event, such as reading books or stealing candy. That obligatorily occurs is an inanimate event like the refraction of light by crystals. Stoffegen’s statement makes it easier to understand where he stands, “affordance is what one can do, not what one must too” (Stoffregen, 2003, p. 119). Stoffregen explains further that affordance exists “only at the level of the animal – environment system” and re-phrases that “affordances are opportunities for action; they are properties of the animal-environment system that determine what can be done” (Stoffregen, 2003, p. 124).

CHAPTER 3: METHOD

3.1 Research Goal

I want to build a descriptive framework for how consumers determine and understand aesthetic longevity and how simplicity and complexity differ. It could be that Berlyne's principles apply throughout or that different principles are required depending on product categories. The framework can suggest how complexity and simplicity interact to increase aesthetic longevity. As an expert in design, I will apply mixed research methods to address research questions. The research hypothesizes that aesthetic longevity emerges when complexity becomes the ingredients of simplicity where the ingredients are not necessarily manifested. Simplicity can only bloom when simplicity is derived from complexity.

3.2 Research Questions

Research Question:

What is the role of visual complexity in consumer products that have long-lasting aesthetic longevity?

Main hypothesis: visual complexity plays a significant role in determining aesthetic longevity.

I have composed five research sub-questions(RSQ) that will help structurally answer the research question.

RSQ.1 How do consumers understand complexity in aesthetic longevity? I aim to determine whether consumers know complexity and simplicity as design elements, whereas simplicity can be defined as visual balance by eliminating ambiguity and disunity (Arnheim, 1954). It is necessary to investigate if complexity has an inverse relationship to simplicity, as simplicity has an opposite meaning.

Hypothesis RSQ.1: participants think that simplicity is 0% when visual complexity becomes 100%

RSQ.2 How do consumers perceive visual entropy regarding complexity? I aim to find out how randomness plays with the overall aesthetic. The scientific definition of entropy is "measurement of disorder." However, the disorder has been interpreted as randomness in various literature reviews, and I believe that randomness is more appropriate to use in the design field. So, I decided to adopt randomness in the context of design. I believe entropy can also affect visual complexity.

Hypothesis RSQ.2: participants believe that complexity increases when visual entropy increases.

RSQ.3 How do consumers' subjective experiences – familiarity, remember, and knowledge – influence aesthetic longevity? I aim to discover the role of familiarity, remember, and knowledge in the context of complexity and aesthetic longevity because subjective experience can change the level of complexity. In contrast, familiarity can have aspects like media exposure, proximity, and frequency of interaction. Therefore, it is necessary to determine the relationship between subject experience and complexity.

Hypothesis RSQ.3: visual complexity exhibits significant positive correlations with knowledge, moderate positive correlations with memory, and weak positive correlations with familiarity.

RSQ.4 How does visual complexity contribute to good design for aesthetic longevity? I aim to investigate the relationship between complexity and simplicity among designs that are recognized as good designs.

Hypothesis RSQ.4: visual complexity is an important factor for aesthetic longevity.

RSQ.5 How does consumers' frequency of interaction and proximity of products influence aesthetic longevity? I aim to find out how the frequency of user interaction and proximity to the users can influence aesthetic longevity because the two attributes can influence the familiarity that ultimately influences aesthetic longevity.

Hypothesis RSQ.5: Increased interaction and closer proximity lead to an increase in aesthetic longevity.

3.3 Research Method

This research used quantitative and mixed methods to investigate the data and answer the research sub-questions. Firstly, the quantitative method was used to analyze data from survey participants, enabling me to employ different statistical models. Statistical models can investigate relationships among the different data sets. In this research, I set variables in table 3.1 and the independent variables will be employed for the purpose of analyzing and addressing the sub-questions, with the ultimate aim of answering the research question.

Research question: *What is the role of visual complexity in consumer products that have long-lasting aesthetic longevity?*

Main hypothesis: Visual complexity plays a significant role in determining aesthetic longevity.

Table 3.1: Variable type(s)

Variable Types	Variable(s)
Dependent Variable	Aesthetic Longevity
Independent Variables	#1 Visual Complexity
	#2 Visual Interest
	#3 Visual Entropy
	#4 Product preference
	#5 Familiarity
	#6 Remember
	#7 Knowledge

Also, the CMYK method is used as a part of the quantitative method, which the author developed and applied. It is a method to convert quantitative data from the participants to a CMYK color combination that visually represents data. As a result, CMYK methods can visually interpret the data set quickly and help categorize the data set effectively. Secondly, mixed methods research was applied through this research in order to validate the relationship from the data set as well as find the participants' insights that are not visible in quantitative method research.

3.3.1 Quantitative Method 1

Overview: it is a form of an interactive survey. The survey participants were able to interact with the sample products (Table 3.2) as stimuli, meaning they could hold, touch, and feel the actual products rather than look at online images. It is crucial for the participants to interact with the actual sample products because online images cannot deliver a sense of scale, textures, and details and have a limited view, which could cause biases and unwanted perceptions. There are six attributes – visual complexity, simplicity, entropy, familiarity, remember, and knowledge – to investigate in this interactive product survey, which aims to determine how the attributes influence product longevity. Also, it aims to investigate the interrelationship among those six attributes. I planned to collect data sets from more than 100 participants who were junior, senior, and graduate students at the University of Illinois at Urbana Champaign. There are three categories of products (Figure 3.1)– the Bluetooth speaker, wristwatch, and game controller – and each category has three products from the same company. However, each category has different levels of visual complexity – high visual complexity, medium visual complexity, and low visual complexity.

Figure 3.1: Images of product samples

Format: Based on the literature review, it showed no effect of viewing time on aesthetic appreciation (McWhinnie, 1993; Smith, Bousquet, Chang, & Smith, 2006); I do not plan to impose a time limit on participants' responses. Each stimulus will be presented until participants respond. Product images matching the actual design samples were provided to the survey participants to increase the effectiveness of the survey process and ensure clarity among the design samples. Also, the corresponding images helped the participants understand the survey questions better. Research Sub-Questions: Sub-question 2.1, 2.2, and 2.3 were investigated with quantitative method 1.

RSQ.1 How do consumers understand complexity and simplicity in aesthetic longevity?

This experiment is based on Berlyne's principles of studying complexity for preference and interest.

Complexity	Mixed (Complexity-simplicity)	Simplicity
 Speaker#1	 Speaker#2	 Speaker#3
 Wristwatch#1	 Wristwatch#2	 Wristwatch#3

Figure 3.2: Complexity, mixed, and simplicity

Complexity	Mixed (Complexity-simplicity)	Simplicity
 Game Controller#1	 Game Controller#2	 Game Controller#3

Figure 3.2 (cont.)

Also, much research has been done on visual complexity, entropy, and beauty. However, many art history or architecture examples show significant complexity and consider the masterpiece, which can be addressed as aesthetic longevity. Although Berlyne's principles substantially contribute to arts through two-dimensional exploration, I need to apply Berylne's principles to three-dimensional objects and investigate complexity related to aesthetic longevity. Participants will be asked to rate the complexity of each of the nine products (Figure 3.2) on a 1 to 5 Likert scale (very simple–very complex). At this stage, complexity will not be defined by participants. Participants were only instructed to focus on their general impression of the visual complexity of each stimulus, not on the complexity involved in manufacturing the products.

RSQ.2 How do consumers perceive visual entropy regarding complexity?

The definition of " visual entropy" will be given to the participants, including visual examples. Participants will be asked to rate the entropy of each of the nine products (Figure 3.3) on a 1 to 5 Likert scale (very high – very low). At this stage, the definition of entropy will be provided to participants. Participants were only instructed to focus on their general impression of the visual entropy of each stimulus and rate four different attributes – visual entropy, visual interest, preference to own, and willingness to keep it for the next ten years.

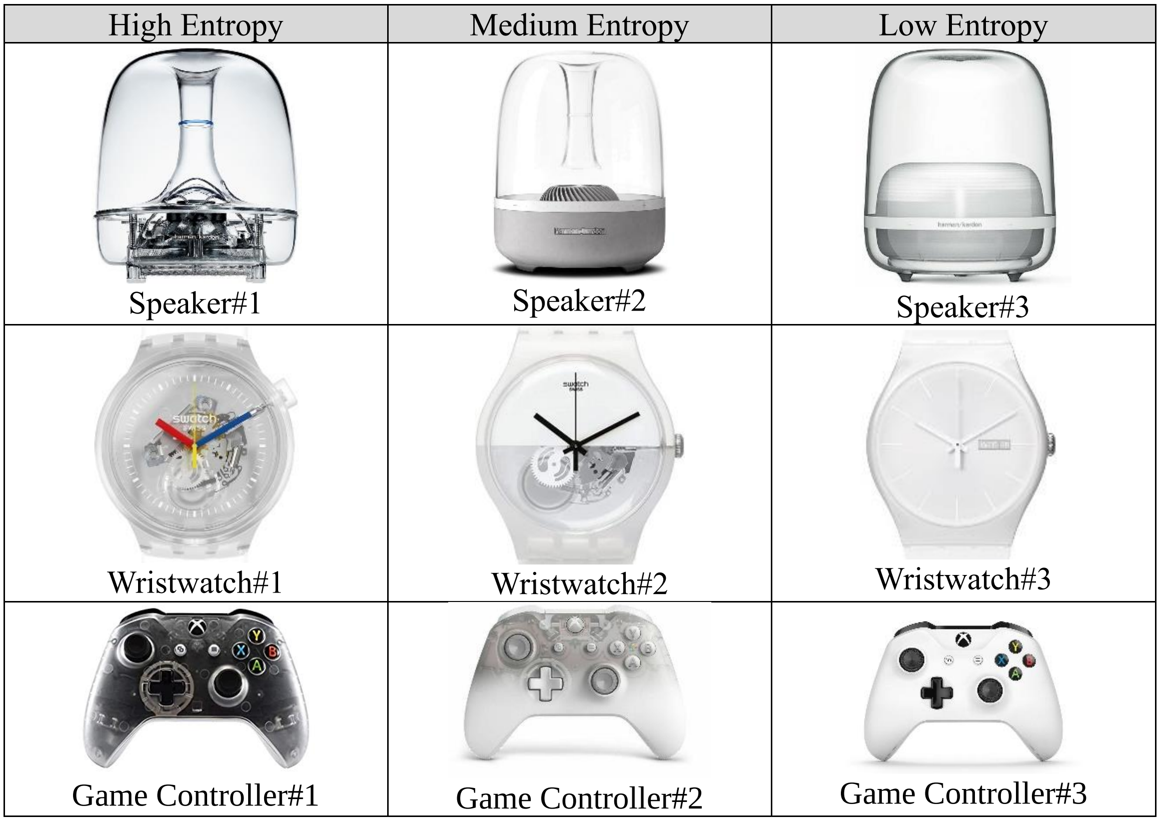


Figure 3.3: High entropy, medium entropy, & low entropy

RSQ.3 How do consumers' subjective experiences – familiarity, remember, and knowledge - influence aesthetic longevity?

I embraced the study by Geraci et al. (2009) to differentiate the definitions of remember, know, and familiar because each word has a different level of consciousness and cognition. To do so, I inserted a corresponding sentence that carries a different level of consciousness and cognition in the survey question.

- I have seen this a long time ago and have seen it many times
- I have seen advertisements for it on TV, in magazines, or online.
- I know exactly what it is and can explain it thoroughly.

Geraci et al. (2009) study finds that ‘remember’ holds a high confidence level, whereas ‘familiar’ holds a medium confidence level. After completing the subjective experience survey, the participants will rate the products based on their aesthetic preference and rate them if they want to keep the next ten years using a 5 points scale.

3.3.2 Quantitative Method 2 – The CMYK Method

Overview: CMYK method is a visual categorization by converting CMYK Scores from numerical data sets generated by the survey participants. In this research method, the participants were asked to look at thirty product design images retrieved from the red dot product design award website, and those images are the best of the best. The participants were asked to rate the images in the criteria of visual complexity, simplicity, entropy, and familiarity. This method aims to collect rich numeric data sets to see if there is any inter-relationship among those four attributes when the products are recognized as having a good design. Also, this CMYK method works well with Multi-Dimensional Scaling (MDS), where MDS analyzes the data sets pairwise and helps understand the overall data set. However, the CMYK method is based on all survey participants' CMYK scores of an individual product. Therefore, the CMYK method can quickly identify the individual’s perceived design judgment and all participants’ design judgments on one design sample product. Once the data sets are collected, the CMYK method can perform,

- Categorizing design elements
- Extract design elements
- Analyzing design elements

- Mapping the extracted design elements
- non-metric multidimensional scaling,
- CMYK Mixer method

Format: the survey participants were asked to look at thirty images that have received red dot product design awards (Figure 3.4) and were asked to rate four criteria – visual complexity, visual simplicity, familiarity, and visual entropy – on each product design image based on their own experience. In order to maintain consistency for the data set, the images were retrieved from one website; all images had the same white background and the exact size of images.

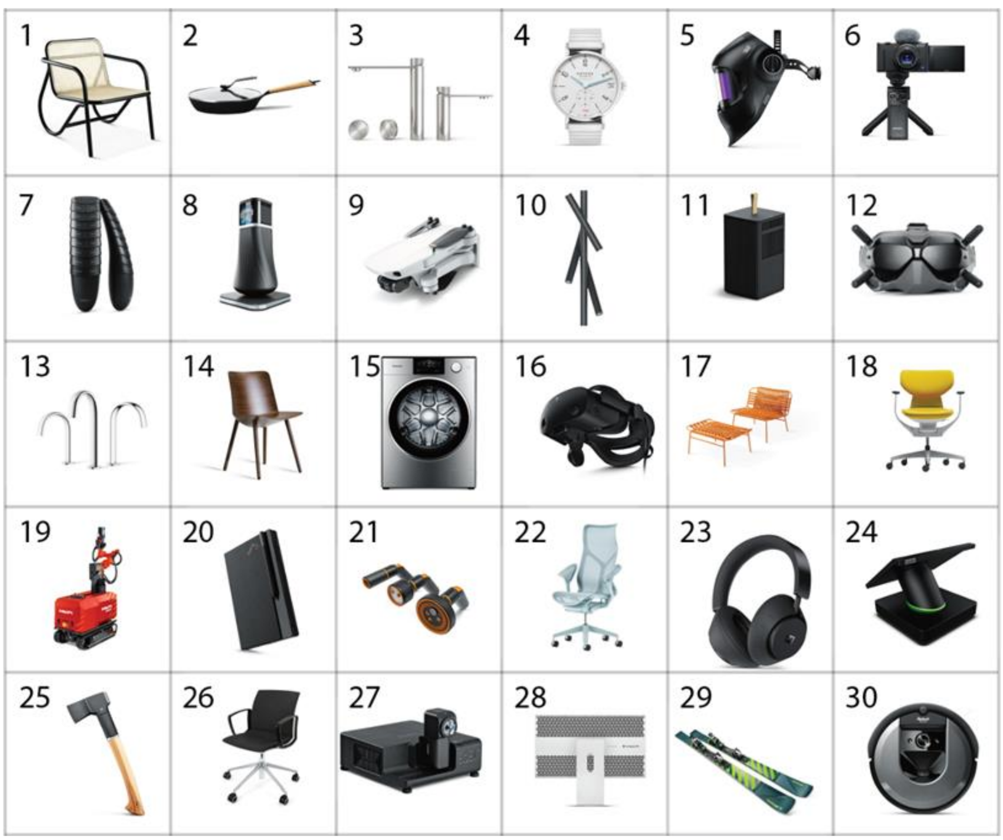


Figure 3.4: Product images that received red dot product design awards

RSQ.4 was explored to address the following:

How is visual complexity contributed to good design for aesthetic longevity?

It is meaningful to investigate the relationship between the attributes outside of controlled environments that the participants had only nine design samples to choose from. Also, it provided an opportunity if the findings from quantitative and mixed methods research could be generalized.

3.3.3 Mixed Methods

Overview: This method was designed to investigate two attributes consumers' frequency of interaction and proximity between users and their products – against product longevity. The interactive survey had opportunities and dedicated areas where the participants could express their thoughts or extended opinions. These qualitative data sets are very helpful in extracting the participants’ insights that numeric data could not express. This method still carries numeric data sets, providing an opportunity to crosscheck and validate if numeric data sets are aligned with qualitative data. Also, the numeric data sets provided another opportunity to analyze how visual complexity influences aesthetic longevity based on the frequency of user interaction and proximity to the users.

Format: the target number of participants was expected to be more than 60 students from the University of Illinois at Urbana Champaign and needed to be at least juniors or seniors. The design sample products were the same as the previous method: speakers, wristwatches, and game controllers, and each category has three products with three different levels of visual complexity.

Attribute#1

Interaction refers to physical touches between the products and users. For example, a game controller interacts highly with the controller and the user, whereas Bluetooth speakers interact less than a computer mouse (Figure 3.5).

Figure 3.5: Types of interaction

Attribute#2

Proximity in this research is defined as the physical distance between the products and the users (Figure 3.6). It means that wearable devices will be close to almost 0 because they typically stay in physical contact. In contrast, Bluetooth speakers can be away from the user from half a foot to roughly 10 feet to enjoy the music from the speakers.

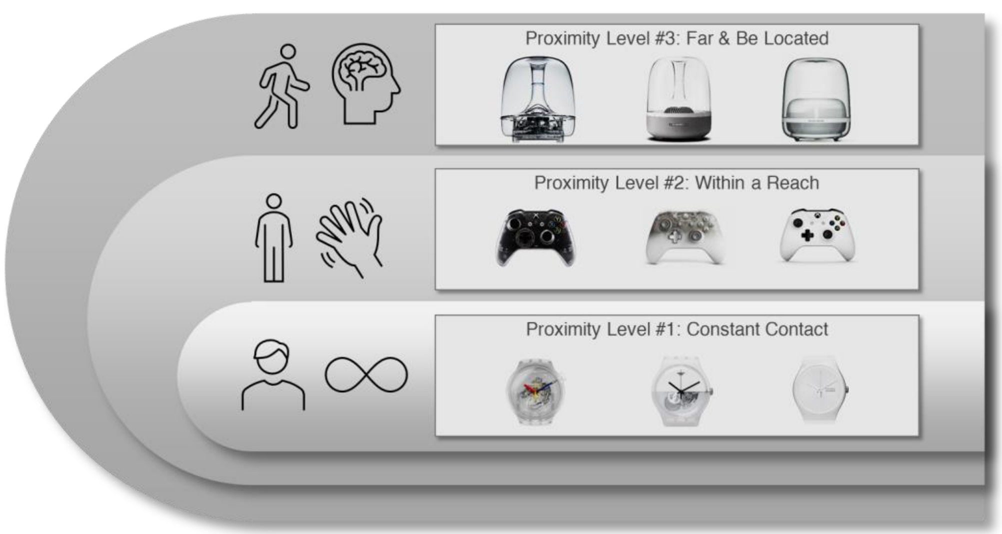


Figure 3.6: Products based on proximity

RSQ.5 was explored to address:

How does consumers' frequency of interaction and proximity of products influence aesthetic longevity?

Aim to find out how frequency of user interaction and proximity to the users can influence aesthetic longevity because the two attributes can influence the familiarity that ultimately influences aesthetic longevity. This question can hypothesize in the context of consumer products that users tend to be less tolerant of complex designs for products with a high frequency of interaction and tend to be more tolerant of products with a lower frequency of interaction. Also, the users tend to be less tolerant of complex designs for proximity and more susceptible to complex designs for remote proximity.

3.4 Data Analysis Methods

3.4.1 Multi-Dimensional Scaling(MDS)

MDS is a statistical technique to visualize the similarities or dissimilarities among objects or variables in a low-dimensional space (Ainsworth, 1969). The MDS algorithm works by calculating the pairwise distances or dissimilarities between objects in the high-dimensional space and then projecting them into a low-dimensional space while preserving their relative distances (Schultz & Joachims, 2003). It is an excellent method to visualize complex data structures and identify patterns and relationships among objects or variables. MDS can also be used to compare different representations of the same data, such as different clustering algorithms or feature selection methods.

3.4.2 The CMYK Method (developed by the author)

The CMYK method is a hybrid method that can quantify visual elements – complexity, simplicity, familiarity, and entropy by numeric data and can visualize the overall perception of design by the mixture of colors: cyan, magenta, yellow, and black. For the CMYK method, cyan represents complexity, magenta is for simplicity, yellow is familiarity, and k represents black. For example, suppose a design shows many red vertical lines from the CMYK method. In that case, most participants think the design is simple and familiar with the design or the product because a mixture between magenta and yellow yields red. Also, participants perceive the design as complex if there are many cool colors like blue or green. Another benefit of the CMYK method is expressing the design using colors. It helps identify the individual design visually, whereas MDS analyzes the designs as pairs. In other words, MDS helps analyze a group of designs or a pair of designs. The CMYK method can be applied to an individual design or many designs to categorize each design quickly by looking at the dominant colors on each design. Of course, if a more precise analysis is needed, the design can be expressed by numbers like 34, 76, 66, and 23. For the example above, participants think that design has a complexity score of 34, a simplicity score of 76, and familiarity score of 66, and an entropy score of 23. The CMYK score, 34,76,66,23, will yield the color brown.

3.4.3 Multi-Level Modeling

Multi-level modeling, or hierarchical linear modeling, is a statistical modeling technique used to analyze data with a hierarchical or nested structure. This type of modeling helps study data where individual observations are nested within larger groups, such as students nested within classrooms, employees nested within companies, or patients nested within hospitals. Multi-level modeling aims to understand how individual and group-level variables interact to influence the outcome variable of interest. Multi-level models estimate both within-group effects, which reflect the influence of individual-level variables on the outcome within each group, and between-group effects, which reflect the influence of group-level variables on the outcome across all groups. Multi-level modeling is beneficial for dealing with issues such as clustering, where observations within the same group are more like each other than in other groups. This modeling approach also allows for the exploration of contextual effects, where the influence of individual-level variables on the outcome varies depending on the group they belong to.

3.4.4 Marginal Distribution

In probability theory and statistics, the marginal distribution of a random variable is the probability distribution of that variable without considering the values of any other variables. In other words, it gives us the probability distribution of one variable by summing or integrating all possible values of the other variables in the joint distribution. The marginal distribution is obtained by "marginalizing out" the other variables. For example, if we have a joint distribution of two random variables, X and Y, their marginal distribution of X would be obtained by summing the probabilities of all possible outcomes of X for every value of Y. Similarly, the marginal distribution of Y would be obtained by summing the probabilities of all possible outcomes of Y for every value of X. Marginal distributions are important in statistics and probability because they allow us to examine the properties of individual variables in a joint distribution without considering the others. This is useful in modeling complex systems and making inferences about individual variables' behavior.

3.4.5 Pros/Cons of Research Methods

This study employs three research methods: product interactive survey(quantitative), the CMYK Method, and survey with the interview (mixed method research). Each research method has pros and cons, and Table 3.2 illustrates each research method.

Table 3.2: Pros/Cons of research methods

Method	**Pros**	**Cons**
#1. Product Interactive Survey (Quantitative)	1. Rich data sets can be created. 2. Participants will have time to interact with natural objects/products. 3. Surveys can include various products in each category.	1. Data noises are expected. 2. The survey could take longer since the participants need to interact with the objects. 3. Certain brands could trigger biases. 4. The questionnaire should not be too long. 5. The survey should not have too many questions.
#2. The CMYK Method	1. Rich data sets can be created. 2. CMYK Mixer method can visualize a data set. 3. The distance between data can be analyzed rather than a linear sequence. 4. Design elements can be extracted. 5. Grouping among design elements is possible.	1. There are two types of data sets – a) Image and b) actual products, which can be an issue. 2. The design elements can be subjective. 3. The data analysis can be complicated.
#3. Survey & Interview (Mixed Research Method)	1. Interviews with real objects could generate a rich data set. 2. The interview data can be used to support the other method.	1. Overall, the interview and processing time can take longer. 2. Analyzing interviews can consume a long time.

CHAPTER 4: FIELD EXPERIMENT DESIGN

4.1 Field Experiment Overview

While designing this field experiment, finding appropriate design samples as stimuli was one of the most challenging tasks for two reasons. First, design can be a very subjective matter. Unlike mathematics, there is no right or wrong answer, and reaching a consensus on good and bad designs is hard. Because of the subjectivity, I added an attribute, familiarity, throughout the field experiment. Familiarity is one of the major attributes that form subjective opinions. It is a very powerful attribute that can sway many things in everyday life, and many studies in psychology have investigated familiarity. The mere exposure effect is a classic example of familiarity that originated in 1876 by Gustav Fechner. Another criterion I implemented throughout the interactive survey is that selecting design samples as stimuli needed to be from a reputable source, and the design needed to be recognized as good design, which receiving reputable design awards like the red dot design award [1]is indisputable.

In this research, there are mainly two different field experiments: an interactive survey for actual design samples and an evaluation of several attributes by looking at product design images that are recognized as good designs and received red dot product design awards. Q1 and Q3 are under the field experiment of the interactive survey category, and Q2 is under the evaluating design attributes of product design images. I chose design samples for Q2 from

[1] The Red Dot Design Award is an internationally recognized design competition that honors outstanding design achievements across various industries. It is organized by the Design Zentrum Nordrhein Westfalen in Essen, Germany. Submissions are evaluated by expert juries based on criteria such as innovation, functionality, and aesthetics. The award has been running since 1955 and has become one of the most prestigious design competitions in the world.

recipients of the "red dot" product design award, established in Germany and one of the most prestigious design awards in the design field. Selecting the design samples from the red dot award eliminates unnecessary debates or arguments and can standardize and equalize the quality of the design.

4.2 Selecting Design Samples as Stimuli

There are nine design samples in 3 categories – 1) tabletop speakers/Bluetooth speakers, 2) wristwatches, and 3) Microsoft Xbox game controllers.

4.2.1 Tabletop Speakers/Bluetooth Speakers

SoundSticks I by Harmon/Kardon was introduced around the same time Apple introduced the clear iMac G3 computer. The SoundSticks shares a similar aesthetic to Apple iMac, using clear plastic transparency, showing complexity and entropy. Because of the transparency and lighting effect from the woofer unit, it is known as a Jellyfish speaker. When SoundSticks I was introduced in July 2000, it received a design award with the Industrial Design Excellence Award (IDEA) 2000. Overall, the design review was positive, as it has been an iconic design for almost two decades. The SoundSticks was added to a collection at the Museum of Modern Art in 2013 and appeared in the movie, "Begin Again," in 2013.

Aura Studio 2 by Harmon/Kardon was introduced at the 2014 CES Las Vegas. It still keeps a similar aesthetic to SoundSticks I, like Jellyfish, and sometimes, consumers get confused with the original design, SoundSticks. The evolved iconic design from

SoundSticks eliminated strong visual complexity and covered strong visual entropy. However, it kept and added a fractal pattern at the center core to deliver a sense of sophistication and simplicity. The core fractal pattern is a focal point of the product and gives visual interest. According to Harmon/Kardon, they emphasized and advocated design as much as sound quality. As a result, the Aura Studio series received a red dot design award in 2013.

SoundSticks four by Harmon/Kardon is a 20th - anniversary edition of the original design, SoundSticks I, and carries some significant meaning regarding its design progress. Unlike the original design, SoundSticks I, in 2000, SoundSticks 4 hides visual complexity as much as possible, which means that it has been significantly simplified compared to other original designs. However, it kept a subtle pattern at the center core as a reminiscence of visual complexity and entropy. However, the pattern does not have to exist to make the overall design very clean. It raises the question, "why does it have to be there? Moreover, what does it do?"

4.2.2 Wristwatch

Big Jellyfish (SO27E100) by Swatch is a succession of the original Jellyfish introduced in 1985. Big Bold Jelly keeps the original design of color pallets and transparent signature material, and it was launched in the 2019 Christmas season. Like the design of SoundSticks, the overall design is clear, which enables us to see the internal components that reveal visual complexity and entropy.

Underwater (SUOW107) by Swatch has a unique design, and it has a watch face that is half clear and half solid white face and was introduced in 2014. Although half of the watch's face (3 o'clock through 9 o'clock) was covered with solid white, most of the watch movement was visible, including a battery. Also, a white gear is clearly visible toward the center, which gives an exciting contrast between the gear and half solid white face.

White Rebel (SUOW701) by Swatch is one of the simplest watch designs introduced in 2010. It does not have any color. The watch is white except for the date in a small window, and the crown is made of stainless steel. It does not have any indication of visual complexity or entropy.

4.2.3 Game Controller

PDP Afterglow controller is a game controller with a clear plastic case that lets you see all internal electronic components. Although it is an after-market game controller, it is a popular model among game enthusiasts. Since it is a typical consumer electronics, many electronic components have random shapes and colors, which deliver visual complexity and entropy to the users.

Phantom controller by Microsoft has described, "*The design is the optimal blend of luxury and sci-fi, embodying a new slant on technical beauty. Moreover, the controller reflects a sense of mystery with rich, neutral colors that fade away to reveal the technology inside,"* by Bree White, Microsoft's global product marketing manager. The upper cover in the controller has half transparency to subtly reveal internal structures that show a sense of visual complexity and entropy, which convey "technical beauty" and "a sense of mystery."

Xbox One controller by Microsoft has no clear plastic to reveal internal components. Overall, the design is simple and clean, so users would not perceive it as complex. However, there are intricate patterns around the thumb control stick and button. Although those patterns would not be the first thing that the user would recognize, there is a small portion that gives a sense of visual complexity.

4.3 Deploying the survey questions

4.3.1 Survey Q1

Q1 is designed to evaluated visual entropy, interest, preference, longevity, familiarity, and aesthetic interest and is the backbone of this field experiment. Although the research questions have been established regarding visual complexity, there are six attributes to explore in Q1 to find out how the visual complexity would interact with other attributes and if there is any relationship that could be established among the six attributes: visual entropy, visual interest, user preference, product longevity, familiarity, and visual aesthetic interest. Entropy is a terminology that originated from thermodynamics. I adopted the definition of entropy to this experiment as visual entropy and provided the definition of visual entropy – visual entropy can be explained as visual randomness with design elements. It can be visual arrangements, material combinations, visual proportions, etc. Also, images that explain the visual entropy were provided to the participants to help them understand visual entropy visually. All participants were asked to rate aesthetic longevity throughout all design samples, "*Please, see the actual products and indicate your willingness to use and keep the product for the next ten years*." I adopted a 10-year frame as part of the criterion of aesthetic longevity from the Long-Life Design Award[2] in Japan where products need to be endorsed by users for more than ten years. Also, the participants were asked to answer questionnaires regarding visual interests, preferences, and familiarity. Those attributes are analyzed with complexity and aesthetic longevity.

4.3.2 Survey Q2

Q2 investigates visual complexity, visual Simplicity, familiarity, and visual entropy. Participants were to evaluate visual complexity, visual simplicity, familiarity, and visual entropy in the series of product design images (Figure 4.1). The product design images were chosen from the Best of Best Design category in the red dot design award to maintain design quality throughout the experiment. Each criterion was scored on a percentile scale, and the four criteria were converted to CMYK scores. The combination of the score delivers a unique color based on the CMYK color method.

[2] Long Life Design Award in Japan (https://www.g-mark.org/activity/2021/longlife.html?locale=en)

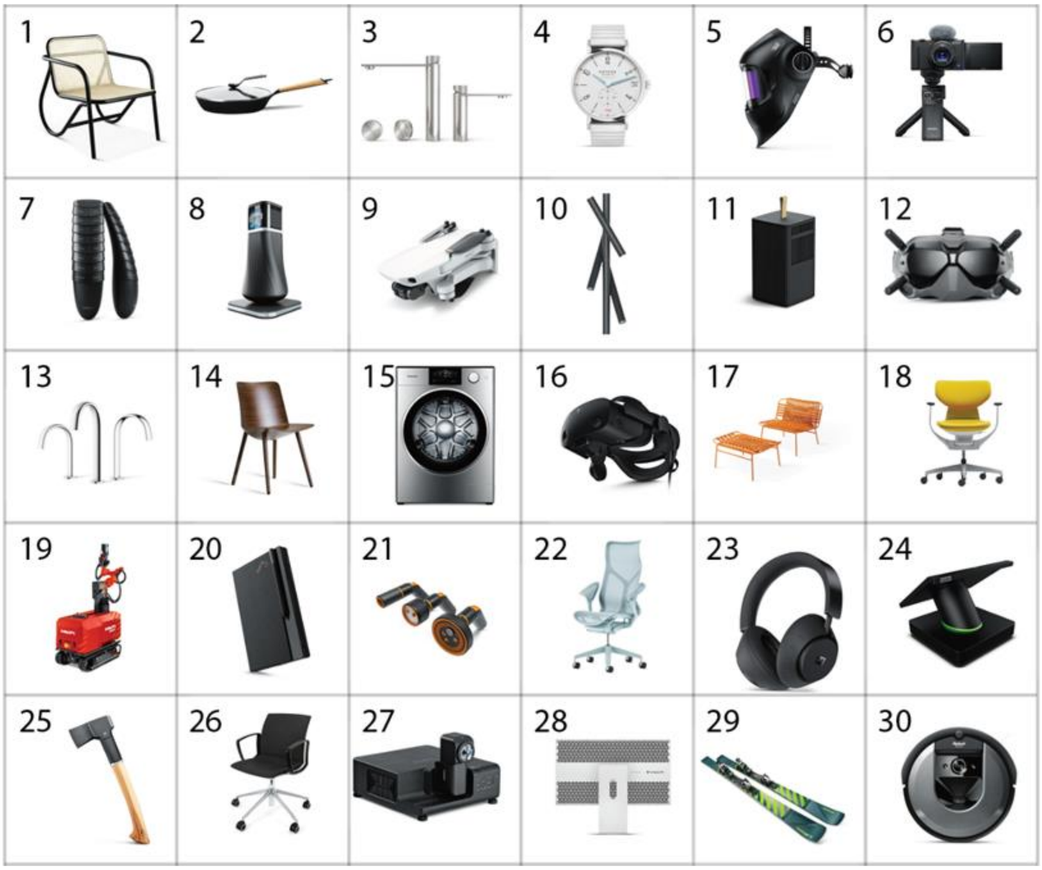


Figure 4.1: Product images that received red dot product design awards

4.3.3 Survey Q3

Q3 explores frequency of interaction, proximity of product between users and product. There are two questions to be answered regarding aesthetic longevity. The first is the frequency of interaction, defined as interaction in this research refers to the tactile experience like the physical touch of the products by users. For example, a smartphone has a high interaction between the smartphone and the user, whereas smartphone chargers have less interaction than smartphones." The Participants were asked to rate the frequency of interaction based on their lifestyle on each design sample. The second question is related to proximity, and it is defined as; proximity in this research is defined as the physical placement between products and users within the users' lifestyle. So, the users believe that the product will perform properly and the benefit from the products will be optimized. For example, rings will have a proximity of close to zero because it typically stays in physical contact. In contrast, TVs can be away from the user anywhere from a foot to roughly 10 feet to watch based on the size of the TVs." The Participants were asked to rate the proximity based on their lifestyle on each design sample. Frequency of interaction and proximity are essential attributes that can change the level of familiarity.

CHAPTER 5: DATA COLLECTION

5.1 Overview

This study examines whether or not aesthetic longevity can be influenced by complexity, simplicity, entropy, or familiarity. Data collected from the study can be used in the future product development process of various consumer products. The product samples in this study are consumer electrical products – Bluetooth speakers, wristwatches, game controllers – that are used as stimuli to determine the aesthetic interest and expected product life span based on the overall design. Participants were provided with tasks to interact with the product samples, and the participants answered the survey questions. The significance of this research is to help find an optimal aesthetic balance between complexity and simplicity and the relationship between complexity and familiarity. Ultimately, this study can be incorporated into the product development process and utilized to create products that will last long without losing aesthetic interest. This experiment-like survey protocol was submitted to UIUC IRB on 7/7/2022 and approved on 8/19/2022. The protocol number, #23250, was issued.

5.2 Participants' Demographics.

The field experiment mentioned in the statement was carried out on two separate occasions. The purpose of this experiment was to gather data and study certain aspects related to the participants involved. The results of the experiment were presented in the form of bar charts, with one set of bars represented in red and the other set in blue. Figure 5.1 provides insights into the races or ethnicities of the participants involved in the experiment. It visually represents the distribution of participants across different racial or ethnic categories using the red and blue bars.

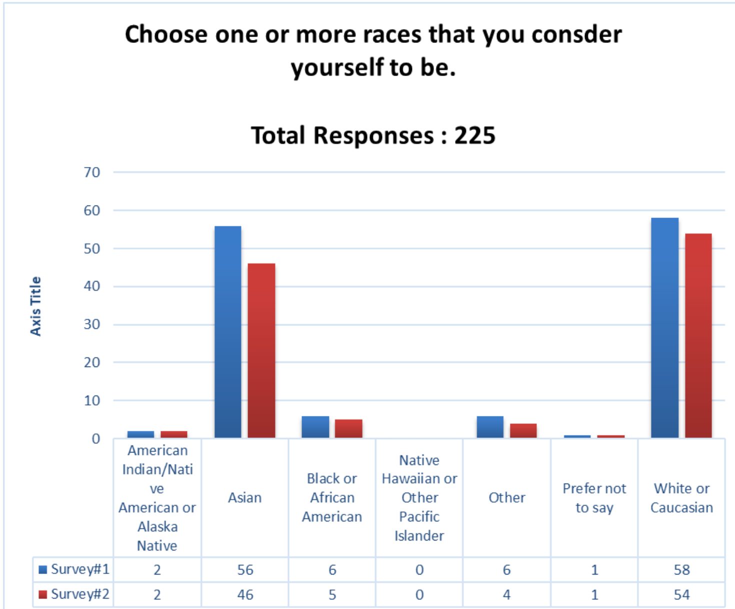


Figure 5.1: Summary of participants' race(s)

Figure 5.2 focuses on the majors or fields of study pursued by the participants. It presents the data in the form of red and blue bar charts, allowing viewers to analyze the distribution of participants across various academic disciplines. This figure helps to determine the representation or prevalence of specific majors or fields of study among the participants.

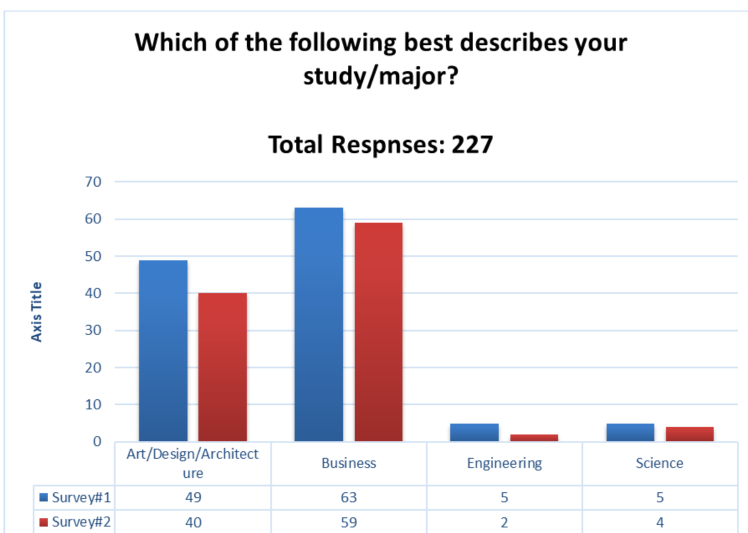
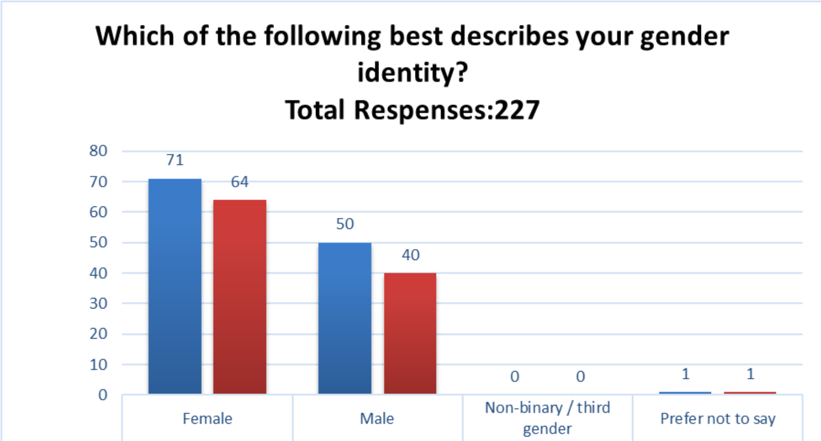


Figure 5.2: Summary of participants' study(major)

Lastly, Figure 5.3 highlights the gender composition of the participants involved in the experiment. This figure provides valuable information about gender diversity or representation within the participant pool.



	Female	Male	Non-binary / third gender	Prefer not to say
Survey#1	71	50	0	1
Survey#2	64	40	0	1

Figure 5.3: Summary of participants' gender identity

Overall, these three figures contribute to a comprehensive understanding of the participant demographics and characteristics relevant to the field experiment. They visually depict the distribution and representation of races/ethnicities, majors/fields of study, and genders, allowing researchers and viewers to interpret the results more effectively.

5.3 Structure

This interactive survey was conducted during the Fall semester of 2022 (Sept. 1^{st}. 2022 ~ Dec. 1^{st}. 2022). Participants were set to be older than 18 years old UIUC body only, and there were no targeted gender and ethnicity in order to eliminate bias from gender and ethnicity. Participants should have completed their 2nd year of college education because this reflects the questionnaires' comprehension level. They must understand and answer the questions while examining the product samples. The participants can expect to spend from 30 min to 50 min to complete the activity. This experiment had no time limits because the activity could run longer than an hour based on the participants' ability to comprehend the questions. Several studies indicated that having extra time for this type of activity did not have much of an impact on the result. No known risks are associated with this research beyond those in daily life. Participants only perform essential activities that resemble what they do in their daily life lives and respond to standard survey questions for a short time Even though the flow state might be induced. It is a positive psychological state characterized by high positive valence and rewarding feelings; thus, the author believes that it will not pose any risk or harm to participants. No violent, sexual, racist, or harmful content will be included. The participants can also stop studying at any point if they feel uncomfortable. The participants were assured that they should only engage in the study if they were willing and comfortable. The participants could terminate their participation at any given point in time.

5.4 Field Experiment Procedures

Immediately after acquiring the participant's consent, they will be asked questions about their experience with consumer electronic products – game controllers, Bluetooth speakers, and Wristwatches – use of technology, and understanding of the context of products in everyday life. The author thoroughly explained the procedure of the survey. The student participants had an opportunity to examine the various products (Bluetooth speakers, wristwatches, and game controllers) while answering the survey questions. The author took pictures of participants while they were answering the questionnaires. The author contacted faculty members in the various units to arrange the activity during their class time. The activity occurred in the School of Art and Design, Geis College of Business, Siebel Center for Design, College of Media, School of Architecture, and School of Labor & Employment Relations.

Qualtrics ® was used for this experiment type of survey because it has a user-friendly interface for survey participants and provides a mobile app format with the participants, which made the entire survey process much easier and more effective. The survey interfaces are optimized based on selecting participants' devices like laptop computers or smart devices such as smartphones or tablets. Also, Qualtrics ® can generate QR codes on each survey, making the activity process smooth. As a result, the participants could focus on evaluating the product rather than spending unnecessary time figuring out how to answer the questions. The consent form was distributed and collected before performing the experiment – like survey, which provided an opportunity to take photographs of the participants. The author did not record audio and video to eliminate stress or nervousness from a sense of "Someone is watching me."

5.5 Data Management and Privacy Protection

Data was collected by Qualtrics ® and stored on a secure server through the UIUC Qualtrics account for all participants. A string of numbers only identifies the participants; no identifying information (e.g., name/birthday) is ever collected. Even though IP addresses are recorded, it is just to ensure that no one participates in the study more than once. No attempts to connect the participants' ID with their identity will be made to ensure the confidentiality of participants.

Within 24 hours of data collection, the research team will go through the dataset to check and remove any identifiable data that might have been accidentally collected. All methods used to safeguard research records during storage – written consent, assent, or parental permission forms are stored separately from the data; direct identifiers are removed from collected data as soon as possible; electronic data is stored in a secure, UIUC – approved location, U of I Box.

5.6 Pilot Interactive Survey

5.6.1 Overview

A pilot activity was performed before visiting classrooms to conduct the survey and collect data. The pilot activity was performed with four senior industrial design students (Figure 5.4) and had three parts – Q1, Q2A/B, and Q3 – in survey questions. Q1 and Q3 have a series of questions, including images corresponding to the sample design samples.

I used images rather than letters or numbers to reduce the participants' cognitive processing time. The purpose of Q1 is to find out how each visual element – complexity and entropy – and subjective experience – familiarity, remember, and knowledge – influences product visual aesthetic longevity. The participants can touch, hold, and lift the design samples – Bluetooth speakers, wristwatches, and game controllers – to fully appreciate the design rather than look at the images online. Q2A/B contains 30 product images awarded in the category of the Best of Best at the red dot design award in Germany.

Figure 5.4: Four students recruited by the author are participating in the pilot survey.

The participants were asked to rate the design in complexity, simplicity, familiarity, and visual entropy(Figure 5.4). This part determines if there is a certain relationship among those four elements when participants see the product design images considered good design. This activity can also determine what elements are dominant to be called good design. Q3 has a series of questions to determine two main attributes in the context of aesthetic longevity. The first attribute is to find if there is a relationship between the aesthetic longevity and proximity of the products from the users. For example, the wristwatch can be 0 regarding product distance because it will constantly contact the user if the user wears it. In contrast, Bluetooth speakers need to keep a certain distance to listen to music. In other words, Q3 investigates if the distance between the products and the users can influence aesthetic longevity and the perception of visual complexity, based on the product distance from the users. The second attribute is to determine if there is a relationship between the aesthetic longevity and frequency of interaction between the products and the users. Although the frequency of interaction can have multiple aspects like utilitarian, needs bases, or preference, the frequency of interaction in this research can be interpreted as preference and familiarity.

5.6.2 The procedure of pilot participants

I recruited four senior design students – participants N, H, AN, and AK – that consisted of fast and slow readers. I purposely included slow readers to gauge the range of expected time frames for data collection in the various participants. Each participant was assigned to perform a different combination of survey questions (Table 5.1).

Table 5.1: Summary of participants' progresses

Participant	Q1	Q2A	Q2B	Q3	Total Time	Most Laborious Part	Further Action
N	√	√		√	100 min	Q1 for 48min	
H	√		√	√	65 min	Q1+Q2B for 55 min	
AK	√	√		√*	51 min	Q1 for 40 min	106 min with Q3
AN	√*		√	√	40 min		55 min with Q1
*Question that was voluntarily performed							

Participant N was assigned for Q1, Q2A, and Q3. Participant H was asked to perform Q1, Q2B, and Q3. Participant AK worked on Q1 and Q2A. Lastly, participant AN was asked to answer Q2B, and Q3. Each participant was assigned to a different combination on purpose in order to find an optimal combination for future participants in actual data collection. This also helped me understand how many questions or parts could be answered without fatiguing participants, directly influencing the data quality. Participant N took one hour and four minutes to complete the activity – Q1, Q2A, and Q3. Among the three parts, participant N took 48 min on the Q1 part. Participant H took one hour and five minutes with Q1, Q2B, and Q3 and spent 55 minutes on Q1 and Q2B parts. Participant AK performed Q1 and Q2A and completed them in 51 minutes. Participants took 40 minutes on

Q1. Also, participant AK insisted on performing in Q3 and was allowed to complete them. As a result, participant AN completed all three parts in one hour and 6 min. Participant AN completed Q2B and Q3 in 40 minutes and took an extra 15 minutes to finish all three parts (Table 5.1).

5.6.3 Findings from the Pilot Activity

The pilot activity revealed several key insights I could implement in data collection and answered my concerns regarding time allocation on each part. First, I learned that Q1 is where participants will spend the most time, and Q1 is the most crucial section among the survey parts. I spent more time on the overall survey flow and user interface to eliminate unnecessary elements that could cause delay or confusion. The main goal was that the participants stayed focused until they finished. The participants from the pilot activity asked a few questions in Q1 regarding question clarification and instructions. It signaled that I would need to deliver more precise instructions to the participants, saving time and delivering better quality responses. For the second part, Q2A/B, all participants expressed that it took a while to establish their phase in Q2A/B. It went smoothly and was not boring once they gained momentum. Also, they had fun and liked Q2A/B because they could see the variety of well-designed product images. For Q3, it was about two attributes: the frequency of interaction and the proximity between the product and the user. Q3 was relatively short compared to Q1, and participants N and H did not take long to complete part Q3.

Overall, all participants shared their experience as fun because they could see, touch, and appreciate the real design samples, which was the primary purpose of this activity. Although I am aware that a design evaluation survey frequently relies on online product images, and it may work, I believe that having actual products will deliver a better-quality data set, eliminate potential confusion, and discover new insights that cannot be done with online images.

5.7 Primary Data Collection

I contacted faculty members to obtain permission to visit and run the survey during their class time. I visited a total of 6 classrooms – the School of Art and Design (Figure 5.5), Geis College of Business, Siebel Center for Design, College of Media, School of Architecture, and School of Labor & Employment Relations (Figure 5.6) – to make sure that I would have enough participants in the end, I was able to have about 130 participants, which I still expected to have a good amount of noise data or outliers.

Figure 5.5: Students in school of art and design participated in the survey

Figure 5.6: Students in school of labor & employment relations read survey instructions

I had confidence in the actual data collection process because I ran the pilot survey and learned several insights that I was able to adjust to increase effectiveness. However, there were always unexpected incidents. One major incident that I did not expect to happen at all was that many participants had not seen the Bluetooth speaker samples I brought because they are relatively old design, so I would have to spend extra time explaining what they were. My bigger concern was whether participants would get biased because I spent more time explaining the speakers. Mostly, the activity in each classroom I visited was completed between 35 min and 50 min. However, I noticed that an average of 10 percent of students in the classroom could not keep up with the speed of the rest of their classmates, which caused them to be stressed out and anxious.

As a result, I witnessed that some students gave up on the activity and could not complete answering the survey questions.

Also, some students asked me if they could continue doing and completing the survey when they returned home because they were aware of those designs. I allowed them to do it and included the data set in the overall data pool. However, it is a case that I would need to investigate further if the data sets from those students who completed it at home were valid. One thing I enjoyed about this data collection process was hearing discussion, with the participants asking questions to each other about their favorite designs and why they chose the ones they did after completing their survey. Although I did not officially record their response or opinion, hearing their reasoning fascinated me. I hope the participants also put that valuable information in the survey.

CHAPTER 6: RESULT

During the fall semester of 2022, I conducted surveys at the University of Illinois at Urbana Champaign involving nine physical product samples. Participants had the opportunity to observe and interact with these product samples. I visited various departments, including the College of Business, School of Art and Design, College of Media, and School of Architecture and Urban Planning. In total, there were 143 participants.

The survey aimed to address seven variables – visual complexity, visual entropy, visual interest, product preference, product longevity, and product familiarity (labeled as #1, #2, and #3) – regarding three distinct sets of product samples. The first three variables – visual complexity, visual entropy, and visual interest – focused on the perception of the participants. These variables represent the mean ratings on a five-point scale. The mean value for visual complexity in each table indicates how participants perceived the visual complexity of the product samples. For instance, participants perceived speaker #1 as having the highest visual complexity, speaker #2 as having medium visual complexity, and speaker #3 as having a simpler design

6.1 Result of Each Variable

The first set of product samples in the survey included tabletop (Bluetooth) speakers, and an important aspect to note is that all three speakers in this group had received prestigious and reputable design awards. The fact that these speakers were recognized with design awards indicates that they possess exceptional design quality and demonstrate innovative features.

Including speakers that have received design awards in the survey serves several purposes. Firstly, it showcases the industry recognition these products have received for their outstanding design elements, functionality, and overall appeal. This recognition enhances the perceived value and credibility of these speakers among participants.

Moreover, selecting award–winning products helps to mitigate personal bias and subjective opinions that individuals may have toward the products. By choosing speakers that have been acknowledged by design experts and professionals, the survey aims to provide a more objective evaluation of their design attributes. This approach adds credibility to the survey results and allows for a more reliable assessment of participants' perceptions and preferences (Table 6.1).

Table 6.1: The highlighted row displays the participants' perception of visual complexity.

Visual Attribute 1:Very Simple 2:Simple 3:Neutral 4:Complex 5:Very Complex	Familiarity 1:Strongly Disagree 2:Disagree 3:Neutral 4:Agree 5:Strongly Agree	 Speaker #1 Mean	 Speaker#2 Mean	 Speaker#3 Mean
Visual Complexity		4.134 **Complex**	2.808 **Mixed/Medium**	2.225 **Simple**
Visual Entropy		4.166	2.848	2.048
Visual Interest		3.031	3.424	3.564
Product Preference		2.420	3.448	3.782
Product Longevity		2.658	3.520	3.854
Product Familiarity #1		1.563	2.080	2.080
Product Familiarity #2		1.484	1.904	1.951
Product Familiarity #3		2.031	2.600	2.725

The second set of product samples in the survey included wristwatches. However, with the growing popularity of smartphones and other smart devices that display time, the use of traditional wristwatches has decreased over time. This societal shift has resulted in participants in the survey potentially being less familiar with wristwatches.

Despite wristwatches having enjoyed past popularity and featuring iconic designs during a specific time period, the current generation of participants may not have as much exposure or experience with them. The decline in the use of wristwatches as timekeeping devices has likely contributed to a decrease in familiarity among participants. Therefore, it is possible that participants in the survey might not be as knowledgeable or accustomed to wristwatches compared to previous generations who relied on them as a primary means of telling time (Table 6.2).

Table 6.2: The highlighted row displays the participants' perception of visual complexity.

Visual Attribute 1:Very Simple 2:Simple 3:Neutral 4:Complex 5:Very Complex	Familiarity 1:Strongly Disagree 2:Disagree 3:Neutral 4:Agree 5:Strongly Agree	 Wristwatch #1 Mean	 Wristwatch #2 Mean	 Wristwatch #3 Mean
Visual Complexity		3.912	3.330	1.701
		Complex	**Mixed/Medium**	**Simple**
Visual Entropy		4.104	3.403	1.725
Visual Interest		3.000	3.677	3.024
Product Preference		2.648	3.620	3.370
Product Longevity		2.520	3.419	3.475
Product Familiarity #1		2.960	2.669	3.451
Product Familiarity #2		2.520	2.411	3.024
Product Familiarity #3		4.104	3.927	4.129

In contrast to the wristwatches, the majority of participants in the survey were already familiar with the product samples of Xbox game controllers. They could easily recognize and identify the brand of these controllers. This suggests that the participants had prior knowledge and experience with Xbox game controllers, making them more likely to be acquainted with their design and functionality. The interactive nature of gaming consoles and their widespread use among different age groups could have contributed to participants' exposure and familiarity with

Xbox game controllers. The prevalence of gaming culture and the widespread availability of these consoles in various settings, such as homes, gaming centers, and social gatherings, may have further enhanced participants' familiarity with the product samples (Table 6.3).

Table 6.3: The highlighted row displays the participants' perception of visual complexity.

Visual Attribute 1:Very Simple 2:Simple 3:Neutral 4:Complex 5:Very Complex	Familiarity 1:Strongly Disagree 2:Disagree 3:Neutral 4:Agree 5:Strongly Agree	 Game Controller #1 Mean	 Game Controller #2 Mean	 Game Controller #3 Mean
Visual Complexity		3.912	3.322	1.959
		Complex	**Mixed/Medium**	**Simple**
Visual Entropy		3.920	3.258	2.008
Visual Interest		3.024	3.556	3.088
Product Preference		2.640	3.475	3.274
Product Longevity		2.672	3.653	3.459
Product Familiarity #1		3.896	3.169	4.508
Product Familiarity #2		3.664	3.032	4.362
Product Familiarity #3		4.192	3.975	4.322

The overall result found that the participants consistently ranked product sample #1 as the most complex design, #2 as a medium/mixed complexity design, and #3 as the simplest design within each category. This demonstrates a pattern in the participants' perceptions of complexity across different product types, suggesting that their judgments were not simply random or subjective. Furthermore, the study found that participants perceived speaker #1 as having the most complex design among all product samples (three speakers, three wristwatches, and three game controllers). This indicates that the participants were able to differentiate between the complexity levels of similar products within the same category. On the other hand, wristwatch #3 was perceived as the simplest design, which shows that participants were also able to differentiate between the simplicity levels of similar products within the same category.

Overall, these findings suggest that participants were able to consistently recognize the complexity and simplicity levels of different products, which is important information that needs to be further explored based on the frequency of interaction and the proximity of the product samples.

6.2 Logistic Regression in R

6.2.1 Initially, I implemented a logistic regression model in R to analyze the relationship between seven independent variables and the outcome variable. The independent variables included visual complexity, visual interest, visual entropy, product longevity, familiarity #1, familiarity #2, and familiarity #3. However, despite trying different approaches, the results were not meaningful. After seeking advice from a statistical expert who was a professor of economics, I received feedback suggesting that the overlapping data among the predictors, due to the similar attributes shared by some predictors, might have caused the lack of meaningful results. The expert recommended running separate logistic regression models for each individual predictor instead of using multiple predictors together. In total, there were nine different product samples and seven predictors, resulting in a total of sixty-three (63) logistic regression models.

6.2.2 Summary of Logistic Regression (Figure 6.1)

		
Speaker #1	Speaker#2	Speaker#3

Figure 6.1: A Set of speakers from Harman/Kardon®

Logistic Regression of Visual Complexity: The predictor variable "complexity" was not found to be significantly associated with product longevity. This means that the level of visual complexity of a product does not have a significant impact on its likelihood of longevity. It is important to note that this result could be influenced by factors such as a small sample size or a weak relationship between complexity and longevity. To further investigate, cross-validation and exploring other predictors or model modifications may be helpful.

Logistic Regression of Visual Entropy: The analysis did not provide strong evidence of a significant association between the predictor variable "entropy" and product longevity. This suggests that the level of visual entropy, which measures the randomness or disorder in visual elements, is not a significant factor in determining the longevity of a product.

Logistic Regression of Visual Interest: The model assessing the relationship between "vi_sp1" (Visual Interest) and "pl_sp1" (Product Longevity) yielded significant results. The analysis indicated a statistically significant positive relationship between visual interest and product longevity. Specifically, for every one-unit increase in visual interest, the odds of product longevity increased by a factor of 1.924, assuming all other variables remain constant. This implies that higher visual interest in a product is associated with a higher likelihood of longevity.

Logistic Regression of Product Preference: The predictor variable "pp_sp1" (Product Preference) was found to have a significant effect on the outcome variable "pl_sp1" (Product Longevity). The model showed a good fit, with a smaller residual deviance compared to the null deviance. The analysis revealed that for each unit increase in product preference, the odds of product longevity increased by a factor of 4.174. This suggests that stronger product preference is associated with a higher likelihood of longevity.

Logistic Regression of Product Familiarity: The analyses for three different levels of product familiarity, labeled as Product Familiarity#1, Product Familiarity#2, and Product Familiarity#3, did not yield significant results. This means that these specific measures of product familiarity were not found to be significant predictors of product longevity.

These patterns of analysis and interpretations were conducted for Speaker #2 and Speaker #3 as well. The goal was to examine the significance and association between various predictor variables (such as visual complexity, visual entropy, visual interest, product preference, and product familiarity) and the likelihood of product longevity. The results help determine which factors have a significant impact on the longevity of products for each speaker.

6.2.3 Summary of Logistic Regression (Figure 6.2)

Wristwatch #1	Wristwatch #2	Wristwatch #3

Figure 6.2: A Set of wristwatches from swatch ®

Logistic Regression of Visual Complexity(wch_vc): The variable measuring visual complexity (vc) does not show a statistically significant association with product longevity for any of the wristwatches (vc_wch1, vc_wch2, vc_wch3). This means that the level of visual complexity in the design of the watches does not have a strong influence on their longevity.

Logistic Regression of Visual Entropy(wch_ent): Similar to visual complexity, the variable measuring visual entropy (ent) does not exhibit a statistically significant association with product longevity for any of the wristwatches (ent_wch1, ent_wch2, ent_wch3). Visual entropy refers to the amount of randomness or disorder in the visual elements of the watches. The results suggest that visual entropy does not play a significant role in determining the longevity of the watches.

Logistic Regression of Visual Interest (wch_vi): The variable measuring visual interest (vi) shows a statistically significant association with product longevity for all three wristwatches (vi_wch1, vi_wch2, vi_wch3). This implies that the level of visual interest in the design of the watches has a strong influence on their longevity. Wristwatches with visually interesting designs are more likely to have longer lifespans.

Logistic Regression of Product Preference (wch_pp): The variable measuring product preference (pp) is statistically significant for all three wristwatches (pp_wch1, pp_wch2, pp_wch3). This indicates that the preference for the wristwatches, possibly based on factors such as brand, features, or overall appeal, significantly affects their longevity. Wristwatches that are more preferred by consumers tend to have longer lifespans.

Logistic Regression of Product Familiarity (wch_fm): The variables measuring product familiarity (pfm1, pfm2, pfm3) have mixed results. For Wristwatch#1, none of the familiarity variables (pfm1_wch1, pfm2_wch1, pfm3_wch1) show consistent statistical significance. For Wristwatch#2, only pfm2_wch2 is statistically significant among the familiarity variables (pfm1_wch2, pfm2_wch2, pfm3_wch2). For Wristwatch#3, again, only pfm2_wch3 is statistically significant among the familiarity variables (pfm1_wch3, pfm2_wch3, pfm3_wch3). These results suggest that product familiarity alone may not be a strong predictor of product longevity, as its impact varies across different wristwatch models.

In summary, the findings indicate that visual interest and product preference are consistently significant factors influencing the longevity of wristwatches. On the other hand, variables such as visual complexity, visual entropy, and product familiarity show mixed results and are not consistently significant predictors of product longevity.

6.2.4 Summary of Logistic Regression (Figure 6.3)

		
Game Controller #1	Game Controller #2	Game Controller #3

Figure 6.3: A Set of game controllers by Microsoft ®

Logistic Regression of Visual Complexity (gc_vc): For Game Controller #1, visual complexity does not have a significant impact on product longevity. However, for Game Controller #2, higher visual complexity is associated with increased odds of longevity. The relationship between visual complexity and longevity is weak and statistically insignificant for Game Controller #3. This suggests that the influence of visual complexity on product longevity may vary across different controllers.

Logistic Regression of Visual Entropy (gc_ent): The analysis does not provide significant evidence for the relationship between visual entropy and product longevity in any of the game controllers. This indicates that the level of randomness or disorder in the visual elements of the controllers may not strongly influence their longevity.

Logistic Regression of Visual Interest (gc_vi): Game Controller #2 and #3 both show a positive and significant association between visual interest and product longevity. This suggests that having visually appealing design features, unique aesthetics, or captivating visual elements can contribute to the longevity of game controllers.

Logistic Regression of Product Preference (gc_pp): All three game controllers exhibit a positive and significant relationship between product preference and longevity. This implies that when users have a stronger preference for a game controller, it is more likely to have a longer lifespan in the market.

Logistic Regression of Product Familiarity (gc_fm): The analysis does not find a significant relationship between product familiarity and product longevity in any of the game controllers. This suggests that consumers' prior knowledge about the brand or similar controllers may not strongly influence the longevity of the products.

Overall, the combination of insights suggests that visual interest and product preference are consistent factors that can influence the longevity of game controllers. While the impact of visual complexity and visual entropy may vary across different controllers, they do not emerge as strong predictors of longevity. The influence of product familiarity on longevity is also not significant in the analyzed data. It is important to note that these conclusions are based on the available analysis and data, and further research and analysis may be needed to validate and refine these insights.

6.2.5 In addition, I have included the lines of an example of R code along with brief descriptions and supplementary information to facilitate the interpretation of the summary results (Table 6.4).

Table 6.4: R code for logistic regression

```
1  > #Longevity vs. complexity
2  > logistic1.1 <- glm(df5.1$pl_sp1 ~ df5.1$vc_sp1, data=df5.1 ,
      family = binomial(logit))
3  > summary(logistic1.1)

4  Call:
5  glm(formula = df5.1$pl_sp1 ~ df5.1$vc_sp1, family = binomial(logit),
      data = df5.1)

6  Deviance Residuals:
       Min        1Q    Median        3Q       Max
   -1.0463   -0.9756   -0.9526    1.3936    1.4202

7  Coefficients: Estimate Std. Error z value Pr(>|z|)
8   (Intercept)   -0.25681    0.79869  -0.322     0.748
9  df5.1$vc_sp1 -0.05959    0.18894  -0.315     0.752

   (Dispersion parameter for binomial family taken to be 1)

10   Null deviance: 161.67  on 121  degrees of freedom
11 Residual deviance: 161.58  on 120  degrees of freedom
12 AIC: 165.58

13 Number of Fisher Scoring iterations: 4
```

Line 1, "#complexity vs. longevity" represents that the analysis is investigating the relationship between complexity and longevity.

Line 2, "logistic1.1 <- glm(df5.1$pl_sp1 ~ df5.1$vc_sp1, data=df5.1 , family = binomial(logit))" specifies the logistic regression model being fitted. It uses the "glm" function in R, where "pl_sp1" represents the dependent variable (longevity) and "vc_sp1" represents the independent variable (complexity). The data used for the analysis is the dataframe "df5.1." The model assumes a binomial distribution with a logit link function.

Line 3, "summary(logistic1.1)" displays the summary of the logistic regression model. It provides information about the model fit and coefficients.

Line 4, "Call" section shows the formula used in the logistic regression model, including the dependent and independent variables.

Line 5 is the line of code logistic1.1 <- glm(df5.1$pl_sp1 ~ df5.1$vc_sp1, data=df5.1 , family = binomial(logit)) fits a logistic regression model to the data contained in the dataframe df5.1. The dependent variable is “df5.1$pl_sp1”, and the independent variable is “df5.1$vc_sp1”. “pl_sp1” represents product longevity for speaker#1 and “vc_sp1” represents visual complexity for speaker#1. “glm()” is the function used to fit generalized linear models in R, with the "glm" standing for "generalized linear model". It is a flexible function that can handle various types of regression models, including logistic regression. “family = binomial(logit)” specifies the family and link function to be used in the logistic regression model. The binomial family is used for binary outcomes, and logit is the link function that relates the linear predictor to the probabilities of the binary outcome (log-odds).

Line 6 presents the deviance residuals, which are a measure of the discrepancy between the observed data and the fitted model. It displays the minimum, first quartile (1Q), median, third quartile (3Q), and maximum values of the deviance residuals.

Line 7, "Coefficients" section displays the estimated coefficients for the intercept and the independent variable. Each coefficient has an estimate, standard error, z-value, and corresponding p-value. The p-value, in statistical hypothesis testing, is a measure that helps determine the strength of evidence against the null hypothesis.

Line 8, the estimated value for the intercept is -0.25681. The z value associated with the intercept is -0.322, p-value (Pr (>|z|)) is 0.748. The p-value represents the probability of observing a coefficient as extreme as the estimated value if the null hypothesis is true. In this case, a p-value greater than 0.05 suggests that the coefficients are not statistically significant at the conventional significance level (assuming a significance level of 0.05). This means that we fail to reject the null hypothesis, which states that the coefficients are not significantly different from zero.

Line 9, the estimated value for the coefficient of the variable "df5.1$vc_sp1" is -0.05959, a standard error of 0.18894, The z value associated with this coefficient is -0.315, and the p-value is 0.752. In the context of logistic regression, the z value is calculated by dividing the estimated coefficient by its standard error. It provides an indication of how far the estimated coefficient deviates from zero in terms of standard deviations.

Line 10, "Null deviance" represents the deviance of a model with no predictor variables. It measures the total variation in the response variable (df5.1$pl_sp1) without considering any predictors. In this case, the null deviance is 161.67, and it is calculated based on 121 degrees of freedom.

Line 11, "Residual deviance" represents the deviance when the independent variable is added to the model. In logistic regression, the residual deviance is a measure of the goodness of fit of the model. A smaller residual deviance indicates a better fit, as it means that the model is able to explain more of the variation in the data. In this case, the residual deviance is 161.58, and it is calculated based on 120 degrees of freedom.

Line 12, AIC (Akaike Information Criterion) is a measure of model quality, with lower values indicating better fit.

Line 13, "Number of Fisher Scoring iterations" indicates the number of iterations performed during the model estimation process.

6.3 Summary of Logistic Regressions for All Independent Variables

6.3.1 Logistic Regression of Visual Complexity to Product Longevity for Speaker#1

Table 6.5: Summary #1-1

Summary #1-1	Product: Speaker#1
Independent Variable: Visual Complexity	
Dependent Variable: Aesthetic Longevity	

```
> # complexity vs. longevity
> logistic1.1 <- glm(df5.1$pl_sp1 ~ df5.1$vc_sp1, data=df5.1 , family =
binomial(logit))
> summary(logistic1.1)

Call:
glm(formula = df5.1$pl_sp1 ~ df5.1$vc_sp1, family = binomial(logit),
data = df5.1)

Deviance Residuals:
Min       1Q   Median      3Q      Max
-1.0463  -0.9756  -0.9526   1.3936   1.4202

Coefficients:
Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.25681    0.79869  -0.322    0.748
df5.1$vc_sp1 -0.05959    0.18894  -0.315    0.752

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 161.67  on 121  degrees of freedom
Residual deviance: 161.58  on 120  degrees of freedom
AIC: 165.58

Number of Fisher Scoring iterations: 4
```

Both Z value and P value in Table 6.5 are greater than 0.05. indicating that there is no strong evidence of a significant association between the predictor variable, complexity (vc) and the response variable, product longevity (pl). The Deviance Residuals table shows the differences between the observed values of the response variable and the predicted values from the model on a deviance scale. The values range from -1.0463 to 1.4202, and the median value is close to zero, indicating that the model fits reasonably well. A model with good fit but non-significant coefficients may indicate that the model is a small sample size or that the relationship between the predictors and the outcome variable is weak. Overall, the results suggest that there is no strong evidence of a significant association between the predictor variable and the response variable. However, the model fit is reasonable. Therefore, cross-validation and other predictors or modifications to the model may be worth exploring.

6.3.2 Logistic Regression of Visual Visual Entropy to Product Longevity for Speaker#1

Table 6.6: Summary #1-2

Summary #1-2	Product: Speaker#1
Independent Variable: Visual Entropy	
Dependent Variable: Aesthetic Longevity	

```
> # Entropy vs. longevity
> logistic1.2 <- glm(df5.1$pl_sp1 ~ df5.1$ent_sp1, data=df5.1 , family =
binomial(logit))
> summary(logistic1.2)

Call:
glm(formula = df5.1$pl_sp1 ~ df5.1$ent_sp1, family = binomial(logit),
    data = df5.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.0143  -0.9748  -0.9618   1.3945   1.4095

Coefficients:              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.36287    0.87431  -0.415    0.678
df5.1$ent_sp1 -0.03359    0.20626  -0.163    0.871

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 161.67  on 121  degrees of freedom
Residual deviance: 161.65  on 120  degrees of freedom
AIC: 165.65
Number of Fisher Scoring iterations: 4
```

Both Z value and P value in Table 6.6 are greater than 0.05. indicating that there is no strong evidence of a significant association between the predictor variable (entropy) and the response (longevity) variable. Overall, the results suggest that there is no strong evidence of a significant association between the predictor variable and the response variable.

6.3.3 Logistic Regression of Visual Interest to Product Longevity for Speaker#1

Table 6.7: Summary #1-3

Summary #1-3	Product: Speaker#1
Independent Variable: Visual Interest	
Dependent Variable: Aesthetic Longevity	

```
> # Interests vs. longevity
> logistic1.3 <- glm(df5.1$pl_sp1 ~ df5.1$vi_sp1, data=df5.1 , family =
binomial(logit))
> summary(logistic1.3)

Call:
glm(formula = df5.1$pl_sp1 ~ df5.1$vi_sp1, family = binomial(logit),
    data = df5.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4812  -0.9278  -0.5205   0.9014   2.0328

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   -2.5860     0.5640  -4.585 4.54e-06 ***
df5.1$vi_sp1   0.6553     0.1580   4.147 3.37e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 161.67  on 121  degrees of freedom
Residual deviance: 141.34  on 120  degrees of freedom
AIC: 145.34

Number of Fisher Scoring iterations: 3
```

The model in Table 6.7 has a residual deviance of 141.34 on 120 degrees of freedom, which indicates that the model fits the data. The AIC value of 145.34 suggests that this model is a better fit for the data than other potential models. odds ratio = exp (0.6553) = 1.924. This means that for a one-unit increase in df5.1$vi_sp1, the odds of df5.1$pl_sp1 increase by a factor of 1.924, assuming all other variables are held constant. The p-value associated with this coefficient is less than 0.001, suggesting that it is statistically significant at conventional levels of significance.

6.3.4 Logistic Regression of Product preference to Product Longevity for Speaker#1

Table 6.8: Summary #1-4

Summary #1-4	Product: Speaker#1
Independent Variable: Product Preference	
Dependent Variable: Aesthetic Longevity	

```
> # Product Preference vs. longevity
> logistic1.4 <- glm(df5.1$pl_sp1 ~ df5.1$pp_sp1, data=df5.1 , family =
binomial(logit))
> summary(logistic1.4)

Call:
glm(formula = df5.1$pl_sp1 ~ df5.1$pp_sp1, family = binomial(logit),
    data = df5.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8790  -0.7009  -0.3595   0.6127   2.3543
Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   -4.1350     0.6806  -6.076 1.23e-09 ***
df5.1$pp_sp1   1.4281     0.2444   5.844 5.10e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 161.67  on 121  degrees of freedom
Residual deviance: 101.33  on 120  degrees of freedom
AIC: 105.33

Number of Fisher Scoring iterations: 5
```

In Table 6.8, the residual deviance is 101.33, which is substantially smaller than the null deviance of 161.67. This suggests that the predictor variable "pp_sp1"(Product Preference) has a significant effect on the outcome variable "pl_sp1"(Product Longevity). The AIC value of 105.33 indicates that this model has a good fit. The odd ratio is exp (1.4281) = 4.174. This means that for every unit increase in the presence of product preference, the odds of product longevity occurrence increase by a factor of 4.174. Overall, this logistic regression model suggests that there is a significant positive relationship between the predictor variable “pp_sp1” (Product Preference), and the binary outcome variable "pl_sp1" (Product Longevity).

6.3.5 Logistic Regression of Product Familiarity#1 to Product Longevity for Speaker#1

Table 6.9: Summary #1-5

Summary #1-5	Product: Speaker#1
Independent Variable: Familarity#1 (Familiar)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#1 - familiar vs. longevity
> logistic1.5 <- glm(df5.1$pl_sp1 ~ df5.1$pfm1_sp1, data=df5.1 , family =
binomial(logit))
> summary(logistic1.5)
Call:
glm(formula = df5.1$pl_sp1 ~ df5.1$pfm1_sp1, family = binomial(logit),
data = df5.1)

Deviance Residuals:
Min       1Q   Median      3Q      Max
-1.1303  -0.9468  -0.9468   1.4143   1.4271

Coefficients:
Estimate Std. Error z value Pr(>|z|)
(Intercept)     -0.6847     0.3536  -1.936   0.0528 .
df5.1$pfm1_sp1   0.1146     0.1871   0.612   0.5403
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 161.67  on 121  degrees of freedom
Residual deviance: 161.30  on 120  degrees of freedom
AIC: 165.3

Number of Fisher Scoring iterations: 4
```

The significance in Table 6.9 codes in the output suggest that the coefficient for “df5.1$pfm1_sp1” (Product Familliarity#1) is not statistically significant at the 0.05 level, since the p-value associated with this coefficient is 0.5403. The intercept is also not statistically significant at the 0.05 level, although it is marginally significant at the 0.1 level (p-value = 0.0528). The AIC value of 165.3 is relatively low, which suggests that the model may be a good fit for the data.

6.3.6 Logistic Regression of Product Familiarity#2 to Product Longevity for Speaker#1

Table 6.10: Summary #1-6

Summary #1-6	Product: Speaker#1
Independent Variable: Familarity#2(Remember)	
Dependent Variable: Aesthetic Longevity	

```
> #Product familairity#2 - remember vs. longevity
> logistic1.6 <- glm(df5.1$pl_sp1 ~ df5.1$pfm2_sp1, data=df5.1 , family =
binomial(logit))
> summary(logistic1.6)

Call:
glm(formula = df5.1$pl_sp1 ~ df5.1$pfm2_sp1, family = binomial(logit),
    data = df5.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.3213  -0.9063  -0.9063   1.4753   1.4753

Coefficients:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)     -1.0142     0.3686  -2.752  0.00593 **
df5.1$pfm2_sp1   0.3366     0.2068   1.627  0.10363
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 161.67  on 121  degrees of freedom
Residual deviance: 158.98  on 120  degrees of freedom
AIC: 162.98
Number of Fisher Scoring iterations: 4
```

The p-value in Table 6.10 associated with the coefficient for df5.1$pfm2_sp1 is 0.10363, which is greater than the common significance level of 0.05. This suggests that there is not enough evidence to conclude that there is a significant relationship between the response variable and the predictor variable. The odds are exp (0.3366) = 1.399, which means that for a one-unit increase in “df5.1$pfm2_sp1” (Product Familiarity #2), the odds of “df5.1$pl_sp1” (Product Longevity) increase by a factor of 1.399. However, since the p-value for “df5.1$pfm2_sp1” (Product Familiarity #2) is not statistically significant at the 0.05 level (p = 0.10363), we cannot conclude that there is a significant association between “df5.1$pfm2_sp1” (Product Familiarity #2) and “df5.1$pl_sp1” (Product Longevity).

6.3.7 Logistic Regression of Product Familiarity#3 to Product Longevity for Speaker#1

Table 6.11: Summary #1-7

Summary #1-7	Product: Speaker#1
Independent Variable: Familarity#2(Knowledge)	
Dependent Variable: Aesthetic Longevity	

```
> #Product familairity#3 - Knowledge vs. longevity
> logistic1.7 <- glm(df5.1$pl_sp1 ~ df5.1$pfm3_sp1, data=df5.1 , family =
binomial(logit))
> summary(logistic1.7)

Call:
glm(formula = df5.1$pl_sp1 ~ df5.1$pfm3_sp1, family = binomial(logit),
    data = df5.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.1347  -0.9701  -0.9183   1.3849   1.4609

Coefficients:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)     -0.7816     0.3755  -2.081   0.0374 *
df5.1$pfm3_sp1   0.1361     0.1569   0.867   0.3860
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 161.67  on 121  degrees of freedom
Residual deviance: 160.93  on 120  degrees of freedom
AIC: 164.93

Number of Fisher Scoring iterations: 4
```

The coefficients in Table 6.11 shows that the intercept is -0.7816 and the estimated coefficient for “df5.1$pfm3_sp1”(Product Familiarity #3) is 0.1361. However, the p-value for the “df5.1$pfm3_sp1”(Product Familiarity #3) coefficient is 0.3860, which means that it is not statistically significant at the 0.05 level. Overall, this model suggests that the predictor variable “df5.1$pfm3_sp1” (Product Familiarity #3) is not a significant predictor of the response variable “df5.1$pl_sp1” (Product Longevity).

6.3.8 Logistic Regression of Visual Complexity to Product Longevity for Speaker#2

Table 6.121: Summary #2-1

Summary #2-1	Product: Speaker#2
Independent Variable: Visual Complexity	
Dependent Variable: Aesthetic Longevity	

```
> #complexity vs. longevity
> logistic5.1 <- glm(df6.1$pl_sp2 ~ df6.1$vc_sp2, data=df6.1 , family =
binomial(logit))
> summary(logistic5.1)

Call:
glm(formula = df6.1$pl_sp2 ~ df6.1$vc_sp2, family = binomial(logit),
    data = df6.1)

Deviance Residuals:
   Min      1Q  Median      3Q     Max
-1.309  -1.289   1.060   1.069   1.088

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.32676    0.66918   0.488    0.625
df6.1$vc_sp2 -0.02245    0.22950  -0.098    0.922

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.02  on 121  degrees of freedom
Residual deviance: 167.01  on 120  degrees of freedom
AIC: 171.01

Number of Fisher Scoring iterations: 3
```

The results in Table 6.12 indicate that the intercept (baseline level of pl_sp2 when vc_sp2 is 0, where pl is product longevity and vc is visual complexity.) is 0.32676, although it is not statistically significant. The coefficient of vc_sp2 is -0.02245, which also does not appear to be statistically significant.

The p-value for the coefficient is not significant ($p = 0.922$), which means that this result is not statistically significant, and we cannot conclude that there is a true association between these variables.

6.3.9 Logistic Regression of Visual Entropy to Product Longevity for Speaker#2

Table 6.13: Summary #2-2

Summary #2-2	Product: Speaker#2
Independent Variable: Visual Entropy	
Dependent Variable: Aesthetic Longevity	

```
> #Entropy vs. longevity
> logistic5.2 <- glm(df6.1$pl_sp2 ~ df6.1$ent_sp2, data=df6.1 , family =
binomial(logit))
> summary(logistic5.2)

Call:
glm(formula = df6.1$pl_sp2 ~ df6.1$ent_sp2, family = binomial(logit),
    data = df6.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4224  -1.3107   0.9508   1.0498   1.2614

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -0.4469     0.6452  -0.693    0.489
df6.1$ent_sp2   0.2516     0.2198   1.145    0.252

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.02  on 121  degrees of freedom
Residual deviance: 165.69  on 120  degrees of freedom
AIC: 169.69

Number of Fisher Scoring iterations: 4
```

The coefficient in Table 6.13 estimates for df6.1$ent_sp2 is 0.2516, with a standard error of 0.2198. The p-value for the coefficient estimate is 0.252, which is not statistically significant at the 0.05 level, where df6.1$ent_sp2 is the visual entropy for speaker#2. The coefficient is not statistically significant. We cannot conclude that there is a meaningful association between df6.1$ent_sp2 and df6.1$pl_sp2, where df6.1$ent_sp2 is visual entropy, and df6.1$pl_sp2 is product longevity for speaker#2.

6.3.10 Logistic Regression of Visual Interest to Product Longevity for Speaker#2

Table 6.14: Summary #2-3

Summary #2-3	Product: Speaker#2
Independent Variable: Visual Interest	
Dependent Variable: Aesthetic Longevity	

```
> #Interests vs. longevity
> logistic5.3 <- glm(df6.1$pl_sp2 ~ df6.1$vi_sp2, data=df6.1 , family =
binomial(logit))
> summary(logistic5.3)

Call:
glm(formula = df6.1$pl_sp2 ~ df6.1$vi_sp2, family = binomial(logit),
    data = df6.1)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8376  -0.8652   0.2588   0.6393   2.9044
Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   -6.0984     1.1605  -5.255 1.48e-07 ***
df6.1$vi_sp2   1.8956     0.3403   5.570 2.55e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.02  on 121  degrees of freedom
Residual deviance: 108.44  on 120  degrees of freedom
AIC: 112.44
Number of Fisher Scoring iterations: 5
```

The coefficient of df6.1$vi_sp2 in Table 6.14 is statistically significant with a p-value < 0.001, where df6.1$vi_sp2 is visual interest for speaker#2. The odds ratio for df6.1$vi_sp2 is exp(1.8956) = 6.656, which means that for every unit increase in df6.1$vi_sp2, the odds of df6.1$pl_sp2 occurring increase by a factor of 6.656, holding all other variables constant. The model has a good fit, as evidenced by the low residual deviance and AIC values.

6.3.11 Logistic Regression of Product preference to Product Longevity for Speaker#2

Table 6.15: Summary #2-4

Summary #2-4	Product: Speaker#2
Independent Variable: Product Preference	
Dependent Variable: Aesthetic Longevity	

```
> #Product Preference vs. longevity
> logistic5.4 <- glm(df6.1$pl_sp2 ~ df6.1$pp_sp2, data=df6.1 , family =
binomial(logit))
> summary(logistic5.4)

Call:
glm(formula = df6.1$pl_sp2 ~ df6.1$pp_sp2, family = binomial(logit),
    data = df6.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.9809  -0.3320   0.1768   0.5505   2.4190

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   -7.5517     1.3836  -5.458 4.82e-08 ***
df6.1$pp_sp2   2.3405     0.4152   5.637 1.73e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.023  on 121  degrees of freedom
Residual deviance:  93.616  on 120  degrees of freedom
AIC: 97.616

Number of Fisher Scoring iterations: 5
```

The p-values for both the intercept and df6.1$pp_sp2 in Table 6.15 are less than 0.001, indicating that both variables are statistically significant in predicting df6.1$pl_sp2, where df6.1$pp_sp2 is product preference and df6.1$pl_sp2 is product longevity for speaker#2. The odds ratio is exp (2.3405) = 10.386, which means that for each unit increase in df6.1$pp_sp2, the odds of df6.1$pl_sp2 occurring increase by a factor of 10.386. The deviance residuals show that the model fits the data well. The AIC value of 97.616 indicates that this model has a good fit as well. There is a positive association between df6.1$pp_sp2 and df6.1$pl_sp2, where higher values of df6.1$pp_sp2 are associated with higher odds of df6.1$pl_sp2.

6.3.12 Logistic Regression of Product Familiarity#1 to Product Longevity for Speaker#2

Table 6.16: Summary #2-5

Summary #2-5	Product: Speaker#2
Independent Variable: Familarity#1(Familiar)	
Dependent Variable: Aesthetic Longevity	

```
> #Product familairity#1 – familiar vs. longevity
> logistic5.5 <- glm(df6.1$pl_sp2 ~ df6.1$pfm1_sp2, data=df6.1 , family =
binomial(logit))
> summary(logistic5.5)
all:
glm(formula = df6.1$pl_sp2 ~ df6.1$pfm1_sp2, family = binomial(logit),
    data = df6.1)
Deviance Residuals:
   Min      1Q  Median      3Q     Max
-1.329  -1.294   1.033   1.065   1.163

Coefficients: Estimate Std. Error z value Pr(>|z|)
(Intercept)     0.42925    0.35831   1.198    0.231
df6.1$pfm1_sp2 -0.07919    0.14706  -0.539    0.590
(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 167.02  on 121  degrees of freedom
Residual deviance: 166.73  on 120  degrees of freedom
AIC: 170.73

Number of Fisher Scoring iterations: 4
```

The p-value in Table 6.16 associated with this coefficient is 0.590, which is not statistically significant at the 0.05 level. The intercept coefficient of 0.42925 is also not significant at the 0.05 level. Therefore, there is no evidence of a significant association between "pl_sp2" and "pfm1_sp2" in this model, where pfm1_sp2 is product familiarity and pl_sp2 is product longevity. The odd ratio of "pfm1_sp2" cannot be calculated for this model as the coefficient is not statistically significant.

6.3.13 Logistic Regression of Product Familiarity#2 to Product Longevity for Speaker#2

Table 6.17: Summary #2-6

Summary #2-6	Product: Speaker#2
Independent Variable: Familarity#2(Remember)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#2 - remember vs. longevity
> logistic5.6 <- glm(df6.1$pl_sp2 ~ df6.1$pfm2_sp2, data=df6.1 , family =
binomial(logit))
> summary(logistic5.6)
Call:
glm(formula = df6.1$pl_sp2 ~ df6.1$pfm2_sp2, family = binomial(logit),
    data = df6.1)
Deviance Residuals:
   Min      1Q  Median      3Q     Max
-1.363  -1.287   1.003   1.055   1.292
Coefficients:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.5982     0.3587   1.667   0.0954 .
df6.1$pfm2_sp2  -0.1726     0.1585  -1.089   0.2761
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 167.02  on 121  degrees of freedom
Residual deviance: 165.83  on 120  degrees of freedom
AIC: 169.83

Number of Fisher Scoring iterations: 4
```

The p-value in Table 6.17 associated with the pfm2_sp2 coefficient estimate is 0.2761, which is not significant at the 0.05 level, where pfm2_sp2 is product familiarity#2. The intercept (or baseline value) is estimated to be 0.5982, but it is not statistically significant at the conventional 0.05 significance level (p = 0.0954). The coefficient for "pfm2_sp2" is estimated to be -0.1726, suggesting that as "pfm2_sp2" increases by one unit, the log-odds of "pl_sp2" decrease by 0.1726. However, this coefficient is also not statistically significant (p = 0.2761). Null deviance and Residual deviance: These deviance values measure the goodness of fit of the model. The null deviance represents the deviance when only the intercept is included in the model, while the residual deviance represents the deviance after including the independent variable. Smaller deviance values indicate a better fit to the data.

Therefore, we cannot reject the null hypothesis that there is no relationship between pfm2_sp2 and pl_sp2, where pfm2_sp2 is product familiarity#2 and pl_sp2 is product longevity.

6.3.14 Logistic Regression of Product Familiarity#3 to Product Longevity for Speaker#2

Table 6.18: Summary #2-7

Summary #2-7	Product: Speaker#2
Independent Variable: Familarity#3(Knowledge)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#3 – Knowledge vs. longevity
> logistic5.7 <- glm(df6.1$pl_sp2 ~ df6.1$pfm3_sp2, data=df6.1 , family =
binomial(logit))
> summary(logistic5.7)
Call:
glm(formula = df6.1$pl_sp2 ~ df6.1$pfm3_sp2, family = binomial(logit),
    data = df6.1)

Deviance Residuals:
   Min      1Q  Median      3Q     Max
-1.335  -1.282   1.028   1.076   1.126

Coefficients:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.4234     0.4119   1.028    0.304
df6.1$pfm3_sp2  -0.0603     0.1392  -0.433    0.665

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.02  on 121  degrees of freedom
Residual deviance: 166.84  on 120  degrees of freedom
AIC: 170.84

Number of Fisher Scoring iterations: 4
```

This coefficient in Table 6.18 is not statistically significant (p-value = 0.665), which means that we cannot reject the null hypothesis that there is no association between pfm3_sp2 and pl_sp2, where pfm3_sp2 is product familiarity#3 and pl_sp2 is product longevity. There is no evidence that pfm3_sp2 is a significant predictor of pl_sp2. The intercept coefficient is 0.4234, which represents the log-odds of pl_sp2 when pfm3_sp2 is equal to zero. However, this coefficient is also not statistically significant (p-value = 0.304), so we cannot draw any meaningful conclusions about its interpretation.

6.3.15 Logistic Regression of Visual Complexity to Product Longevity for Speaker#3

Table 6.19: Summary #3-1

Summary #3-1	Product: Speaker#3
Independent Variable: Visual Complexity	
Dependent Variable: Aesthetic Longevity	

```
> #complexity vs. longevity
> logistic9.1 <- glm(df7.1$pl_sp3 ~ df7.1$vc_sp3, data=df7.1 , family =
binomial(logit))
> summary(logistic9.1)
Call:
glm(formula = df7.1$pl_sp3 ~ df7.1$vc_sp3, family = binomial(logit),
    data = df7.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6769   0.7499   0.7511   0.7511   0.7546

Coefficients: Estimate Std. Error z value Pr(>|z|)
(Intercept)   1.12839    0.46753   2.414   0.0158 *
df7.1$vc_sp3 -0.00355    0.18991  -0.019   0.9851
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 136.1  on 121  degrees of freedom
Residual deviance: 136.1  on 120  degrees of freedom
AIC: 140.1
Number of Fisher Scoring iterations: 4
```

The coefficients table in Table 6.19 shows that the intercept is statistically significant (p-value = 0.0158), which means that the log odds of pl_sp3 is significantly different from zero when vc_sp3 is zero, where vc_sp3 is visual complexity and pl_sp3 is product longevity for speaker#3. However, the coefficient for vc_sp3 is not statistically significant (p-value = 0.9851), which means that there is no evidence of a linear association between vc_sp3 and the log odds of pl_sp3. There is no significant relationship between df7.1$vc_sp3 and df7.1$pl_sp3.

6.3.16 Logistic Regression of Visual Entropy to Product Longevity for Speaker#3

Table 6.20: Summary #3-2

Summary #3-2	Product: Speaker#3
Independent Variable: Visual Entropy	
Dependent Variable: Aesthetic Longevity	

```
> # Entropy vs. longevity
> logistic9.2 <- glm(df7.1$pl_sp3 ~ df7.1$ent_sp3, data=df7.1 , family =
binomial(logit))
> summary(logistic9.2)

Call:
glm(formula = df7.1$pl_sp3 ~ df7.1$ent_sp3, family = binomial(logit),
    data = df7.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7394   0.7055   0.7482   0.7482   0.8875

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)     1.3978     0.5030   2.779  0.00546 **
df7.1$ent_sp3  -0.1339     0.2175  -0.616  0.53821
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 136.10  on 121  degrees of freedom
Residual deviance: 135.73  on 120  degrees of freedom
AIC: 139.73
Number of Fisher Scoring iterations: 4
```

The results in Table 6.20 show that the coefficient for df7.1$ent_sp3 is negative and statistically not significant (p-value = 0.54), meaning that there is no evidence of a relationship between df7.1$ent_sp3 and df7.1$pl_sp3, where df7.1$ent_sp3 is visual entropy and df7.1$pl_sp3 is product longevity for speaker#3. There is not enough evidence to conclude that there is a significant relationship between df7.1$ent_sp3 and df7.1$pl_sp3.

6.3.17 Logistic Regression of Visual Interest to Product Longevity for Speaker#3

Table 6.21: Summary #3-3

Summary #3-3	Product: Speaker#3
Independent Variable: Visual Interest	
Dependent Variable: Aesthetic Longevity	

```
> # Interests vs. longevity
> logistic9.3 <- glm(df7.1$pl_sp3 ~ df7.1$vi_sp3, data=df7.1 , family =
binomial(logit))
> summary(logistic9.3)

Call:
glm(formula = df7.1$pl_sp3 ~ df7.1$vi_sp3, family = binomial(logit),
    data = df7.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1681   0.2147   0.4476   0.4476   1.5157

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   -3.7851     0.9255  -4.090 4.32e-05 ***
df7.1$vi_sp3   1.5088     0.2900   5.203 1.96e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 136.10  on 121  degrees of freedom
Residual deviance:  92.68  on 120  degrees of freedom
AIC: 96.68

Number of Fisher Scoring iterations: 5
```

The intercept in Table 6.21 is -3.7851 which means that the log odds of pl_sp3 are -3.7851 when vi_sp3 is zero. The coefficient of vi_sp3 is 1.5088, indicating that for every one unit increase in vi_sp3, the log odds of pl_sp3 increase by 1.5088, where vi_sp3 is visual interest. The p-value associated with vi_sp3 is less than 0.05, suggesting that vi_sp3 is a significant predictor of pl_sp3. The odds ratio for vi_sp3 is calculated by taking the exponent of the coefficient, which is e^1.5088 = 4.519. This means that for every one unit increase in vi_sp3, the odds of pl_sp3 increase by a factor of 4.519, holding all other variables constant. The confidence interval and p-value provided in the output indicate that this result is statistically significant.

6.3.18 Logistic Regression of Product preference to Product Longevity for Speaker#3

Table 6.22: Summary #3-4

Summary #3-4	Product: Speaker#3
Independent Variable: Product Preference	
Dependent Variable: Aesthetic Longevity	

```
> # Product Preference vs. longevity
> logistic9.4 <- glm(df7.1$pl_sp3 ~ df7.1$pp_sp3, data=df7.1 , family =
binomial(logit))
> summary(logistic9.4)

Call:
glm(formula = df7.1$pl_sp3 ~ df7.1$pp_sp3, family = binomial(logit),
    data = df7.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.0784   0.2081   0.2081   0.4951   1.8591

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   -5.1023     1.1544  -4.420 9.87e-06 ***
df7.1$pp_sp3   1.7849     0.3346   5.335 9.55e-08 ***
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 136.1  on 121  degrees of freedom
Residual deviance:  84.8  on 120  degrees of freedom
AIC: 88.8

Number of Fisher Scoring iterations: 5
```

The p-value in Table 6.22 for the coefficient estimate of df7.1$pp_sp3 is less than 0.001, indicating that the predictor variable is significantly associated with df7.1$pl_sp3, where df7.1$pp_sp3 is product preference for speaker#3. The odds ratio is exp(1.7849) = 5.97, indicating that the odds of df7.1$pl_sp3 are almost 6 times higher for each unit increase in df7.1$pp_sp3, holding all other variables constant. The AIC value of 88.8 suggests that this model is a good fit for the data.

6.3.19 Logistic Regression of Product Familiarity#1 to Product Longevity for Speaker#3

Table 6.23: Summary #3-5

Summary #3-5	Product: Speaker#3
Independent Variable: Familarity#1(Familiar)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#1 – familiar vs. longevity
> logistic9.5 <- glm(df7.1$pl_sp3 ~ df7.1$pfm1_sp3, data=df7.1 , family =
binomial(logit))
> summary(logistic9.5)

Call:
glm(formula = df7.1$pl_sp3 ~ df7.1$pfm1_sp3, family = binomial(logit),
    data = df7.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6787   0.7486   0.7486   0.7511   0.7588

Coefficients:  Estimate Std. Error z value Pr(>|z|)
(Intercept)     1.136631   0.403569   2.816  0.00486 **
df7.1$pfm1_sp3 -0.007784   0.166929  -0.047  0.96281
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 136.1  on 121  degrees of freedom
Residual deviance: 136.1  on 120  degrees of freedom
AIC: 140.1
Number of Fisher Scoring iterations: 4
```

The logistic regression model in Table 6.23 shows that there is no significant relationship between the response variable, pl_sp3, and the predictor variable, pfm1_sp3. The intercept (or baseline value) is estimated to be 1.136631. It is statistically significant at the 0.05 significance level (p = 0.00486), indicated by the double asterisks (**) in the "Signif. codes" column. The coefficient for "pfm1_sp3" is estimated to be -0.007784. However, it is not statistically significant (p = 0.96281), as indicated by the lack of asterisks in the "Signif. codes" column. These deviance values measure the goodness of fit of the model. The null deviance represents the deviance when only the intercept is included in the model, while the residual deviance represents the deviance after including the independent variable. In this case, both deviance values are equal to 136.1, indicating that the model does not improve the fit significantly. The AIC value is a measure of the model's quality, considering both goodness of fit and model complexity. The lower AIC value of 140.1 indicates a better trade-off between fit and complexity compared to other models.

6.3.20 Logistic Regression of Product Familiarity#2 to Product Longevity for Speaker#3

Table 6.24: Summary #3-6

Summary #3-6	Product: Speaker#3
Independent Variable: Familarity#2(Remember)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#2 – remember vs. longevity
> logistic9.6 <- glm(df7.1$pl_sp3 ~ df7.1$pfm2_sp3, data=df7.1 , family =
binomial(logit))
> summary(logistic9.6)
Call:
glm(formula = df7.1$pl_sp3 ~ df7.1$pfm2_sp3, family = binomial(logit),
   data = df7.1)
Deviance Residuals:
   Min       1Q   Median      3Q      Max
-1.7166   0.7074   0.7503   0.7650   0.7650
oefficients:  Estimate Std. Error z value Pr(>|z|)
(Intercept)     1.03448     0.41714   2.480   0.0131 *
df7.1$pfm2_sp3  0.04466    0.18828   0.237   0.8125
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
   Null deviance: 136.10  on 121  degrees of freedom
Residual deviance: 136.04  on 120  degrees of freedom
AIC: 140.04
```

The predictor variable df7.1$pfm2_sp3 in Table 6.24 is not significant at the 0.05 level, as indicated by the high p-value (0.8125), where df7.1$pfm2_sp3 is product familiarity#2 for speaker#3.

The p-value for df7.1$pfm2_sp3 is not significant (p = 0.8125), we cannot conclude that there is a significant relationship between df7.1$pfm2_sp3 and pl_sp3.

6.3.21 Logistic Regression of Product Familiarity#3 to Product Longevity for Speaker#3

Table 6.25: Summary #3-7

Summary #3-7	Product: Speaker#3
Independent Variable: Familarity#2(Knowledge)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#3 - Knowledge vs. longevity
> logistic9.7 <- glm(df7.1$pl_sp3 ~ df7.1$pfm3_sp3, data=df7.1 , family =
binomial(logit))
> summary(logistic9.7)

Call:
glm(formula = df7.1$pl_sp3 ~ df7.1$pfm3_sp3, family = binomial(logit),
    data = df7.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.9386   0.5757   0.6449   0.8025   0.8909

Coefficients:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.4708     0.4592   1.025    0.305
df7.1$pfm3_sp3   0.2485     0.1628   1.527    0.127

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 136.10  on 121  degrees of freedom
Residual deviance: 133.68  on 120  degrees of freedom
AIC: 137.68

Number of Fisher Scoring iterations: 4
```

The logistic regression model in Table 6.25 shows that the relationship between the response variable pl_sp3 and the predictor variable pfm3_sp3 is not statistically significant, as the p-value (0.127) is greater than the commonly used threshold of 0.05. The intercept (or baseline value) is estimated to be 0.4708. It is not statistically significant at the conventional 0.05 significance level (p = 0.305). The coefficient for "pfm3_sp3" is estimated to be 0.2485, suggesting that as "pfm3_sp3" increases by one unit, the log-odds of "pl_sp3" increase by 0.2485. However, this coefficient is not statistically significant (p = 0.127). These deviance values measure the goodness of fit of the model. The null deviance represents the deviance when only the intercept is included in the model, while the residual deviance represents the deviance after including the independent variable. In this case, the residual deviance (133.68) is lower than the null deviance (136.10), indicating that the model improves the fit. A lower AIC value of 137.68 indicates a better trade-off between fit and complexity compared to other models.

6.3.22 Logistic Regression of Visual Complexity to Product Longevity for Wristwatch#1

Table 6.26: Summary #4-1

Summary #4-1	Product: Wristwatch#1
Independent Variable: Visual Complexity	
Dependent Variable: Aesthetic Longevity	

```
> # complexity vs. longevity
> logistic13.1 <- glm(df8.1$pl_wch1 ~ df8.1$vc_wch1, data=df8.1 , family =
binomial(logit))
> summary(logistic13.1)
 Call:
glm(formula = df8.1$pl_wch1 ~ df8.1$vc_wch1, family = binomial(logit),
    data = df8.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.8135  -0.8088  -0.8088   1.5917   1.6166

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -1.00474    0.80857  -1.243    0.214
df8.1$vc_wch1  0.01377    0.20035   0.069    0.945

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 144.38  on 121  degrees of freedom
Residual deviance: 144.37  on 120  degrees of freedom
AIC: 148.37

Number of Fisher Scoring iterations: 4
```

Neither the intercept nor the coefficient of the predictor variable is statistically significant at the 5% level, as their p-values are 0.214 and 0.945, respectively. There is no strong evidence that the predictor variable is associated with the response variable (Table 6.26).

6.3.23 Logistic Regression of Visual Entropy to Product Longevity for Wristwatch#1

Table 6.27: Summary #4-2

Summary #4-2	Product: Wristwatch#1
Independent Variable: Visual Entropy	
Dependent Variable: Aesthetic Longevity	

```
> # Entropy vs. longevity
> logistic13.2 <- glm(df8.1$pl_wch1 ~ df8.1$ent_wch1, data=df8.1 , family =
binomial(logit))
> summary(logistic13.2)
Call:
glm(formula = df8.1$pl_wch1 ~ df8.1$ent_wch1, family = binomial(logit),
    data = df8.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.8258  -0.8091  -0.8091   1.5866   1.6084

Coefficients:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)    -0.85231    1.09927  -0.775    0.438
df8.1$ent_wch1 -0.02409    0.26405  -0.091    0.927

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 144.38  on 121  degrees of freedom
Residual deviance: 144.37  on 120  degrees of freedom
AIC: 148.37

Number of Fisher Scoring iterations: 4
```

Neither the intercept nor the coefficient of the predictor variable is statistically significant at the 5% level, as their p-values are 0.438 and 0.927, respectively.

Table 6.27 suggests that there is no strong evidence that the predictor variable is associated with the response variable.

6.3.24 Logistic Regression of Visual Interest to Product Longevity for Wristwatch#1

Table 6.28: Summary #4-3

Summary #4-3	Product: Wristwatch#1
Independent Variable: Visual Interest	
Dependent Variable: Aesthetic Longevity	

```
> # Interests vs. longevity
> logistic13.3 <- glm(df8.1$pl_wch1 ~ df8.1$vi_wch1, data=df8.1 , family =
binomial(logit))
> summary(logistic13.3)
Call:
```

Table 6.28 (cont.)

```
glm(formula = df8.1$pl_wch1 ~ df8.1$vi_wch1, family = binomial(logit),
    data = df8.1)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6077  -0.6535  -0.3715   0.8013   2.3271

Coefficients: Estimate Std. Error z value Pr(>|z|)
(Intercept)    -5.0452     0.9815   -5.14 2.74e-07 ***

df8.1$vi_wch1   1.2033     0.2555    4.71 2.48e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 144.38  on 121  degrees of freedom
Residual deviance: 107.79  on 120  degrees of freedom
AIC: 111.79
Number of Fisher Scoring iterations: 5
```

Both the intercept and the coefficient of the predictor variable in Table 6.28 are statistically significant at the 5% level, as their p-values are very small (less than 0.001 and 0.01, respectively). This suggests that there is strong evidence that the predictor variable is associated with the response variable. The deviance residuals indicate the difference between the predicted and observed responses and are used to assess the goodness of fit of the model. The AIC (Akaike Information Criterion) provides a measure of the relative quality of the model, where lower values indicate a better fit. In this case, the AIC is 111.79, which suggests that the model is a good fit for the data.

The odds ratio for the variable df8.1$vi_wch1 in the logistic regression model is exp(1.2033) = 3.33, where df8.1$vi_wch1is visual interest for wristwatch#1.

This means that holding all other variables constant, a one-unit increase in df8.1$vi_wch1 is associated with an increase in the odds of the outcome variable df8.1$pl_wch1 by a factor of 3.33. In other words, the odds of df8.1$pl_wch1 are 3.33 times higher for each unit increase in df8.1$vi_wch1.

6.3.25 Logistic Regression of Product Preference to Product Longevity for Wristwatch#1

Table 6.29: Summary #4-4

Summary #4-4	Product: Wristwatch#1
Independent Variable: Product Preference	
Dependent Variable: Aesthetic Longevity	

```
> # Product Preference vs. longevity
> logistic13.4 <- glm(df8.1$pl_wch1 ~ df8.1$pp_wch1, data=df8.1 , family =
binomial(logit))
> summary(logistic13.4)

Call:
glm(formula = df8.1$pl_wch1 ~ df8.1$pp_wch1, family = binomial(logit),
    data = df8.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4350  -0.6589  -0.1531   0.4448   2.3771

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -6.1160     1.1161  -5.480 4.26e-08 ***
df8.1$pp_wch1   1.6759     0.3198   5.241 1.60e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 144.38  on 121  degrees of freedom
Residual deviance:  89.87  on 120  degrees of freedom
AIC: 93.87

Number of Fisher Scoring iterations: 6
```

The coefficient for pp_wch1 is 1.6759 with a standard error of 0.3198 and a z-value of 5.241, which indicates that it is statistically significant at the 0.05 level, where df8.1$pp_wch1is product preference (Table 6.29). The odds ratio for pp_wch1 is exp (1.6759) = 5.346. This means that for every one-unit increase in df8.1$pp_wch1, the odds of df8.1$pl_wch1 increase by a factor of approximately 5.34, assuming all other variables in the model are held constant, where df8.1$pp_wch1is product preference and df8.1$pl_wch1is product longevity.

6.3.26 Logistic Regression of Product Familiarity#1 to Product Longevity for Wristwatch#1

Table 6.30: Summary #4-5

Summary #4-5	Product: Wristwatch#1
Independent Variable: Familarity#1(Familiar)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#1 - familiar vs. longevity
> logistic13.5 <- glm(df8.1$pl_wch1 ~ df8.1$pfm1_wch1, data=df8.1 , family =
binomial(logit))
> summary(logistic13.5)
Call:
glm(formula = df8.1$pl_wch1 ~ df8.1$pfm1_wch1, family = binomial(logit),
    data = df8.1)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.9016  -0.8540  -0.7639   1.4810   1.7167

Coefficients: Estimate Std. Error z value Pr(>|z|)
(Intercept)      -1.3439     0.4697  -2.861  0.00422 **
df8.1$pfm1_wch1   0.1307     0.1381   0.947  0.34374
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 144.38  on 121  degrees of freedom
Residual deviance: 143.47  on 120  degrees of freedom
AIC: 147.47
Number of Fisher Scoring iterations: 4
```

The p-value in Table 6.30 for this coefficient is greater than 0.05, indicating that this coefficient is not statistically significant and the relationship between pfm1_wch1 and pl_wch1 might be due to chance. The AIC value is also relatively high, suggesting that there may be better models to explain the relationship between the predictor and outcome variables.

6.3.27 Logistic Regression of Product Familiarity#2 to Product Longevity for Wristwatch#1

Table 6.31: Summary #4-6

Summary #4-6	Product: Wristwatch#1
Independent Variable: Familarity#2(Remember)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#2 - remember vs. longevity
> logistic13.6 <- glm(df8.1$pl_wch1 ~ df8.1$pfm2_wch1, data=df8.1 , family =
binomial(logit))
> summary(logistic13.6)
Call:
glm(formula = df8.1$pl_wch1 ~ df8.1$pfm2_wch1, family = binomial(logit),
    data = df8.1)
Deviance Residuals:
```

Table 6.31 (cont.)

```
   Min       1Q   Median       3Q      Max
-0.9831  -0.8370  -0.7062   1.3850   1.7384

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)      -1.4580     0.4211  -3.462 0.000535 ***
df8.1$pfm2_wch1   0.1965     0.1382   1.422 0.155033
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 144.38  on 121  degrees of freedom
Residual deviance: 142.35  on 120  degrees of freedom
AIC: 146.35

Number of Fisher Scoring iterations: 4
```

The p-value in Table 6.31 for the intercept is less than 0.001, which indicates that the intercept is statistically significant. However, it is important to note that the significance of the intercept does not provide information about the usefulness of the model as a whole.

6.3.28 Logistic Regression of Product Familiarity#3 to Product Longevity for Wristwatch#1

Table 6.32: Summary #4-7

Summary #4-7	Product: Wristwatch#1
Independent Variable: Familarity#3(Knowledge)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#3 - Knowledge vs. longevity
> logistic13.7 <- glm(df8.1$pl_wch1 ~ df8.1$pfm3_wch1, data=df8.1 , family =
binomial(logit))
> summary(logistic13.7)

Call:
glm(formula = df8.1$pl_wch1 ~ df8.1$pfm3_wch1, family = binomial(logit),
    data = df8.1)

Deviance Residuals:
   Min       1Q   Median       3Q      Max
-1.0260  -0.8123  -0.7482   1.4004   1.6793

Coefficients:  Estimate Std. Error z value Pr(>|z|)
(Intercept)      -0.1763     0.7553  -0.233    0.815
df8.1$pfm3_wch1  -0.1908     0.1810  -1.054    0.292

(Dispersion parameter for binomial family taken to be 1)
```

Table 6.32 (cont.)

```
Null deviance: 144.38  on 121  degrees of freedom
Residual deviance: 143.29  on 120  degrees of freedom
AIC: 147.29

Number of Fisher Scoring iterations: 4
```

In this logistic regression model (Table 6.31), the predictor variable is df8.1$pfm3_wch1 and the response variable is df8.1$pl_wch1, where df8.1$pfm3_wch1 is product familiarity#3 for wristwatch. The coefficient for the predictor variable is -0.1908 with a standard error of 0.1810. The z-value is -1.054 and the associated p-value is 0.292, which is not significant at a conventional level (e.g., alpha=0.05).

6.3.29 Logistic Regression of Visual Complexity to Product Longevity for Wristwatch#2

Table 6.33: Summary #5-1

Summary #5-1	Product: Wristwatch#2
Independent Variable: Visual Complexity	
Dependent Variable: Aesthetic Longevity	

```
> # complexity vs. longevity
> logistic17.1 <- glm(df9.1$pl_wch2 ~ df9.1$vc_wch2, data=df9.1 , family =
binomial(logit))
> summary(logistic17.1)

Call:
glm(formula = df9.1$pl_wch2 ~ df9.1$vc_wch2, family = binomial(logit),
    data = df9.1)

Deviance Residuals:
   Min      1Q  Median      3Q     Max
-1.355  -1.292   1.038   1.048   1.087
Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.45739    0.77179   0.593    0.553
df9.1$vc_wch2 -0.04809    0.22498  -0.214    0.831
(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 166.46  on 121  degrees of freedom
Residual deviance: 166.42  on 120  degrees of freedom
AIC: 170.42
```

The intercept in Table 6.33 estimate is 0.45739 and the slope estimate is -0.04809. The z value and associated p-value for each coefficient indicate the significance of the estimate. In this case, the intercept is not significant (p = 0.553) and the slope is not significant (p = 0.831).

6.3.30 Logistic Regression of Visual Entropy to Product Longevity for Wristwatch#2

Table 6.34: Summary #5-2

Summary #5-2	Product: Wristwatch#2
Independent Variable: Visual Entropy	
Dependent Variable: Aesthetic Longevity	

```
> # Entropy vs. longevity
> logistic17.2 <- glm(df9.1$pl_wch2 ~ df9.1$ent_wch2, data=df9.1 , family =
binomial(logit))
> summary(logistic17.2)
Call:
glm(formula = df9.1$pl_wch2 ~ df9.1$ent_wch2, family = binomial(logit),
   data = df9.1)

Deviance Residuals:
   Min      1Q  Median      3Q     Max
-1.310  -1.304   1.053   1.055   1.058

Coefficients:  Estimate Std. Error z value Pr(>|z|)
(Intercept)     0.319633   0.834946   0.383    0.702
df9.1$ent_wch2 -0.006579   0.239441  -0.027    0.978

(Dispersion parameter for binomial family taken to be 1)
   Null deviance: 166.46  on 121  degrees of freedom
Residual deviance: 166.46  on 120  degrees of freedom
AIC: 170.46
Number of Fisher Scoring iterations: 4
```

The Intercept term in Table 6.34 has an estimated coefficient of 0.319633 and a standard error of 0.834946. The coefficient estimate indicates that when ent_wch2 is zero, the log-odds of pl_wch2 is expected to be 0.319633, where ent_wch2 is visual entropy for wristwatch#2. Since the p-value is not significant (p=0.702), we cannot reject the null hypothesis that the true value of the coefficient is zero. The ent_wch2 term has an estimated coefficient of -0.006579 and a standard error of 0.239441. The coefficient estimate indicates that for a one-unit increase in ent_wch2, the log-odds of pl_wch2 is expected to decrease by -0.006579. However, since the p-value is not significant (p=0.978), we cannot reject the null hypothesis that the true value of the coefficient is zero.

6.3.31 Logistic Regression of Visual Interest to Product Longevity for Wristwatch#2

Table 6.35: Summary #5-3

Summary #5-3	Product: Wristwatch#2
Independent Variable: Visual Interest	
Dependent Variable: Aesthetic Longevity	

```
> # Interests vs. longevity
> logistic17.3 <- glm(df9.1$pl_wch2 ~ df9.1$vi_wch2, data=df9.1 , family =
binomial(logit))
> summary(logistic17.3)

Call:
glm(formula = df9.1$pl_wch2 ~ df9.1$vi_wch2, family = binomial(logit),
    data = df9.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.4321  -0.8136   0.3266   0.7968   1.5916

Coefficients: Estimate Std. Error z value Pr(>|z|)
(Intercept)    -6.6954     1.2941  -5.174 2.29e-07 ***
df9.1$vi_wch2   1.9199     0.3475   5.525 3.30e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 166.46  on 121  degrees of freedom
Residual deviance: 108.31  on 120  degrees of freedom
AIC: 112.31

Number of Fisher Scoring iterations: 5
```

The vi_wch2 term in Table 6.35 has an estimated coefficient of 1.9199 and a standard error of 0.3475. The coefficient estimate indicates that for a one-unit increase in vi_wch2, the log-odds of pl_wch2 is expected to increase by 1.9199. This predictor variable is also statistically significant ($p < 0.001$), indicating that there is a significant association between vi_wch2 and pl_wch2. The odds ratio for the variable df9.1$vi_wch2 is exp(1.9199) = 6.828. So, holding all other variables constant, a one-unit increase in df9.1$vi_wch2 is associated with an odds ratio of 6.828 for the outcome variable df9.1$pl_wch2.

6.3.32 Logistic Regression of Product Preference to Product Longevity for Wristwatch#2

Table 6.36: Summary #5-4

Summary #5-4	Product: Wristwatch#2
Independent Variable: Product Preference	
Dependent Variable: Aesthetic Longevity	

```
> # Product Preference vs. longevity
> logistic17.4 <- glm(df9.1$pl_wch2 ~ df9.1$pp_wch2, data=df9.1 , family =
binomial(logit))
> summary(logistic17.4)

Call:
glm(formula = df9.1$pl_wch2 ~ df9.1$pp_wch2, family = binomial(logit),
    data = df9.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.9411  -0.5222   0.1632   0.6579   1.8316

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -10.1438     1.8803  -5.395 6.86e-08 ***
df9.1$pp_wch2   2.8911     0.5116   5.652 1.59e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 166.462  on 121  degrees of freedom
Residual deviance:  73.737  on 120  degrees of freedom
AIC: 77.737

Number of Fisher Scoring iterations: 6
```

The p-value for the coefficient is less than 0.001, which suggests that the predictor variable is statistically significant and has a significant effect on the response variable (Table 6.36). The intercept is also statistically significant, indicating that the log odds of success when pp_wch2 = 0 is significantly different from zero, where pp_wch2 is product preference for wristwatch#2. Odds ratio is exp (2.8911) = 18.0527. Therefore, the odds of df9.1$pl_wch2 increase by a factor of 18.0527 for each one-unit increase in df9.1$pp_wch2, holding all other variables constant.

6.3.33 Logistic Regression of Product Familiarity#1 to Product Longevity for Wristwatch#2

Table 6.37: Summary #5-5

Summary #5-5	Product: Wristwatch#2
Independent Variable: Familarity#1(Familiar)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#1 - familiar vs. longevity
> logistic17.5 <- glm(df9.1$pl_wch2 ~ df9.1$pfm1_wch2, data=df9.1 , family =
binomial(logit))
> summary(logistic17.5)

Call:
glm(formula = df9.1$pl_wch2 ~ df9.1$pfm1_wch2, family = binomial(logit),
    data = df9.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.3716  -1.2922   0.9949   1.0668   1.1412

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.53578    0.40999   1.307    0.191
df9.1$pfm1_wch2 -0.08998    0.13775  -0.653    0.514
(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 166.46  on 121  degrees of freedom
Residual deviance: 166.03  on 120  degrees of freedom
AIC: 170.03

Number of Fisher Scoring iterations: 4
```

The model in Table 6.37 is testing the relationship between the dependent variable pl_wch2 and the independent variable pfm1_wch2. The results suggest that the coefficient estimate for pfm1_wch2 is negative but not statistically significant (p-value = 0.514). This means that there is no evidence to suggest that pfm1_wch2 has a significant effect on pl_wch2.

6.3.34 Logistic Regression of Product Familiarity#2 to Product Longevity for Wristwatch#2

Table 6.38: Summary #5-6

Summary #5-6	Product: Wristwatch#2
Independent Variable: Familarity#2(Remember)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#2 - remember vs. longevity
> logistic17.6 <- glm(df9.1$pl_wch2 ~ df9.1$pfm2_wch2, data=df9.1 , family =
binomial(logit))
> summary(logistic17.6)

Call:
glm(formula = df9.1$pl_wch2 ~ df9.1$pfm2_wch2, family = binomial(logit),
    data = df9.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4884  -1.2348   0.8955   1.0049   1.3685

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)       0.9931     0.4005   2.480   0.0131 *
df9.1$pfm2_wch2  -0.2864     0.1447  -1.979   0.0478 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 166.46  on 121  degrees of freedom
Residual deviance: 162.45  on 120  degrees of freedom

AIC: 166.45
```

The coefficient for df9.1$pfm2_wch2 in Table 6.38 is -0.2864, which indicates that for each unit increase in df9.1$pfm2_wch2, the log-odds of the dependent variable decreases by 0.2864. The p-value for df9.1$pfm2_wch2 is 0.0478, which is less than 0.05, suggesting that df9.1$pfm2_wch2 is a significant predictor of the dependent variable. The odds ratio is given by exp(-0.2864) = 0.7502. This means that for a one-unit increase in df9.1$pfm2_wch2, the odds of df9.1$pl_wch2 occurring decrease by a factor of 0.7502 or approximately 25%.

6.3.35 Logistic Regression of Product Familiarity#3 to Product Longevity for Wristwatch#2

Table 6.39: Summary #5-7

Summary #5-7	Product: Wristwatch#2
Independent Variable: Familarity#3(Knowledge)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#3 - Knowledge vs. longevity
> logistic17.7 <- glm(df9.1$pl_wch2 ~ df9.1$pfm3_wch2, data=df9.1 , family =
binomial(logit))
> summary(logistic17.7)
Call:
glm(formula = df9.1$pl_wch2 ~ df9.1$pfm3_wch2, family = binomial(logit),
    data = df9.1)
Deviance Residuals:
   Min      1Q  Median      3Q     Max
-1.315  -1.306   1.049   1.054   1.057

Coefficients:  Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.323343   0.650930   0.497    0.619
df9.1$pfm3_wch2 -0.006658   0.159377  -0.042    0.967

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 166.46  on 121  degrees of freedom
Residual deviance: 166.46  on 120  degrees of freedom
AIC: 170.46

Number of Fisher Scoring iterations: 4
```

The output in Table 6.39 shows the coefficients of the intercept and df9.1$pfm3_wch2 with their corresponding standard errors, z-values, and p-values. The coefficient of df9.1$pfm3_wch2 is negative, but not statistically significant as its p-value is greater than 0.05. The intercept (or baseline value) is estimated to be 0.323343. It is not statistically significant at the conventional 0.05 significance level (p = 0.619). The coefficient for "pfm3_wch2" is estimated to be -0.006658, suggesting that as "pfm3_wch2" increases by one unit, the log-odds of "pl_wch2" decrease by 0.006658. However, this coefficient is not statistically significant (p = 0.967). The deviance values measure the goodness of fit of the model. The null deviance represents the deviance when only the intercept is included in the model, while the residual deviance represents the deviance after including the independent variable. In this case, both deviance values are equal to 166.46, indicating that the model does not improve the fit significantly. The AIC value is a measure of the model's quality, considering both goodness of fit and model complexity. The AIC value of 170.46 indicates the trade-off between fit and complexity compared to other models.

6.3.36 Logistic Regression of Visual Complexity to Product Longevity for Wristwatch#3

Table 6.40: Summary #6-1

Summary #6-1	Product: Wristwatch#3
Independent Variable: Visual Complexity	
Dependent Variable: Aesthetic Longevity	

```
> # complexity vs. longevity
> logistic21.1 <- glm(df10.1$pl_wch3 ~ df10.1$vc_wch3, data=df10.1 , family =
binomial(logit))
> summary(logistic21.1)
Call:
glm(formula = df10.1$pl_wch3 ~ df10.1$vc_wch3, family = binomial(logit),
    data = df10.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5050  -1.2486   0.9914   1.1079   1.1079

Coefficients: Estimate Std. Error z value Pr(>|z|)
(Intercept)     0.02127    0.38912   0.055    0.956
df10.1$vc_wch3  0.14444    0.20584   0.702    0.483

(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 167.02  on 121  degrees of freedom
Residual deviance: 166.52  on 120  degrees of freedom
AIC: 170.52
Number of Fisher Scoring iterations: 4
```

Overall, the output in Table 6.40 suggests that the predictor variable vc_wch3 is not a significant predictor of the event pl_wch3, as the p-value associated with this variable is greater than the usual significance level of 0.05. The coefficient for vc_wch3 is not statistically significant at the 0.05 level (as indicated by the p-value of 0.483), which suggests that there is not strong evidence to support a relationship between vc_wch3 and pl_wch3.

6.3.37 Logistic Regression of Visual Entropy to Product Longevity for Wristwatch#3

Table 6.41: Summary #6-2

Summary #6-2	Product: Wristwatch#3
Independent Variable: Visual Entropy	
Dependent Variable: Aesthetic Longevity	

```
> # Entropy vs. longevity
> logistic21.2 <- glm(df10.1$pl_wch3 ~ df10.1$ent_wch3, data=df10.1 , family =
binomial(logit))
> summary(logistic21.2)

Call:
glm(formula = df10.1$pl_wch3 ~ df10.1$ent_wch3, family = binomial(logit),
    data = df10.1)

Deviance Residuals:
   Min      1Q  Median      3Q     Max
-1.312  -1.292   1.065   1.071   1.074

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)       0.2287     0.4464   0.512    0.608
df10.1$ent_wch3   0.0206     0.2392   0.086    0.931

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.02  on 121  degrees of freedom
Residual deviance: 167.02  on 120  degrees of freedom
AIC: 171.02

Number of Fisher Scoring iterations: 3
```

The output in Table 6.41 suggests that the predictor variable ent_wch3 is not a significant predictor of the event pl_wch3, as the p-value associated with this variable is greater than the usual significance level of 0.05. This means there is no statistically significant relationship between ent_wch3 and pl_wch3 in this model. The odds ratio for the variable df10.1$ent_wch3 in the logistic regression model is exp(0.0206) = 1.0208. This means that for a one-unit increase in the value of df10.1$ent_wch3, the odds of the response variable df10.1$pl_wch3 being equal to 1 (versus 0) increase by a factor of 1.0208, all else being equal. However, since the p-value for the coefficient is not significant (p-value = 0.931), we cannot conclude that there is a significant relationship between df10.1$ent_wch3 and df10.1$pl_wch3.

6.3.38 Logistic Regression of Visual Interest to Product Longevity for Wristwatch#3

Table 6.42: Summary #6-3

Summary #6-3	Product: Wristwatch#3
Independent Variable: Visual Interest	
Dependent Variable: Aesthetic Longevity	

```
> # Interests vs. longevity
> logistic21.3 <- glm(df10.1$pl_wch3 ~ df10.1$vi_wch3, data=df10.1 , family =
binomial(logit))
> summary(logistic21.3)

Call:
glm(formula = df10.1$pl_wch3 ~ df10.1$vi_wch3, family = binomial(logit),
   data = df10.1)
Deviance Residuals:
   Min       1Q   Median      3Q      Max
-2.1431  -0.9232   0.4605   1.0495   1.8770
Coefficients:  Estimate Std. Error z value Pr(>|z|)
(Intercept)     -2.5140     0.6269   -4.01 6.06e-05 ***
df10.1$vi_wch3   0.9409     0.2032    4.63 3.66e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)

   Null deviance: 167.02  on 121  degrees of freedom
Residual deviance: 138.89  on 120  degrees of freedom
AIC: 142.89
Number of Fisher Scoring iterations: 3
```

The p-value for the coefficient of vi_wch3 in Table 6.42 is very small ($p < 0.001$), indicating that the association between vi_wch3 and pl_wch3 is statistically significant. The residual deviance of 138.89 on 120 degrees of freedom indicates that the model fits the data reasonably well. The odds ratio for vi_wch3 can be calculated by exponentiating the coefficient, i.e., exp (0.9409) = 2.56. Therefore, for each unit increase in vi_wch3, the odds of pl_wch3 increase by a factor of 2.56. This means that for a one unit increase in df10.1$vi_wch3, the odds of df10.1$pl_wch3 increase by a factor of 2.561, holding all other variables constant.

6.3.39 Logistic Regression of Product Preference to Product Longevity for Wristwatch#3

Table 6.43: Summary #6-4

Summary #6-4	Product: Wristwatch#3
Independent Variable: Product Preference	
Dependent Variable: Aesthetic Longevity	

```
> # Product Preference vs. longevity
> logistic21.4 <- glm(df10.1$pl_wch3 ~ df10.1$pp_wch3, data=df10.1 , family =
binomial(logit))
> summary(logistic21.4)
Call:
glm(formula = df10.1$pl_wch3 ~ df10.1$pp_wch3, family = binomial(logit),
   data = df10.1)

Deviance Residuals:
   Min       1Q   Median       3Q      Max
-2.3166  -0.5784   0.3762   0.7340   1.9343

Coefficients:  Estimate Std. Error z value Pr(>|z|)
(Intercept)     -4.5809     0.9453  -4.846 1.26e-06 ***
df10.1$pp_wch3   1.4387     0.2686   5.356 8.52e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
   Null deviance: 167.02  on 121  degrees of freedom
Residual deviance: 117.58  on 120  degrees of freedom
AIC: 121.58
Number of Fisher Scoring iterations: 5
```

The intercept in Table 6.43 estimate is -4.5809 and the slope estimate is 1.4387. The z value and associated p-value for each coefficient indicate the significance of the estimate. In this case, both the intercept and the slope are significant ($p < 0.001$). The odds ratio for pp_wch3 is exp (1.4387) = 4.21, which means that for a one-unit increase in pp_wch3, the odds of pl_wch3 increase by a factor of 4.21, assuming all other variables are held constant. The p-value for the coefficient of pp_wch3 is less than 0.001, indicating that it is statistically significant at the 0.001 level. This suggests that pp_wch3 is a significant predictor of pl_wch3.

6.3.40 Logistic Regression of Product Familiarity#1 to Product Longevity for Wristwatch#3

Table 6.44: Summary #6-5

Summary #6-5	Product: Wristwatch#3
Independent Variable: Familarity#1(Familiar)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#1 - familiar vs. longevity
> logistic21.5 <- glm(df10.1$pl_wch3 ~ df10.1$pfm1_wch3, data=df10.1 , family
= binomial(logit))
> summary(logistic21.5)
Call:
glm(formula = df10.1$pl_wch3 ~ df10.1$pfm1_wch3, family = binomial(logit),
    data = df10.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4536  -1.2506   0.9243   1.0130   1.3021

Coefficients:
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)       -0.5180     0.4502  -1.150   0.2500
df10.1$pfm1_wch3   0.2295     0.1211   1.895   0.0581 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.02  on 121  degrees of freedom
Residual deviance: 163.36  on 120  degrees of freedom
AIC: 167.36
Number of Fisher Scoring iterations: 4
```

The coefficient for df10.1$pfm1_wch3 in Table 6.44 is 0.2295 with a standard error of 0.1211 and a z-value of 1.895. The p-value for this coefficient is 0.0581, which is marginally significant at a 5% level. The odds ratio for df10.1$pfm1_wch3 is given by exp (0.2295) = 1.258. This means that for a one unit increase in df10.1$pfm1_wch3, the odds of df10.1$pl_wch3 being 1 (versus 0) are multiplied by a factor of 1.258, holding all other variables constant. The p-value for this predictor (Pr(>|z|) column) is 0.0581, which is greater than 0.05, indicating that the effect of df10.1$pfm1_wch3 on the response may not be statistically significant at the 5% level of significance.

6.3.41 Logistic Regression of Product Familiarity#2 to Product Longevity for Wristwatch#3

Table 6.45: Summary #6-6

Summary #6-6	Product: Wristwatch#3
Independent Variable: Familarity#2(Remember)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#2 - remember vs. longevity
> logistic21.6 <- glm(df10.1$pl_wch3 ~ df10.1$pfm2_wch3, data=df10.1 , family
= binomial(logit))
> summary(logistic21.6)
Call:
glm(formula = df10.1$pl_wch3 ~ df10.1$pfm2_wch3, family = binomial(logit),
   data = df10.1)
Deviance Residuals:
   Min       1Q   Median       3Q      Max
-1.5100  -1.1871   0.8780   0.9696   1.2727
Coefficients: Estimate Std. Error z value Pr(>|z|)
(Intercept)      -0.4652     0.4020  -1.157   0.2472
df10.1$pfm2_wch3   0.2440     0.1207   2.022   0.0432 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
   Null deviance: 167.02  on 121  degrees of freedom
Residual deviance: 162.84  on 120  degrees of freedom
AIC: 166.84
Number of Fisher Scoring iterations: 4
```

The p-value for the coefficient in Table 6.45 is 0.0432, which is less than 0.05, indicating that the coefficient is statistically significant at the 0.05 level. The odds ratio for the predictor variable df10.1$pfm2_wch3 in the logistic regression model is exp (0.2440), which is approximately equal to 1.276. This means that for a one-unit increase in df10.1$pfm2_wch3, the odds of df10.1$pl_wch3 increase by a factor of 1.276 after controlling for other variables in the model. The intercept is not statistically significant (p-value = 0.2472), this interpretation may not be very meaningful.

6.3.42 Logistic Regression of Product Familiarity#3 to Product Longevity for Wristwatch#3

Table 6.46: Summary #6-7

Summary #6-7	Product: Wristwatch#3
Independent Variable: Familarity#3(Knowledge)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#3 - Knowledge vs. longevity
> logistic21.7 <- glm(df10.1$pl_wch3 ~ df10.1$pfm3_wch3, data=df10.1 , family
= binomial(logit))
> summary(logistic21.7)
Call:
glm(formula = df10.1$pl_wch3 ~ df10.1$pfm3_wch3, family = binomial(logit),
    data = df10.1)
Deviance Residuals:
   Min      1Q  Median      3Q     Max
-1.340  -1.285   1.023   1.073   1.230

Coefficients:
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)       -0.2474     0.7062  -0.350    0.726
df10.1$pfm3_wch3   0.1242     0.1659   0.749    0.454

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.02  on 121  degrees of freedom
Residual deviance: 166.46  on 120  degrees of freedom
AIC: 170.46
Number of Fisher Scoring iterations: 4
```

The p-value for df10.1$pfm3_wch3 in Table 6.46 is not significant (p-value = 0.454). It suggests that the effect of df10.1$pfm3_wch3 on the outcome variable df10.1$pl_wch3 may not be statistically significant. The intercept (or baseline value) is estimated to be -0.2474. It is not statistically significant at the conventional 0.05 significance level (p = 0.726). The coefficient for "pfm3_wch3" is estimated to be 0.1242, suggesting that as "pfm3_wch3" increases by one unit, the log-odds of "pl_wch3" increase by 0.1242. However, this coefficient is not statistically significant (p = 0.454). The deviance values measure the goodness of fit of the model. The null deviance represents the deviance when only the intercept is included in the model, while the residual deviance represents the deviance after including the independent variable. In this case, the residual deviance (166.46) is slightly lower than the null deviance (167.02), indicating a slight improvement in fit. The AIC value is a measure of the model's quality, considering both goodness of fit and model complexity. The AIC value of 170.46 indicates the trade-off between fit and complexity compared to other models.

6.3.43 Logistic Regression of Visual Complexity to Product Longevity for Game Controller#1

Table 6.47: Summary #7-1

Summary #7-1	Product: Game Controller#1
Independent Variable: Visual Complexity	
Dependent Variable: Aesthetic Longevity	

```
> # complexity vs. Longevity
> logistic25.1 <- glm(df11.1$pl_gc1 ~ df11.1$vc_gc1, data=df11.1 , family =
binomial(logit))
> summary(logistic25.1)

Call:
glm(formula = df11.1$pl_gc1 ~ df11.1$vc_gc1, family = binomial(logit),
    data = df11.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.0005  -0.8672  -0.7460   1.3653   1.9946

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -2.1946     0.8868  -2.475   0.0133 *
df11.1$vc_gc1   0.3526     0.2136   1.651   0.0987 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 151.35  on 121  degrees of freedom
Residual deviance: 148.38  on 120  degrees of freedom
AIC: 152.38

Number of Fisher Scoring iterations: 4
```

The coefficients in Table 6.47 shows the estimated regression coefficients, their standard errors, and the associated test statistics and p-values. The intercept is estimated to be -2.1946 with a standard error of 0.8868. The coefficient for df11.1$vc_gc1 is estimated to be 0.3526 with a standard error of 0.2136. The p-value associated with this coefficient is 0.0987, which is not statistically significant at the conventional level of

0.05. This model suggests that df11.1$vc_gc1 may have a weak positive association with df11.1$pl_gc1, although the evidence for this is not statistically significant. The odds ratio for the predictor variable df11.1$vc_gc1 is exp (0.3526) = 1.422. This means that for a one-unit increase in df11.1$vc_gc1, the odds of the response variable df11.1$pl_gc1 being equal to 1 (as opposed to 0) increase by a factor of 1.422. However, since the p-value associated with the coefficient estimate for df11.1$vc_gc1 is not statistically significant at the conventional level of 0.05, it is important to interpret this result with caution and consider the possibility that the observed association may be due to chance.

6.3.44 Logistic Regression of Visual Entropy to Product Longevity for Game Controller#1

Table 6.48: Summary #7-2

Summary #7-2	Product: Game Controller#1
Independent Variable: Visual Entropy	
Dependent Variable: Aesthetic Longevity	

```
> # Entropy vs. longevity
> logistic25.2 <- glm(df11.1$pl_gc1 ~ df11.1$ent_gc1, data=df11.1 , family =
binomial(logit))
> summary(logistic25.2)
Call:
glm(formula = df11.1$pl_gc1 ~ df11.1$ent_gc1, family = binomial(logit),
    data = df11.1)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.9754  -0.8681  -0.7687   1.3938   1.7798
Coefficients:              Estimate Std. Error z value Pr(>|z|)
(Intercept)     -1.9266     0.8961  -2.150   0.0316 *
df11.1$ent_gc1   0.2862     0.2179   1.313   0.1891
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 151.35  on 121  degrees of freedom
Residual deviance: 149.54  on 120  degrees of freedom
AIC: 153.54
Number of Fisher Scoring iterations: 4
```

The p-value for the ent_gc1 variable in Table 6.48 is 0.1891, which is not statistically significant at the usual significance level of 0.05. Therefore, we cannot conclude that there is a significant relationship between the product longevity and visual entropy.

The odds ratio is exp (0.2862) = 1.33. This means that for every one unit increase in df11.1$ent_gc1, the odds of df11.1$pl_gc1 increase by a factor of 1.33 (or 33%). However, since the p-value for df11.1$ent_gc1 is not significant (p = 0.1891), we cannot conclude that this relationship is statistically significant.

6.3.45 Logistic Regression of Visual Interest to Product Longevity for Game Controller#1

Table 6.49: Summary #7-3

Summary #7-3	Product: Game Controller#1
Independent Variable: Visual Interest	
Dependent Variable: Aesthetic Longevity	

```
# Interests vs. longevity
> logistic25.3 <- glm(df11.1$pl_gc1 ~ df11.1$vi_gc1, data=df11.1 , family =
binomial(logit))
> summary(logistic25.3)

Call:
glm(formula = df11.1$pl_gc1 ~ df11.1$vi_gc1, family = binomial(logit),
    data = df11.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7077  -0.7075  -0.4005   0.7278   2.7322

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -4.9337     0.9271  -5.322 1.03e-07 ***
df11.1$vi_gc1   1.2254     0.2447   5.008 5.49e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 151.35  on 121  degrees of freedom
Residual deviance: 111.02  on 120  degrees of freedom
AIC: 115.02

Number of Fisher Scoring iterations: 5
```

The p-value in Table 6.49 associated with df11.1$vi_gc1 is very small (5.49e-07), which suggests that df11.1$vi_gc1 is a significant predictor of df11.1$pl_gc1, where df11.1$vi_gc1 is visual complexity and df11.1$pl_gc1 is product longevity. The odd ratio of df11.1$vi_gc1 is exp(1.2254) = 3.408, which means that for a one-unit increase in df11.1$vi_gc1, the odds of df11.1$pl_gc1 increase by a factor of 3.408, assuming that all other variables are held constant.

6.3.46 Logistic Regression of Product Preference to Product Longevity for Game Controller#1

Table 6.50: Summary #7-4

Summary #7-4	Product: Game Controller#1
Independent Variable: Product Preference	
Dependent Variable: Aesthetic Longevity	

```
> # Product Preference vs. longevity
> logistic25.4 <- glm(df11.1$pl_gc1 ~ df11.1$pp_gc1, data=df11.1 , family =
binomial(logit))
> summary(logistic25.4)

Call:
glm(formula = df11.1$pl_gc1 ~ df11.1$pp_gc1, family = binomial(logit),
    data = df11.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7394  -0.2964  -0.1004   0.5917   2.5090

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -7.4711     1.2972  -5.759 8.45e-09 ***
df11.1$pp_gc1   2.1838     0.3801   5.746 9.14e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)
Null deviance: 151.347  on 121  degrees of freedom
Residual deviance:  74.361  on 120  degrees of freedom
AIC: 78.361

Number of Fisher Scoring iterations: 6
```

The p-values for both coefficients in Table 6.50 are < 0.001, indicating that both variables are statistically significant predictors of the response variable. The odds ratio for df11.1$pp_gc1 is exp (2.1838) = 8.876, which means that for a one-unit increase in df11.1$pp_gc1, the odds of the response variable increase by a factor of 8.876, holding all other variables constant. The AIC value is 78.361, which is relatively low, indicating a good balance between model fit and complexity.

6.3.47 Logistic Regression of Product Familiarity#1 to Product Longevity for Game Controller#1

Table 6.51: Summary #7-5

Summary #7-5	Product: Game Controller#1
Independent Variable: Familarity#1(Familiar)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#1 - familiar vs. longevity
> logistic25.5 <- glm(df11.1$pl_gc1 ~ df11.1$pfm1_gc1, data=df11.1 , family =
binomial(logit))
> summary(logistic25.5)

Call:
glm(formula = df11.1$pl_gc1 ~ df11.1$pfm1_gc1, family = binomial(logit),
    data = df11.1)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.8698  -0.8698  -0.8620   1.5201   1.5460

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)     -0.84895    0.60173  -1.411    0.158
df11.1$pfm1_gc1  0.01435    0.14641   0.098    0.922

(Dispersion parameter for binomial family taken to be 1)
Null deviance: 151.35  on 121  degrees of freedom
Residual deviance: 151.34  on 120  degrees of freedom
AIC: 155.34

Number of Fisher Scoring iterations: 4
```

The p-value in Table 6.51 for this coefficient is not significant (0.922), which means that we cannot conclude with sufficient evidence that the relationship is statistically significant. The intercept coefficient is negative (-0.84895) but also not significant (p-value of 0.158), which indicates that the probability of keeping the product is not significantly different from zero when the is zero.

6.3.48 Logistic Regression of Product Familiarity#2 to Product Longevity for Game Controller#1

Table 6.52: Summary #7-6

Summary #7-6	Product: Game Controller#1
Independent Variable: Familarity#2(Remember)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#2 - remember vs. longevity
> logistic25.6 <- glm(df11.1$pl_gc1 ~ df11.1$pfm2_gc1, data=df11.1 , family =
binomial(logit))
> summary(logistic25.6)

Call:
glm(formula = df11.1$pl_gc1 ~ df11.1$pfm2_gc1, family = binomial(logit),
    data = df11.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.0905  -0.8304  -0.7535   1.3666   1.6720
Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.01855    0.54250   0.034    0.973
df11.1$pfm2_gc1 -0.22651    0.14363  -1.577    0.115

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 151.35  on 121  degrees of freedom
Residual deviance: 148.86  on 120  degrees of freedom
AIC: 152.86
```

The log odds of the probability of having a positive outcome in the pl_gc1 variable decreases by 0.22651 units for each unit increase in the pfm2_gc1 variable, holding all other variables constant. However, this relationship (Table 6.52) is not statistically significant, with a p-value of 0.115. The intercept term is also not statistically significant, with a p-value of 0.973, where pfm2_gc1 is product familarity#2.

6.3.49 Logistic Regression of Product Familiarity#3 to Product Longevity for Game Controller#1

Table 6.53: Summary #7-7

Summary #7-7	Product: Game Controller#1
Independent Variable: Familarity#3(Knowledge)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#3 - Knowledge vs. longevity
> logistic25.7 <- glm(df11.1$pl_gc1 ~ df11.1$pfm3_gc1, data=df11.1 , family =
binomial(logit))
> summary(logistic25.7)

Call:
glm(formula = df11.1$pl_gc1 ~ df11.1$pfm3_gc1, family = binomial(logit),
    data = df11.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.9218  -0.9218  -0.8465   1.4567   1.8266

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)      -1.6651     0.8657  -1.923   0.0544 .
df11.1$pfm3_gc1   0.2058     0.1967   1.046   0.2954
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 151.35  on 121  degrees of freedom
Residual deviance: 150.18  on 120  degrees of freedom
AIC: 154.18

Number of Fisher Scoring iterations: 4
```

The p-value for the coefficient in Table 6.53 is 0.2954, which is greater than 0.05, indicating that the coefficient is not statistically significant at the 5% significance level. The intercept coefficient is -1.6651, indicating that when the value of df11.1$pfm3_gc1 is 0, the odds of df11.1$pl_gc1 occurring is estimated to be exp(-1.6651) = 0.1897, holding all other variables constant. However, the p-value for the intercept coefficient is 0.0544, which is greater than 0.05 but very close to the threshold, so we might consider it marginally significant, where df11.1$pfm3_gc1 is product familarity#3 and df11.1$pl_gc1 is product longevity.

6.3.50 Logistic Regression of Visual Complexity to Product Longevity for Game Controller#2

Table 6.54: Summary #8-1

Summary #8-1	Product: Game Controller#1
Independent Variable: Visual Complexity	
Dependent Variable: Aesthetic Longevity	

```
> # complexity vs. longevity
> logistic29.1 <- glm(df12.1$pl_gc2 ~ df12.1$vc_gc2, data=df12.1 , family =
binomial(logit))
> summary(logistic29.1)

Call:
glm(formula = df12.1$pl_gc2 ~ df12.1$vc_gc2, family = binomial(logit),
    data = df12.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5694  -1.3671   0.9125   0.9989   1.1839

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -0.2408     0.6823  -0.353    0.724
df12.1$vc_gc2   0.2254     0.2005   1.124    0.261

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 161.67  on 121  degrees of freedom
Residual deviance: 160.39  on 120  degrees of freedom
AIC: 164.39

Number of Fisher Scoring iterations: 4
```

The coefficient for df12.1$vc_gc2 in Table 6.54 is positive (0.2254) but not statistically significant (p = 0.261), indicating that there may be some weak evidence of a positive association between df12.1$vc_gc2 and df12.1$pl_gc2, but it is not strong enough to reject the null hypothesis that the coefficient is equal to zero, where df12.1$vc_gc2 is visual complexity and df12.1$pl_gc2 is product longevity.

6.3.51 Logistic Regression of Visual Entropy to Product Longevity for Game Controller#2

Table 6.55: Summary #8-2

Summary #8-2	Product: Game Controller#2
Independent Variable: Visual Entropy	
Dependent Variable: Aesthetic Longevity	

```
> # Entropy vs. longevity
> logistic29.2 <- glm(df12.1$pl_gc2 ~ df12.1$ent_gc2, data=df12.1 , family =
binomial(logit))
> summary(logistic29.2)

Call:
glm(formula = df12.1$pl_gc2 ~ df12.1$ent_gc2, family = binomial(logit),
    data = df12.1)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6360  -1.3659   0.8857   1.0000   1.1218

Coefficients:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)     -0.4691     0.7686  -0.610    0.542
df12.1$ent_gc2   0.3006     0.2323   1.294    0.196

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 161.67  on 121  degrees of freedom
Residual deviance: 159.97  on 120  degrees of freedom
AIC: 163.97

Number of Fisher Scoring iterations: 4
```

The p-value for df12.1$ent_gc2 in Table 6.55 is 0.196, which is not significant at the 0.05 level, indicating that there is not strong evidence that df12.1$ent_gc2 has a significant effect on df12.1$pl_gc2, where df12.1$ent_gc2 is visual entropy and df12.1$pl_gc2 is product longevity. The intercept (or baseline value) is estimated to be -0.4691. It is not statistically significant at the conventional 0.05 significance level (p = 0.542). The coefficient for "ent_gc2" is estimated to be 0.3006, suggesting that as "ent_gc2" increases by one unit, the log-odds of "pl_gc2" increase by 0.3006. However, this coefficient is not statistically significant (p = 0.196). The deviance values measure the goodness of fit of the model. The null deviance represents the deviance when only the intercept is included in the model, while the residual deviance represents the deviance after including the independent variable. In this case, the residual deviance (159.97) is slightly lower than the null deviance (161.67), indicating a slight improvement in fit. The AIC value is a measure of the model's quality, considering both goodness of fit and model complexity. The AIC value of 163.97 indicates the trade-off between fit and complexity compared to other models.

6.3.52 Logistic Regression of Visual Interest to Product Longevity for Game Controller#2

Table 6.56: Summary #8-3

Summary #8-3	Product: Game Controller#2
Independent Variable: Visual Interest	
Dependent Variable: Aesthetic Longevity	

```
> # Interests vs. longevity
> logistic29.3 <- glm(df12.1$pl_gc2 ~ df12.1$vi_gc2, data=df12.1 , family = 
binomial(logit))
> summary(logistic29.3)

Call:
glm(formula = df12.1$pl_gc2 ~ df12.1$vi_gc2, family = binomial(logit), 
    data = df12.1)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-1.7716  -1.0071   0.3482   0.6833   1.8615  

Coefficients:
              Estimate Std. Error z value Pr(>|z|)    
(Intercept)    -4.4117     0.9496  -4.646 3.39e-06 ***
df12.1$vi_gc2   1.4369     0.2747   5.231 1.68e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 161.67  on 121  degrees of freedom
Residual deviance: 118.08  on 120  degrees of freedom
AIC: 122.08

Number of Fisher Scoring iterations: 4
```

The p-value for "vi_gc2" in Table 6.56 is very small (1.68e-07), indicating that the effect of "vi_gc2" on the response variable is statistically significant at the 5% level. The odds ratio for "vi_gc2" is 4.206, which means that for a one-unit increase in "vi_gc2", the odds of the response variable being 1 increase by a factor of 4.206, while holding all other variables constant. The output indicates that the model is a good fit to the data and that "vi_gc2" has a statistically significant effect on the response variable, with a positive coefficient indicating that higher values of "vi_gc2" are associated with higher odds of the response variable being 1, where vi_gc2 is visual interest. The odds ratio is exp (1.4369) = 4.206. This means that for a one-unit increase in "vi_gc2", the odds of the response variable being 1 increase by a factor of 4.206, while holding all other variables constant. Alternatively, we can say that the odds of the response variable being 1 are 4.206 times higher for every one-unit increase in "vi_gc2".

6.3.53 Logistic Regression of Product Preference to Product Longevity for Game Controller#2

Table 6.57: Summary #8-4

Summary #8-4	Product: Game Controller#2
Independent Variable: Product Preference	
Dependent Variable: Aesthetic Longevity	

```
> #Longevity vs. Product Preference
> logistic29.4 <- glm(df12.1$pl_gc2 ~ df12.1$pp_gc2, data=df12.1 , family =
binomial(logit))
> summary(logistic29.4)

Call:
glm(formula = df12.1$pl_gc2 ~ df12.1$pp_gc2, family = binomial(logit),
    data = df12.1)

Deviance Residuals:
   Min      1Q  Median      3Q     Max
-2.694  -0.541   0.232   0.557   2.716

Coefficients:  Estimate Std. Error z value Pr(>|z|)
(Intercept)    -5.4807     1.0912  -5.023 5.10e-07 ***
df12.1$pp_gc2   1.8164     0.3307   5.492 3.97e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 161.675  on 121  degrees of freedom
Residual deviance:  98.198  on 120  degrees of freedom
AIC: 102.2
Number of Fisher Scoring iterations: 5
```

The coefficient for df12.1$pp_gc2 in Table 6.57 is estimated to be 1.8164, with a standard error of 0.3307. The p-value for the coefficient is very small (3.97e-08), indicating that the coefficient is statistically significant. The output shows that the coefficient for df12.1$pp_gc2 is 1.8164, and its standard error is 0.3307.

The odds ratio = exp (1.8164) = 6.147. This means that for a one-unit increase in df12.1$pp_gc2, the odds of df12.1$pl_gc2 increase by a factor of 6.147, assuming all other variables in the model remain constant. For example, if we have two individuals, one with a value of df12.1$pp_gc2 of 0 and another with a value of df12.1$pp_gc2 of 1, the odds of the first individual having a positive value of the response variable are exp (-5.4807) = 0.004, while the odds of the second individual having a positive value of the response variable are exp (-5.4807 + 1.8164) = 0.021. This means that the odds of the second individual having a positive value of the response variable are approximately 5.4 times higher than the odds of the first individual having a positive value of the response variable.

6.3.54 Logistic Regression of Product Familiarity#1 to Product Longevity for Game Controller#2

Table 6.58: Summary #8-5

Summary #8-5	Product: Game Controller#2
Independent Variable: Familarity#1(Familiar)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#1 - familiar vs. longevity
> logistic29.5 <- glm(df12.1$pl_gc2 ~ df12.1$pfm1_gc2, data=df12.1 , family =
binomial(logit))
> summary(logistic29.5)

Call:
glm(formula = df12.1$pl_gc2 ~ df12.1$pfm1_gc2, family = binomial(logit),
    data = df12.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4575  -1.3746   0.9211   0.9923   1.0167
```

Table 6.58 (cont.)

```
Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.69967    0.45600   1.534    0.125
df12.1$pfm1_gc2 -0.06181    0.12946  -0.477    0.633

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 161.67  on 121  degrees of freedom
Residual deviance: 161.45  on 120  degrees of freedom
AIC: 165.45

Number of Fisher Scoring iterations: 4
```

The coefficient in Table 6.57 estimates for df12.1$pfm1_gc2 is -0.06181 with a standard error of 0.12946. The p-value for the coefficient is 0.633, which indicates that there is no statistically significant relationship between df12.1$pfm1_gc2 and df12.1$pl_gc2. The intercept estimate is 0.69967 with a p-value of 0.125, which is also not statistically significant.

6.3.55 Logistic Regression of Product Familiarity#2 to Product Longevity for Game Controller#2

Table 6.59: Summary #8-6

Summary #8-6	Product: Game Controller#2
Independent Variable: Familarity#2(Remember)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#2 - remember vs. longevity
> logistic29.6 <- glm(df12.1$pl_gc2 ~ df12.1$pfm2_gc2, data=df12.1 , family =
binomial(logit))
> summary(logistic29.6)
Call:
glm(formula = df12.1$pl_gc2 ~ df12.1$pfm2_gc2, family = binomial(logit),
    data = df12.1)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4530  -1.3713   0.9249   0.9951   1.0192
Coefficients:  Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.68885    0.43615   1.579    0.114
df12.1$pfm2_gc2 -0.06093    0.12787  -0.476    0.634
(Dispersion parameter for binomial family taken to be 1)
   Null deviance: 161.67  on 121  degrees of freedom
Residual deviance: 161.45  on 120  degrees of freedom
AIC: 165.45

Number of Fisher Scoring iterations: 4
```

The coefficient in Table 6.59 estimates for df12.1$pfm2_gc2 is -0.06093, which means that a one-unit increase in the predictor is associated with a decrease of 0.06093 units in the log-odds of the outcome. However, the p-value for this coefficient is 0.634, indicating that it is not statistically significant at the conventional level of 0.05. This suggests that there is no strong evidence to support a relationship between df12.1$pfm2_gc2 and df12.1$pl_gc2 in this model.

6.3.56 Logistic Regression of Product Familiarity#3 to Product Longevity for Game Controller#2

Table 6.60: Summary #8-7

Summary #8-7	Product: Game Controller#2
Independent Variable: Familarity#3(Knowledge)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#3 - Knowledge vs. longevity
> logistic29.7 <- glm(df12.1$pl_gc2 ~ df12.1$pfm3_gc2, data=df12.1 , family =
binomial(logit))
> summary(logistic29.7)

Call:
glm(formula = df12.1$pl_gc2 ~ df12.1$pfm3_gc2, family = binomial(logit),
    data = df12.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4291  -1.3978   0.9451   0.9719   1.0551

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.22480    0.64269    0.35    0.727
df12.1$pfm3_gc2  0.06996    0.15555    0.45    0.653

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 161.67  on 121  degrees of freedom
Residual deviance: 161.47  on 120  degrees of freedom
AIC: 165.47

Number of Fisher Scoring iterations: 4
```

The coefficient for pfm3_gc2 in Table 6.60 is 0.06996 with a standard error of 0.15555 and a p-value of 0.653. This means that for a one-unit increase in pfm3_gc2, the log-odds of pl_gc2 is estimated to increase by 0.06996. However, neither of the coefficients are statistically significant at the conventional level of 0.05, based on their p-values. Therefore, we cannot conclude that there is a statistically significant relationship between pl_gc2 and pfm3_gc2 in this model.

6.3.57 Logistic Regression of Visual Complexity to Product Longevity for Game Controller#3

Table 6.61: Summary #9-1

Summary #9-1	Product: Game Controller#3
Independent Variable: Visual Complexity	
Dependent Variable: Aesthetic Longevity	

```
> # complexity vs. longevity
> logistic33.1 <- glm(df13.1$pl_gc3 ~ df13.1$vc_gc3, data=df13.1 , family =
binomial(logit))
> summary(logistic33.1)

Call:
glm(formula = df13.1$pl_gc3 ~ df13.1$vc_gc3, family = binomial(logit),
    data = df13.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4053  -1.3801   0.9655   0.9874   1.0548

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.57772    0.44665   1.293    0.196
df13.1$vc_gc3 -0.05644    0.20708  -0.273    0.785

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 162.64  on 121  degrees of freedom
Residual deviance: 162.57  on 120  degrees of freedom
AIC: 166.57

Number of Fisher Scoring iterations: 4
```

The coefficients of the model in Table 6.61 indicate the relationship between the response and predictor variables. The intercept term is 0.57772 and the coefficient for df13.1$vc_gc3 is -0.05644. A negative coefficient indicates that as the value of the predictor variable increases, the probability of the response variable decreases.

The p-value for df13.1$vc_gc3 is 0.785, which is not significant at the conventional alpha level of 0.05.

6.3.58 Logistic Regression of Visual Entropy to Product Longevity for Game Controller#3

Table 6.62: Summary #9-2

Summary #9-2	Product: Game Controller#3
Independent Variable: Visual Entropy	
Dependent Variable: Aesthetic Longevity	

```
> # Entropy vs. longevity
> logistic33.2 <- glm(df13.1$pl_gc3 ~ df13.1$ent_gc3, data=df13.1 , family =
binomial(logit))
> summary(logistic33.2)

Call:
glm(formula = df13.1$pl_gc3 ~ df13.1$ent_gc3, family = binomial(logit),
    data = df13.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5373  -1.3808   0.9200   0.9868   1.0561

Coefficients:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.1179     0.5375   0.219    0.826
df13.1$ent_gc3   0.1743     0.2530   0.689    0.491

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 162.64  on 121  degrees of freedom
Residual deviance: 162.16  on 120  degrees of freedom
AIC: 166.16

Number of Fisher Scoring iterations: 4
```

The coefficients of the model in Table 6.62 indicate the relationship between the response and predictor variables. The intercept term is 0.1179 and the coefficient for df13.1$ent_gc3 is 0.1743. A positive coefficient indicates that as the value of the predictor variable increases, the probability of the response variable also increases.

The standard errors and p-values associated with each coefficient provide information on the statistical significance of the coefficients. In this case, the p-value for df13.1$ent_gc3 is 0.491, which is not significant at the conventional alpha level of 0.05, where df13.1$ent_gc3 is visual entropy for game controller#3.

6.3.59 Logistic Regression of Visual Interest to Product Longevity for Game Controller#3

Table 6.62: Summary #9-3

Summary #9-3	Product: Game Controller#3
Independent Variable: Visual Interest	
Dependent Variable: Aesthetic Longevity	

```
> # Interests vs. longevity
> logistic33.3 <- glm(df13.1$pl_gc3 ~ df13.1$vi_gc3, data=df13.1 , family =
binomial(logit))
> summary(logistic33.3)

Call:
glm(formula = df13.1$pl_gc3 ~ df13.1$vi_gc3, family = binomial(logit),
    data = df13.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.0293  -1.0703   0.7270   0.9857   1.6134

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -1.7104     0.5806  -2.946 0.003221 **
df13.1$vi_gc3   0.7266     0.1872   3.882 0.000104 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 162.64  on 121  degrees of freedom
Residual deviance: 145.00  on 120  degrees of freedom
AIC: 149

Number of Fisher Scoring iterations: 4
```

The coefficients of the model in Table 6.62 indicate the relationship between the response and predictor variables. The intercept term is -1.7104 and the coefficient for df13.1$vi_gc3 is 0.7266. A positive coefficient indicates that as the value of the predictor variable increases, the probability of the response variable also increases, where df13.1$vi_gc3 is visual interest. The standard errors and p-values associated with each coefficient provide information on the statistical significance of the coefficients. In this case, both the intercept and df13.1$vi_gc3 coefficient have significant p-values, indicated by the '***' signif. codes, at the conventional alpha level of 0.05. This means that both the intercept and the coefficient for df13.1$vi_gc3 are statistically significant predictors of the response variable. The AIC value is 149, which is the lowest among the three models, indicating that this model may be the best fit for the data. The odds of pl_gc3 increase by a factor of exp(0.7266) = 2.07 for each unit increase in vi_gc3, holding all other variables constant. In other words, the odds of the outcome variable pl_gc3 are 2.07 times higher for each unit increase in the predictor variable vi_gc3. The p-value of the predictor variable vi_gc3 is less than 0.05, indicating that it is statistically significant in predicting the outcome variable pl_gc3.

6.3.60 Logistic Regression of Product preference to Product Longevity for Game Controller#3

Table 6.64: Summary #9-4

Summary #9-4	Product: Game Controller#3
Independent Variable: Product Preference	
Dependent Variable: Aesthetic Longevity	

```
> # Product Preference vs. longevity
> logistic33.4 <- glm(df13.1$pl_gc3 ~ df13.1$pp_gc3, data=df13.1 , family =
binomial(logit))
> summary(logistic33.4)
Call:
glm(formula = df13.1$pl_gc3 ~ df13.1$pp_gc3, family = binomial(logit),
   data = df13.1)
Deviance Residuals:
   Min       1Q   Median      3Q      Max
-2.0842  -0.9346   0.7364   0.7364   1.8387
Coefficients:  Estimate Std. Error z value Pr(>|z|)
(Intercept)    -2.3710     0.7010  -3.382 0.000719 ***
df13.1$pp_gc3   0.8844     0.2114   4.183 2.88e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
   Null deviance: 162.64  on 121  degrees of freedom
Residual deviance: 140.84  on 120  degrees of freedom
AIC: 144.84
Number of Fisher Scoring iterations: 4
```

The coefficient in Table 6.64 estimate of product preference pp_gc3 is 0.8844, with a standard error of 0.2114. The p-value associated with the coefficient estimate is less than 0.05 ($p < 0.001$), which suggests that the predictor variable pp_gc3 is statistically significant in predicting the outcome variable pl_gc3. For each unit increase in product preference, the odds of having high longevity increase by exp(0.8844) = 2.42 times, holding all other variables constant. This means that individuals with a higher product preference are more likely to have high longevity compared to those with lower product preference.

6.3.61 Logistic Regression of Product Familiarity#1 to Product Longevity for Game Controller#3

Table 6.65: Summary #9-5

Summary #9-5	Product: Game Controller#3
Independent Variable: Familarity#1(Familiar)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#1 - familiar vs. longevity
> logistic33.5 <- glm(df13.1$pl_gc3 ~ df13.1$pfm1_gc3, data=df13.1 , family =
binomial(logit))
> summary(logistic33.5)

Call:
glm(formula = df13.1$pl_gc3 ~ df13.1$pfm1_gc3, family = binomial(logit),
 data = df13.1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4639  -1.3056   0.9157   0.9157   1.5172

Coefficients: Estimate Std. Error z value Pr(>|z|)
(Intercept)      -1.1265     0.9023  -1.248    0.212
df13.1$pfm1_gc3   0.3558     0.1971   1.805    0.071 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 162.64  on 121  degrees of freedom
Residual deviance: 159.27  on 120  degrees of freedom
AIC: 163.27

Number of Fisher Scoring iterations: 4
```

The coefficient for df13.1$pfm1_gc3in Table 6.65 is 0.3558, which means that for a one-unit increase in df13.1$pfm1_gc3, the log-odds of df13.1$pl_gc3 increases by 0.3558, where df13.1$pfm1_gc3 is product preference for game controller#3. The p-value associated with df13.1$pfm1_gc3 is 0.071, which is greater than the commonly used threshold of 0.05, suggesting that the association between df13.1$pfm1_gc3 and df13.1$pl_gc3 may not be statistically significant.

6.3.62 Logistic Regression of Product Familiarity#2 to Product Longevity for Game Controller#3

Table 6.66: Summary #9-6

Summary #9-6	Product: Game Controller#3
Independent Variable: Familarity#2(Remember)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#2 - remember vs. longevity
> logistic33.6 <- glm(df13.1$pl_gc3 ~ df13.1$pfm2_gc3, data=df13.1 , family =
binomial(logit))
> summary(logistic33.6)

Call:
glm(formula = df13.1$pl_gc3 ~ df13.1$pfm2_gc3, family = binomial(logit),
    data = df13.1)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4308  -1.3564   0.9436   0.9436   1.2155

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)      -0.2560     0.7679  -0.333    0.739
df13.1$pfm2_gc3   0.1669     0.1724   0.968    0.333

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 162.64  on 121  degrees of freedom
Residual deviance: 161.71  on 120  degrees of freedom
AIC: 165.71

Number of Fisher Scoring iterations: 4
```

The estimated coefficient for df13.1$pfm2_gc3 in Table 6.66 is 0.1669, which means that for a one-unit increase in df13.1$pfm2_gc3, the log odds of df13.1$pl_gc3 increase by 0.1669, holding all other variables constant. However, the p-value associated with this coefficient is 0.333, which is not statistically significant at the 0.05 level, where df13.1$pfm2_gc3 is product familarity#2 and df13.1$pl_gc3 is product longevity.

6.3.63 Logistic Regression of Product Familiarity#3 to Product Longevity for Game Controller#3

Table 6.67: summary #9-7

Summary #9-7	Product: Game Controller#3
Independent Variable: Familarity#3(Knowledge)	
Dependent Variable: Aesthetic Longevity	

```
> # Product familairity#3 - Knowledge vs. longevity
> logistic33.7 <- glm(df13.1$pl_gc3 ~ df13.1$pfm3_gc3, data=df13.1 , family =
binomial(logit))
> summary(logistic33.7)

Call:
glm(formula = df13.1$pl_gc3 ~ df13.1$pfm3_gc3, family = binomial(logit),
data = df13.1)

Deviance Residuals:
Min       1Q   Median      3Q      Max
-1.4621  -1.3485   0.9173   0.9173   1.3382

Coefficients:
Estimate Std. Error z value Pr(>|z|)
(Intercept)      -0.6249     0.8052  -0.776     0.438
df13.1$pfm3_gc3   0.2546     0.1831   1.391     0.164

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 162.64  on 121  degrees of freedom
Residual deviance: 160.69  on 120  degrees of freedom
AIC: 164.69

Number of Fisher Scoring iterations: 4
```

The estimated coefficient for pfm3_gc3in Table 6.67 is 0.2546 with a standard error of 0.1831. The z-value is 1.391 and the p-value is 0.164, which is not statistically significant at the 5% level. This indicates that there is no significant association between pfm3_gc3 and the probability of pl_gc3, where pfm3_gc3 is product familiarity#3 and pl_gc3 is product longevity. The intercept term has an estimated coefficient of -0.6249 with a standard error of 0.8052, which is not statistically significant at the 5% level. Therefore, we can conclude that there is no significant association between pfm3_gc3 and pl_gc3, based on this model.

CHAPTER 7: ANALYSIS

7.1 Analysis of Product Samples

Based on the collected data and analysis conducted using the R programming language, I was able to calculate the mean values for each variable. The means provided insights into how participants perceived the complexity of different speakers, wristwatches, and game controllers. For the speakers, the mean values indicated that participants considered speaker #1 to have a complex design. Speaker #2 was perceived as having a design that was neutral or mixed, falling somewhere between complex and simple. Speaker #3, on the other hand, was seen as having a simple design. Similarly, the analysis of the wristwatches and game controllers revealed a similar pattern. For the wristwatches, wristwatch #1 was considered to have a complex design, while wristwatch #2 was perceived as having a design that was neutral or mixed between complex and simple. Wristwatch #3, like speaker #3, was seen as having a simple design. The same pattern was observed for the game controllers, where the participants perceived controller #1 as complex in design, controller #2 as neutral or mixed, and controller #3 as simple in design. These findings suggest that participants consistently associated certain designs with different levels of complexity across the speakers, wristwatches, and game controllers. The specific variables and metrics used to determine complexity are not mentioned in the provided information, but the mean values helped reveal the overall trend in participants' perceptions.

I performed logistic regression analyses of the field experiment that was approved by IRB using the R programming language to examine the relationship between several variables and product longevity. The variables included visual complexity, visual interest, visual preference, visual entropy, and familiarity.

After running the logistic regression, I found that two variables, namely visual interest and product preference, were determined to be statistically significant in relation to product longevity and a created a table based on regression analysis by the R package from the result in the previous chapter. Please, see the table 7.1 below.

Table 7.1: P-value for visual interest and product preference from regression analysis

Product Samples		**P-value for Visual Interest**	**P-value for Product Preference**
Speaker# 1		4.54e-06 *** 3.37e-05 ***	1.23e-09 *** 5.10e-09 ***
Speaker#2		1.48e-07 *** 2.55e-08 ***	4.82e-08 *** 1.73e-08 ***
Speaker#3		1.48e-07 *** 2.55e-08 ***	4.82e-08 *** 1.73e-08 ***
Wrist watch#1		2.74e-07 *** 2.48e-06 ***	4.26e-08 *** 1.60e-07 ***
Wrist watch#2		2.29e-07 *** 3.30e-08 ***	6.86e-08 *** 1.59e-08 ***
Wrist watch#3		6.06e-05 *** 3.66e-06 ***	1.26e-06 *** 8.52e-08 ***
Game Controller #1		1.03e-07 *** 5.49e-07 ***	8.45e-09 *** 9.14e-09 ***
Game Controller #2		3.39e-06 *** 1.68e-07 ***	10e-07 *** 3.97e-08 ***
Game Controller#3		0.003221 ** 0.000104 ***	0.000719 *** 2.88e-05 ***

This means that these two variables have a meaningful impact on the likelihood of a product's longevity. The logistic regression analysis helps to assess the association between the independent variables (visual complexity, visual interest, visual preference, visual entropy, and familiarity) and the dependent variable (product longevity). By determining which variables are statistically significant, you can identify the specific factors that influence the longevity of a product. It is important to note that logistic regression provides information about the probability of an outcome, in this case, product longevity, based on the values of the independent variables. The statistical significance of visual interest and visual preference suggests that these two variables have a significant influence on the likelihood of a product having a longer lifespan.

Calculating the odds ratio for the variables visual interest and visual preference in the context of the logistic regression analysis can provide valuable insights. The odds ratio measures the strength and direction of the association between these variables and the likelihood of product longevity. The odds ratio represents the ratio of the odds of an event occurring between two groups with different values of the independent variable. In logistic regression, it helps us understand how the presence or absence of a particular variable affects the odds of the product's longevity.

When interpreting the odds ratio, it is important to consider whether the value is above or below 1. If the odds ratio is greater than 1, it indicates a positive association. In this case, an increase in the values of visual interest or visual preference would be associated with an increased likelihood of product longevity. Conversely, if the odds ratio is less than 1, it suggests a negative association. This means that higher values of visual interest or visual preference would be associated with a decreased likelihood of product longevity. An odds ratio of 0.5, for instance, would imply that the odds of product longevity are 50% lower for individuals with higher visual interest or visual preference compared to those with lower values. Additionally, the magnitude of the odds ratio provides information about the strength of the association. A larger odds ratio signifies a stronger relationship between the variables and the outcome.

By considering the calculated odds ratio for visual interest and visual preference (Table 7.2), we can gain meaningful insights into the specific impact these variables have on product longevity.

Table 7.2: Odds ratio for visual interest and product preference

Speaker #1	**Odds Ratio**
Visual Interest	Exp (0.6553) = 1.924
Product Preference	Exp (1.4281) = 4.174

It suggests that both visual interest and visual preference have a positive association with product longevity. For visual interest with an odds ratio of 1.924, higher values of visual interest are associated with approximately 1.924 times higher odds of product longevity. This indicates that an increased level of visual interest in a product makes it more likely to have a longer lifespan. Similarly, for visual preference with an odds ratio of 4.174, higher values of visual preference are associated with approximately 4.174 times higher odds of product longevity. This suggests that when individuals have a stronger preference for the visual aspects of a product, it significantly increases the likelihood of that product having a longer lifespan. Both odds ratios being greater than 1 indicate positive associations, suggesting that higher levels of visual interest and visual preference contribute to a greater probability of product longevity. Therefore, the odds ratio of 1.924 for visual interest and 4.174 for visual preference indicate a positive and statistically significant relationship with product longevity. Both variables play a meaningful role in influencing the likelihood of a product having a longer lifespan, highlighting the importance of considering visual appeal and preference in product design.

Table 7.3: Odds ratio for speaker #1, #2, & #3

Product Sample Unit	**Odds Ratios**	
	Product Longevity to Product Preference	**Product Longevity to Visual Interest**
Speaker#1	exp(1.4281) = 4.174	exp(0.6553) = 1.924
Speaker#2	exp(2.3405) = 10.386	exp(1.8956) = 6.656
Speaker#3	exp(1.7849) = 5.97	exp(1.5088) = 4.519

The analysis in Table 7.3 for the set of speakers and the set of wristwatches conducted on visual interest and product preference for the set of speakers (Speakers #1, #2, and #3) revealed intriguing insights.

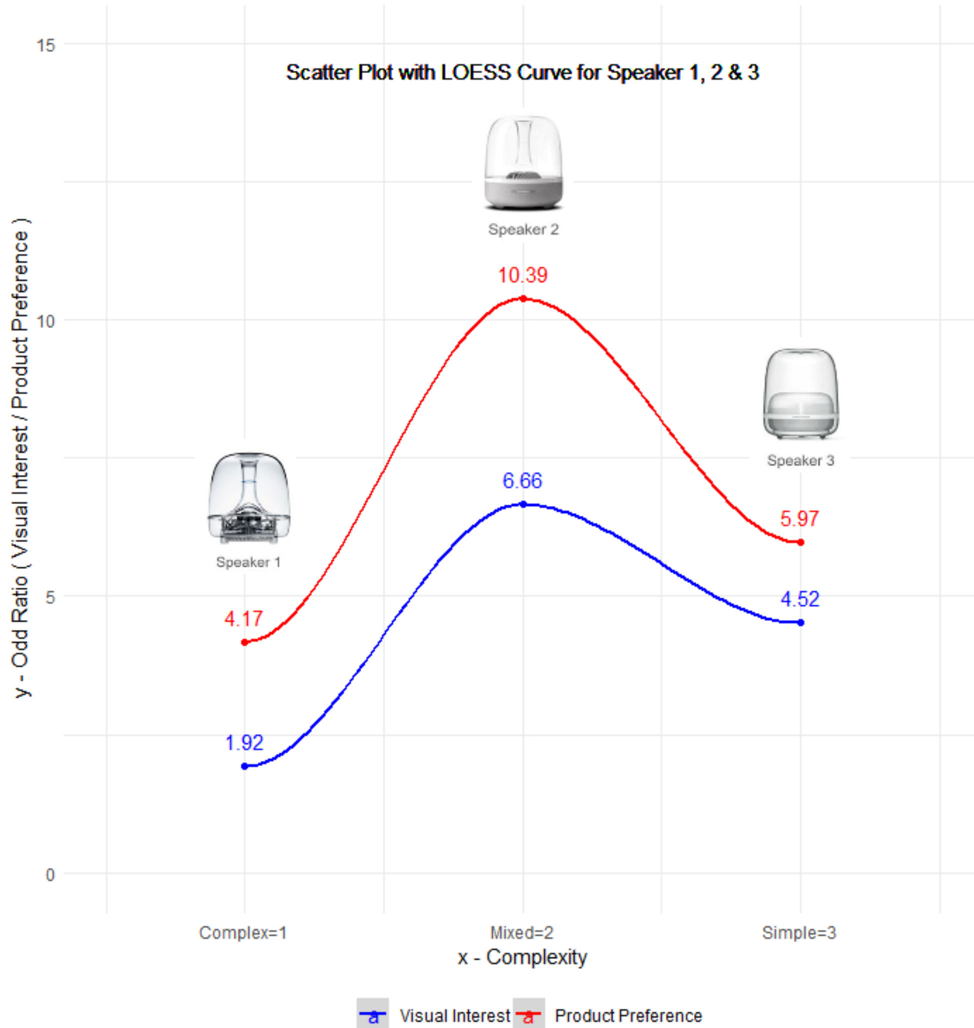


Figure 7.1: Loess curve for speaker #1, #2, & #3

The odds ratios calculated for these speakers were 1.92 for complex design, 6.66 for mixed design, and 4.52 for simple design in relation to product longevity (Figure 7.1). Surprisingly, the relationship between visual interest and product longevity displayed an upside-down U shape, resembling D. E. Berlyne's proposed curve regarding the relationship between complexity and interest. D. E. Berlyne was a research psychologist known for his research in aesthetics and the psychology of art. He put forth a theoretical framework suggesting a curvilinear relationship between stimulus complexity and the level of interest and preference it elicits. According to

Berlyne's curve, interest tends to increase as the stimulus becomes more complex up to a certain point, after which interest begins to decline. It is important to note that Berlyne's curve was originally established with 2D patterns, while this study focused on 3D products and introduced an additional variable, namely product longevity. This adds complexity to the analysis and highlights the nuances of the relationship between visual interest, complexity, and preference. Interestingly, the study revealed a lower odds ratio for complex and simple design and a higher odds ratio for simple and complex mixed design. Participants expressed a strong desire to keep the product for 10 years when they perceived mixed elements that combined complexity and simplicity. This finding challenges the general perception that has emerged recently, which tends to favor simple designs. In other words, a simple design may not necessarily be desirable for aesthetic longevity in this particular context.

Table 7.4: Odds ratio for wristwatch #1, #2, & #3

Product Sample Unit	**Odds Ratios**	
	Product Longevity to Product Preference	**Product Longevity to Visual Interest**
Wristwatch#1	exp (1.6759) = 5.346	exp (1.2033) = 3.33
Wristwatch#2	exp (2.8911) = 18.0527	exp (1.9199) = 6.828
Wristwatch#3	exp(1.4387) = 4.21	exp (0.9409) = 2.56

A set of wristwatches in Table 7.4 shows a similar result of odds ratio between product longevity and visual interest and between product longevity and product preference as the result of a set of speakers. However, the wristwatch that has mixed design between complex and simple shows a significantly higher odds ratio in product preference. The mixed design for wristwatches has the odds ratio of 18.05, whereas the complex design for the wristwatch has 5.97 (Figure 7.2).

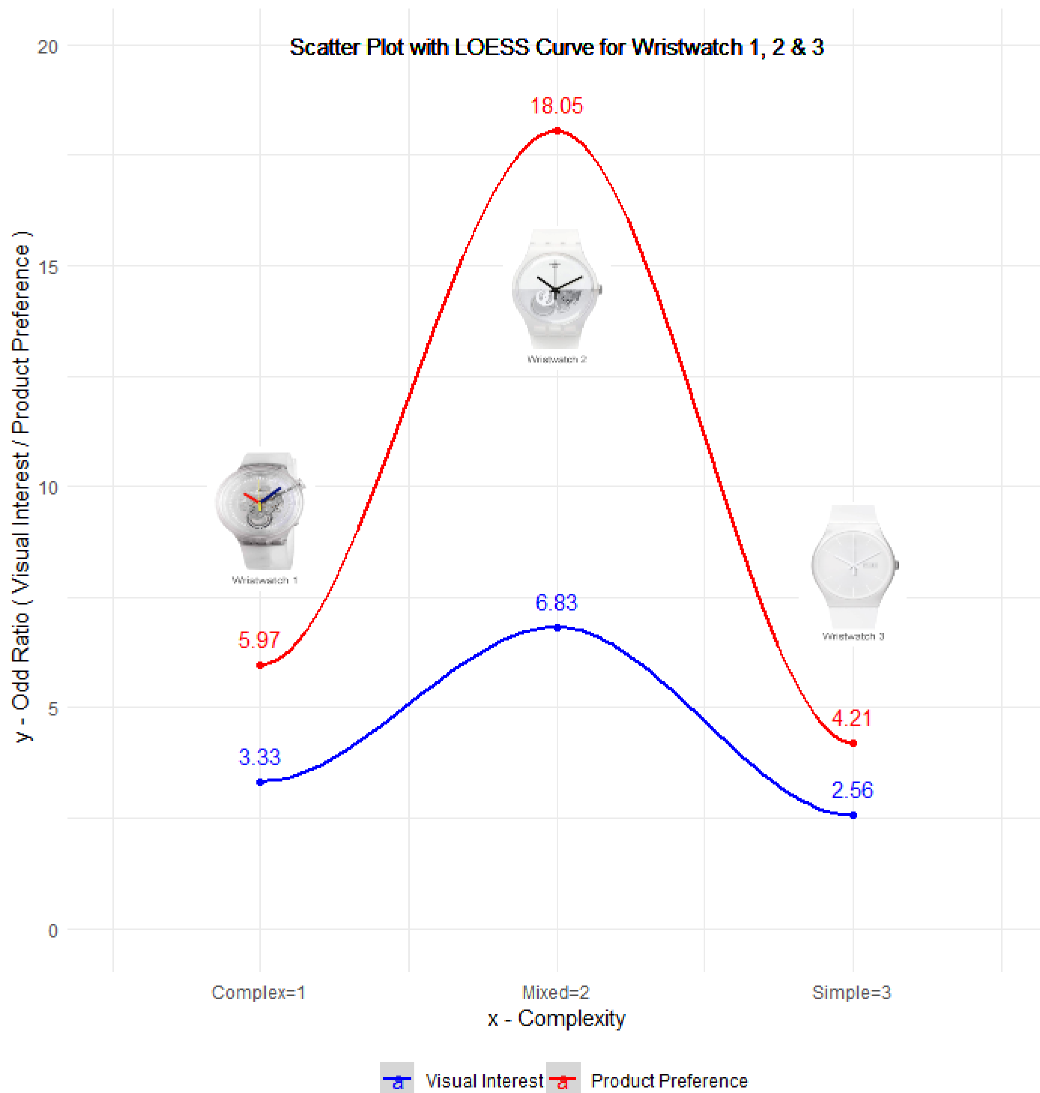


Figure 7.2 : Loess curves for wristwatches #1, #2, & #3

The odds ratio between product longevity and visual interest was similar for both the wristwatches and the speakers, indicating that participants do not necessarily prefer a product solely based on its longevity or visual appeal. However, the odds ratio between product longevity and product preference was also similar for both the wristwatches and the speakers, suggesting that consumers do value longevity when making a purchase decision. The significant difference in odds ratio between the mixed design and complex design wristwatches in terms of product preference indicates that design is a crucial factor in the participants' preference. The mixed design wristwatch was significantly more preferred than the complex design wristwatch, suggesting that consumers prefer a balanced mix of complexity and simplicity in product design. This finding is consistent with previous results from a set of speakers that has shown that consumers tend to prefer products with a moderate level of complexity that are easy to use and understand. A mixed design approach can help to achieve this balance and make a product more appealing to consumers. The study provides valuable insights into the factors that influence consumer preferences in product design. While product longevity and visual interest are important factors, a mixed design approach that balances complexity and simplicity may be the key to achieving higher product preference among consumers.

Table 7.5: Odds ratio for game controller #1, #2, & #3

Product Sample Unit	**Odds Ratios**	
	Product Longevity to Product Preference	**Product Longevity to Visual Interest**
Wristwatch#1	exp (2.1838) = 8.876	exp (1.2254) = 3.408
Wristwatch#2	exp (1.8164) = 6.149	exp (1.4369) = 4.206
Wristwatch#3	exp (0.8844) = 2.42	exp (0.7266) = 2.07

The study in Table 7.5 collected data on the odds ratios of visual interest for three game controllers and three wristwatches. The results showed that the odds ratios of visual interest for both the game controllers and wristwatches were relatively similar. However, participants showed a stronger visual preference for complex designs than simple designs for both products.

Specifically, the odds ratio of visual interest for game controllers #1, #2, and #3 were 3.41, 4.21, and 2.07, respectively, while the odds ratios of visual interest for wristwatches were 3.33, 6.83, and 2.56 (Figure 7.3).

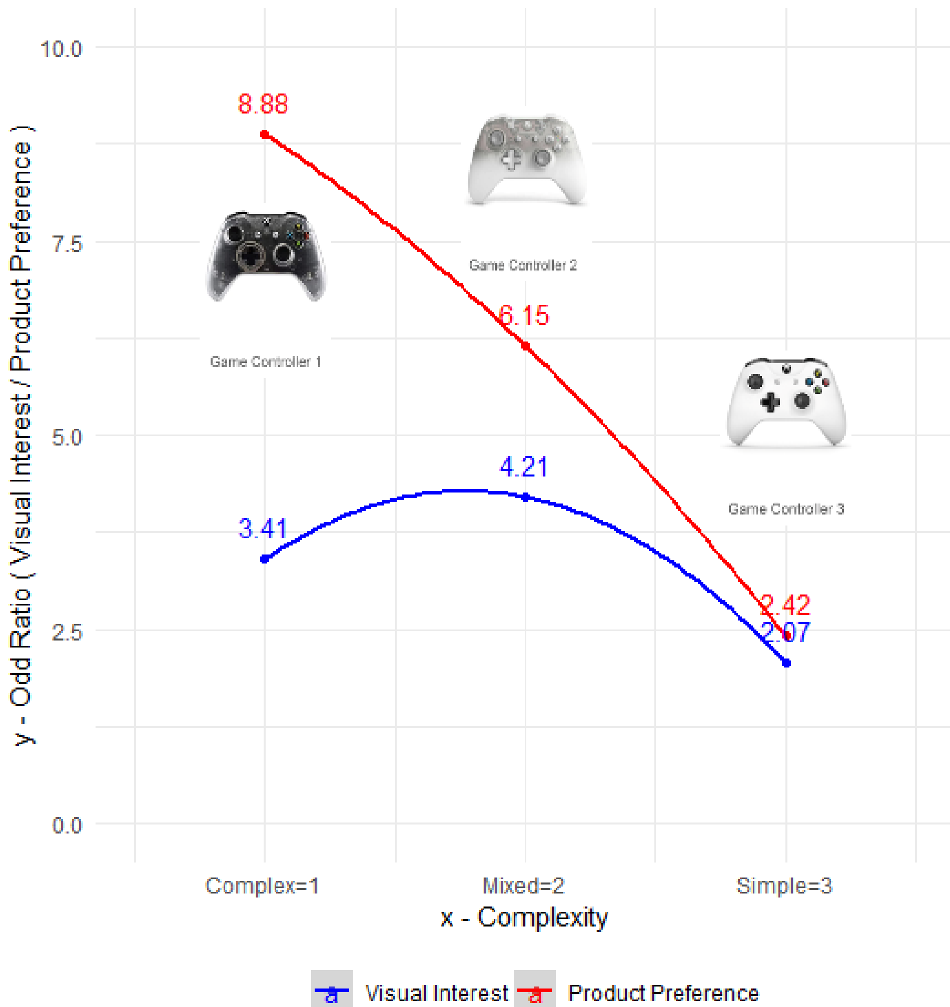


Figure 7.3: Loess curves for game controllers #1, #2, & #3

This finding is counterintuitive since minimalist and simple designs are often considered mainstream and popular. It suggests that consumers may be seeking out unique and intricate designs that stand out from the norm. This could have important implications for product designers, as they may need to consider incorporating more complex and visually appealing elements into their designs in order to appeal to consumers.

The study also found an interesting inverse relationship between product preference and complex design for game controllers. The game controller with a complex design had the highest odds ratio for product preference, while the one with a simple design had the lowest. This suggests that consumers may be willing to sacrifice simplicity for a more aesthetically pleasing and unique design when it comes to product longevity.

The study also found that complex designs were associated with higher product longevity for the game controllers. The game controller with a complex design had the highest odds ratio for product longevity, indicating that consumers may be willing to keep a complex design game controller for a longer time. In addition to the findings above, the intricate design of a game controller may potentially demonstrate the user's level of experience and higher skill sets, which could be a desirable trait for some consumers. As such, game controllers with more complex designs may be viewed as status symbols among avid gamers. Therefore, a game controller with a unique and intricate design could not only satisfy consumers' visual preferences but also serve as a long-term investment in terms of signaling their gaming abilities.

7.2 Proximity and Frequency of Interaction

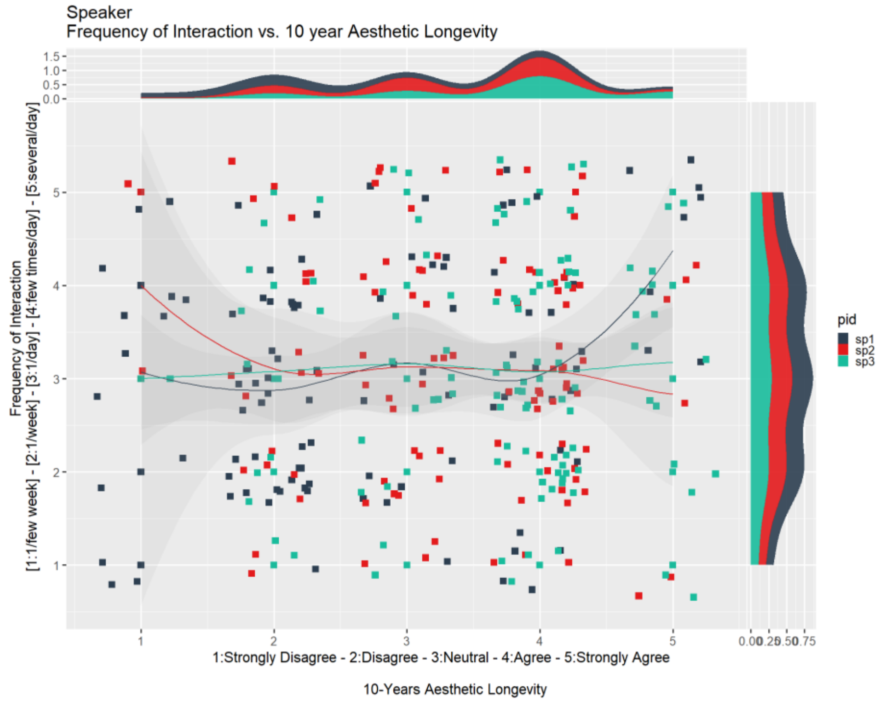


Figure 7.4: Frequency of interaction vs. 10 year aesthetic longevity

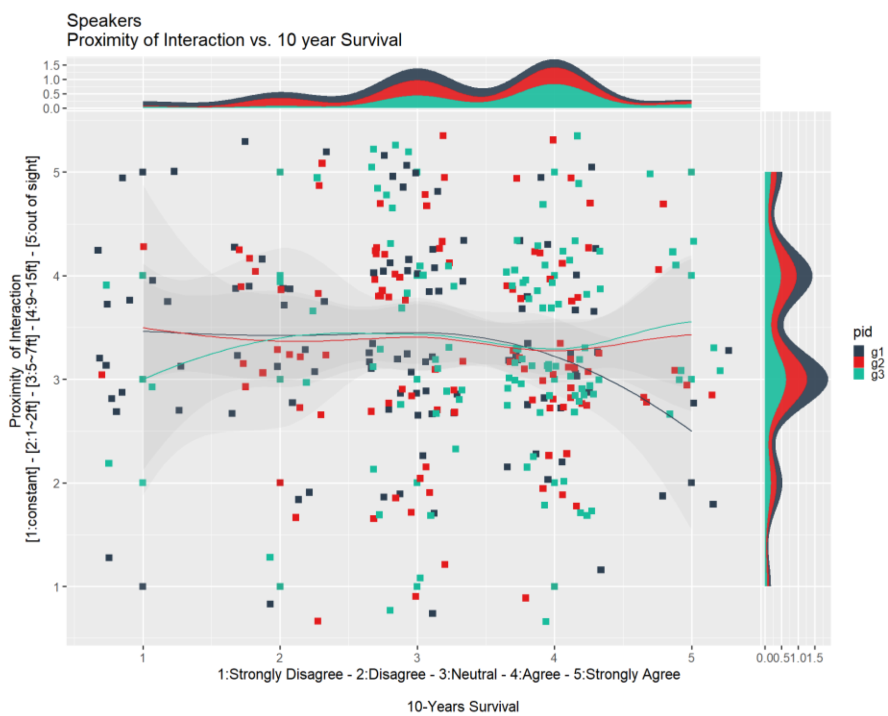


Figure 7.5: Proximity of interaction vs. 10 year aesthetic longevity

One of the goals of this study was to investigate the relationship between the frequency of interaction and product longevity (i.e., the ability of a product to last for ten years) by asking participants about their usage and intention to keep the product for the next ten years (Figure 7.4). This study is among the participants who would want to keep and use the speaker for the next 10 years and visualized the data by using the marginal distribution method. The data shows that the highest density of responses for the frequency of interaction is at level 3, which means "once a day." The highest density of responses for product longevity is at level 4, which means "agree," indicating that most participants intend to keep the product for ten years. However, the frequency of interaction for product id 2 and 3 is distributed relatively evenly between level 2 (once a week) and level 4 (a few times a day), while the frequency of interaction for pid sp1 is concentrated at level 3 (once a day). This suggests that different products may have different usage patterns that could impact their longevity. Regarding the proximity of interactions (Figure 7.5), the highest density of responses for all three speakers is at level 3, indicating that participants would like to place the speakers 5ft. to 7ft. away. The second-highest density of responses is at level 4, indicating that participants would also consider placing the speakers 9ft. to 15ft. away. The study shows that the 5ft ~15ft is the proximity of interaction between users and products that feels comfortable and could impact on their longevity. Specifically, products that are closer to the users may have a higher chance of survival than those that are far away.

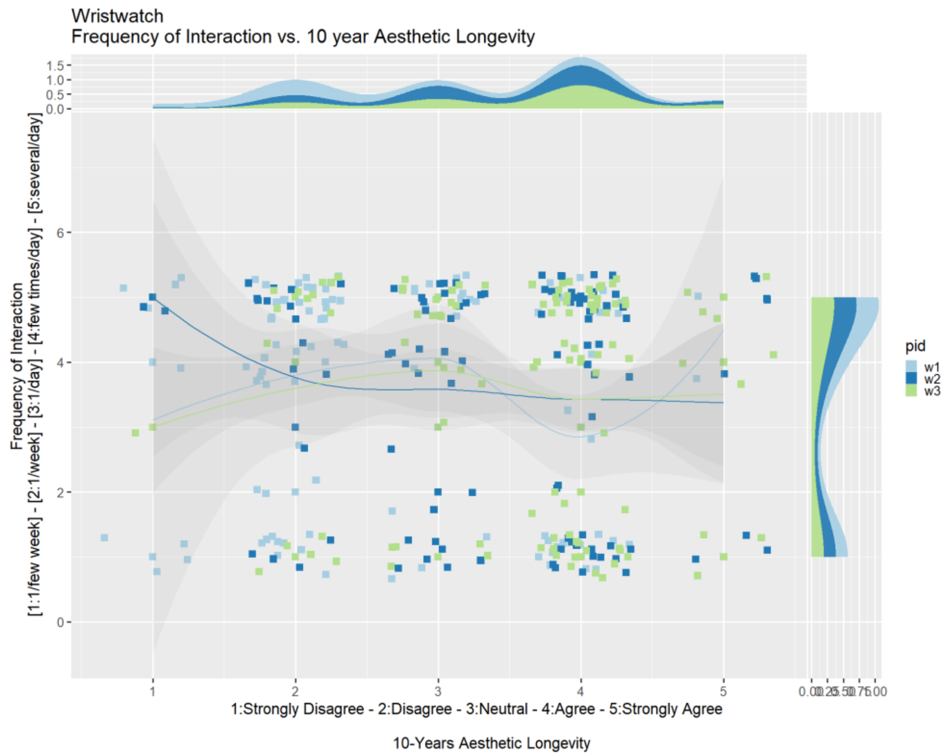


Figure 7.6: Frequency of interaction vs. 10 year aesthetic longevity

This study is among the participants who would want to keep and use the wristwatch for the next 10 years. The participants show clear indications to retain the next ten years on a set of wristwatches since it is considered to be a personal item. Most participants expressed that frequency of interaction is either level 5 – that is several times a day – or level 1– that is once every few weeks (Figure 7.6). It means that there are two types of users for the wristwatch: participants who answered “several times a day” would consider the wristwatch as a functional item, whereas participants who answered as once every few weeks consider the wristwatch as a decorative item.

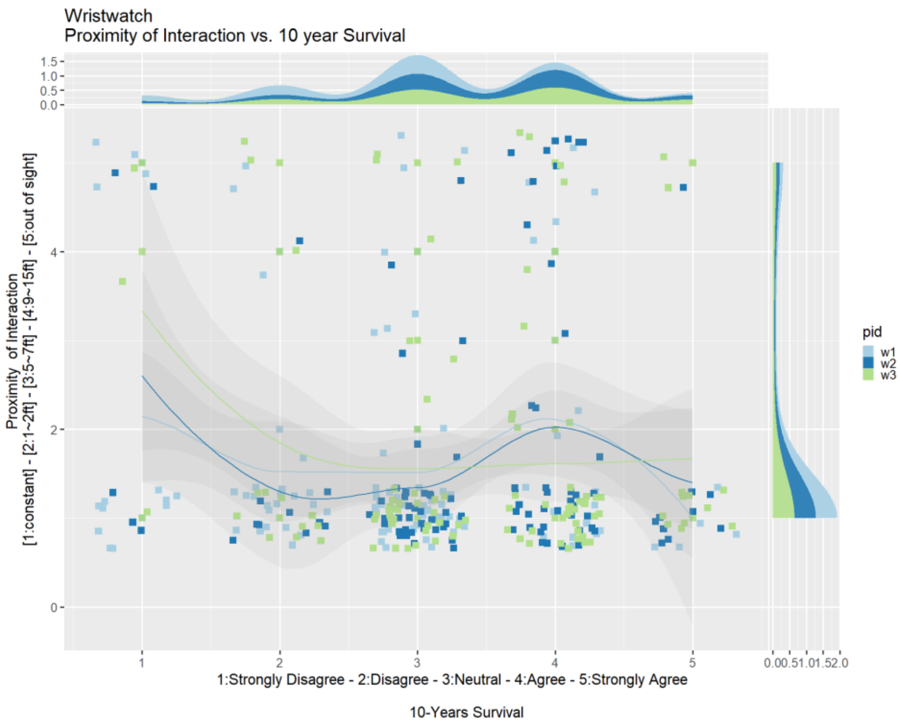


Figure 7.7: Proximity of interaction vs. 10 year aesthetic longevity

The study found that among the participants who indicated their intention to keep and use the product for the next 10 years (level 4), the highest density of responses for proximity of interaction was at level 1, which means "constant." This suggests that participants who are most committed to using and keeping the product for a long time also prefer a closer proximity of interaction with the product (Figure 7.7). The finding that smaller proximity has a higher impact on product longevity could be explained by several factors. First, a closer proximity of interaction may mean that the product is more accessible and easier to use, which could lead to more frequent usage and less wear and tear on the product. Second, closer proximity may also allow users to better maintain and care for the product, which could extend its lifespan. Finally, a closer proximity of interaction may also mean that the product is more integrated into the user's daily life, which could increase its perceived value and encourage users to keep it for a longer period of time. Overall, the study suggests that proximity of interaction is an important factor in product longevity, and that designers should consider the preferences of users who intend to keep and use the product for a long time when designing the product's physical interaction with users.

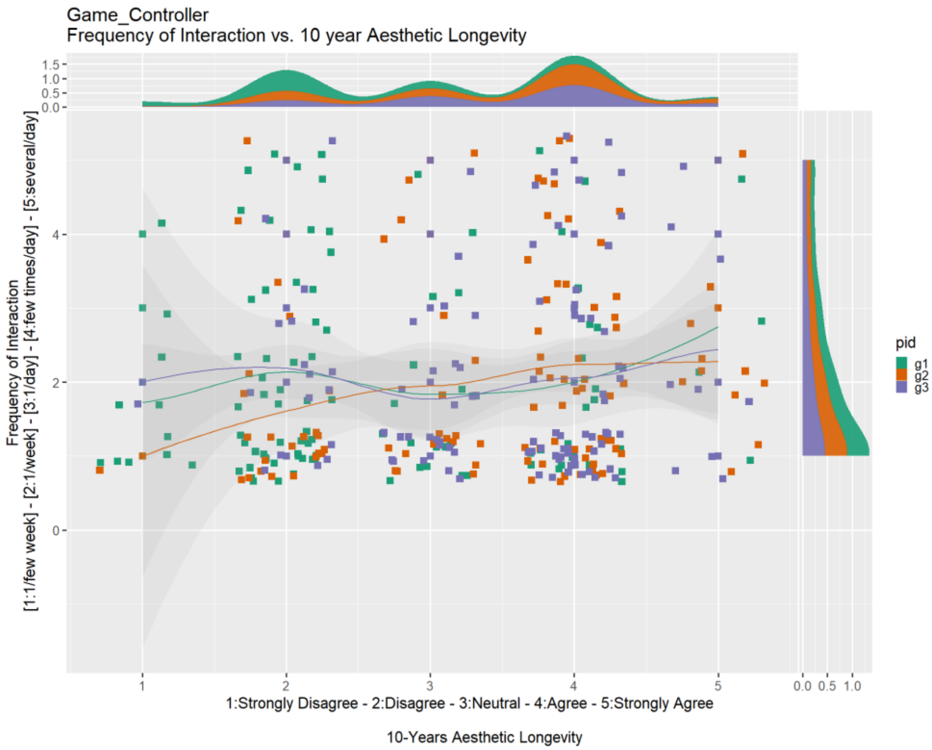


Figure 7.8: Frequency of interaction vs. 10 year aesthetic longevity

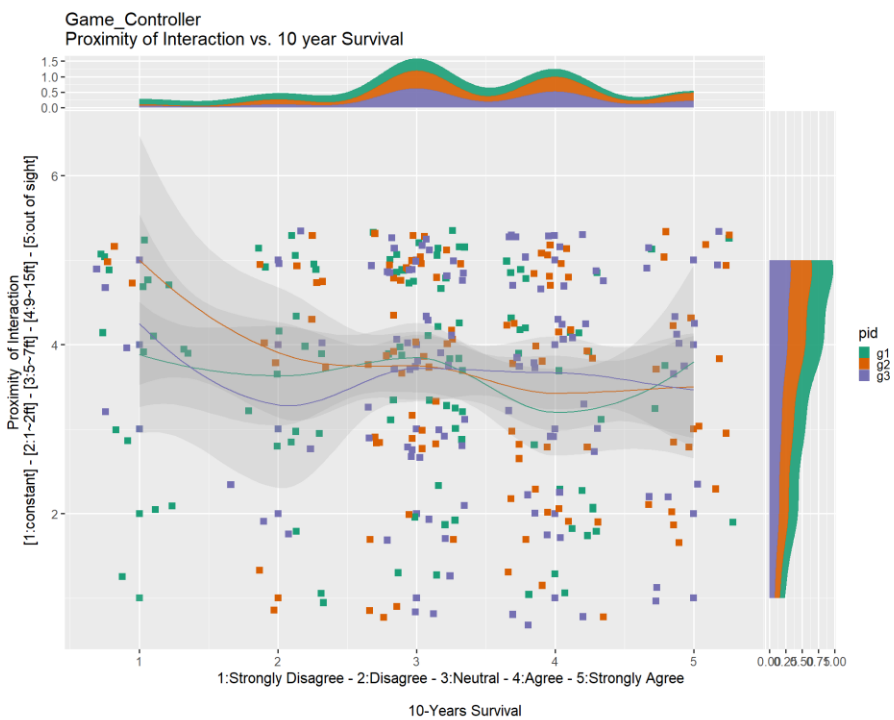


Figure 7.9: Proximity of interaction vs. 10 year aesthetic longevity

In the game controller survey depicted in data visualization ##, the participants provided some interesting insights. The majority of those who expressed an intention to keep and use their controllers for the next decade reported a level 1 frequency of interaction, meaning they use their controllers only once every few weeks, regardless of the design complexity whether complex, mixed, or simple (Figure 7.8). However, there was a significant density of "Disagree" responses for the complex design product ID (PID) #1 and a higher density of "Agree" responses for the mixed design PID #2. This suggests that participants prefer the mixed design controller and plan to keep it for a long time, despite only using it occasionally. Regarding proximity of interaction (Figure 7.9), the highest density was found at level 5, which indicates that the controllers are "out of sight," and the participants expressed a neutral intention to keep them for the next ten years. The participants who answered "Agree" and expressed a willingness to keep their controllers for the next decade represented the second-highest density. Within the "Agree" segment, the proximity of interaction was distributed between level 1 ("constant": slightly low density) and level 5 ("out of sight": slightly high density). This suggests that proximity of interaction has a lesser impact on the participants' decision to keep their game controllers.

7.3 CMYK Method

As I mentioned in the previous chapter, the CMYK Method is a unique and innovative approach to analyzing visual elements in design. Rather than relying on subjective opinions or vague descriptions, it provides a more structured and quantitative approach. By assigning specific colors to represent different visual elements, the method can offer a more concrete understanding of how people perceive a design. Cyan, the first color in the CMYK sequence, represents complexity (Figure 7.10). This means that designs with intricate details, multiple layers, or a high level of sophistication will likely have a higher cyan score. Magenta, the second color, represents simplicity. Designs that have a clean and minimalist look or that are easy to understand will have a higher magenta score. Yellow, the third color, represents familiarity. This means that designs that are easily recognizable or have a strong sense of brand identity will have a higher yellow score. Finally, black represents entropy, which refers to the unpredictability or randomness in a design. Designs that have a chaotic or disorganized appearance will have a higher black score. In addition to the color representation, the CMYK method allows for a more numeric approach to analyzing visual elements.

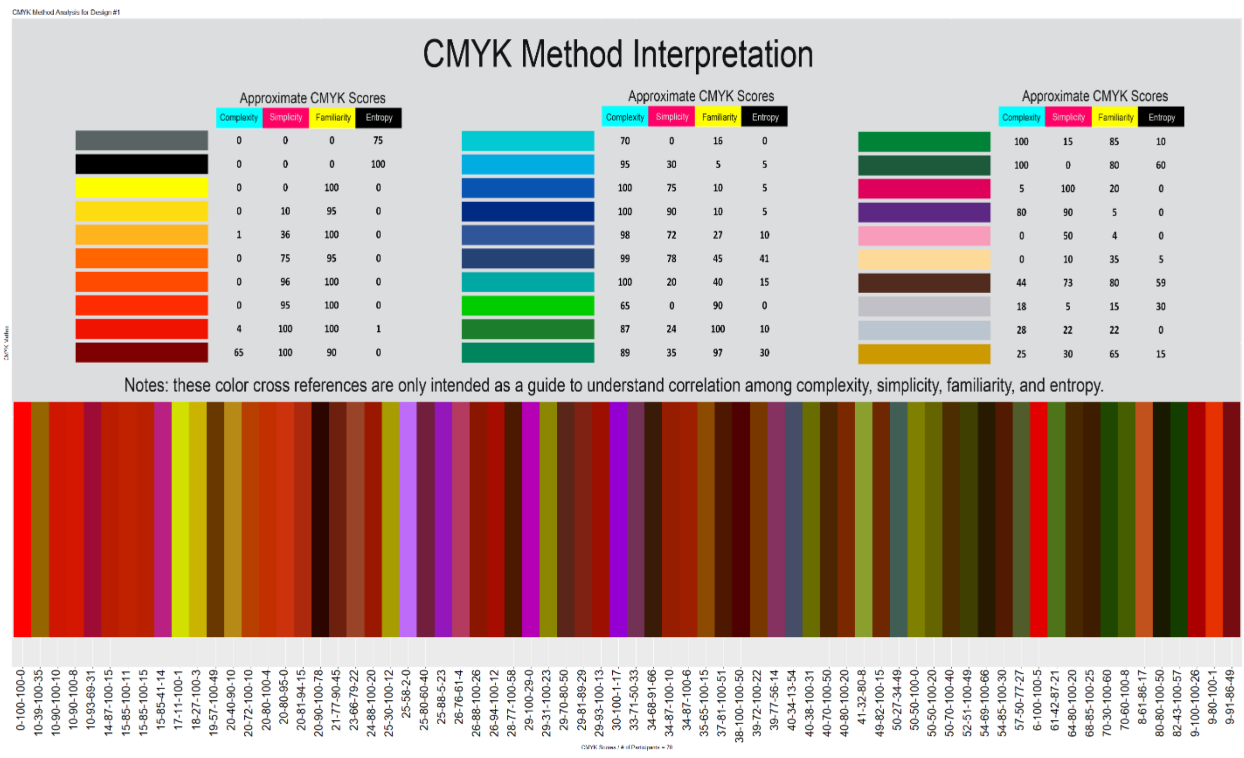


Figure 7.10: The CMYK method interpretation & scores

The order of the color bars corresponds to the sequence in which participants completed the survey, with each bar representing an individual's score (Please, see figure 7.9). Scores can be assigned for each of the four elements, which can then be used to calculate an overall score for the design. This approach provides a reasonably objective and consistent way of evaluating designs, making it easier to compare and contrast different options. The CMYK scores can be combined to yield a color that represents the overall perception of the design. The CMYK Interpretation Chart provides a quick reference for interpreting the color combinations and their associated scores. On the CMYK Interpretation Chart (Figure 7.11), colors that are in the family of red mean that both complexity and entropy have low scores and both simplicity and familiarity have high scores. Also, cool colors like blue indicate that participants answered with low scores in simplicity, familiarity, and entropy and high scores in complexity. One thing that needs to be noted is that purple means that complexity and simplicity have high scores and familiarity and entropy have low scores. This color can be used as a quick reference to communicate the design's overall complexity, simplicity, familiarity, and entropy. There is an important observation regarding the color black in terms of entropy. There are two possible scenarios that could result in the color black. First, black may appear when the complexity (cyan), simplicity (magenta), and familiarity (yellow) factors reach 100%. Second, black may occur when entropy reaches 100%. The occurrence of these scenarios depends on participants' opinions within the context of color theory approach. This highlights the limitation of quantitative research and underscores the need for qualitative research in parallel.

If black becomes prominent, there is a good chance that the participants could have different background, experience level, or perspective. Also, the product could potentially possess a design that could lack a consensus of the general audience whereas fine art pieces may have much higher chances to gain from the presence of black since it is more geared toward individual interpretation. However, despite the variations in stimuli and experimental goals, it remains advantageous to explore alternative approaches in the event that black becomes a prominent element and to represent the findings in a more comprehensive manner.

The CMYK method (Figure 7.11a & 7.11b) provides a more structured, objective, and quantitative way of analyzing visual design elements. It can be a valuable tool for designers, marketers, and other professionals who need to quickly and effectively communicate the perception of a design to others.

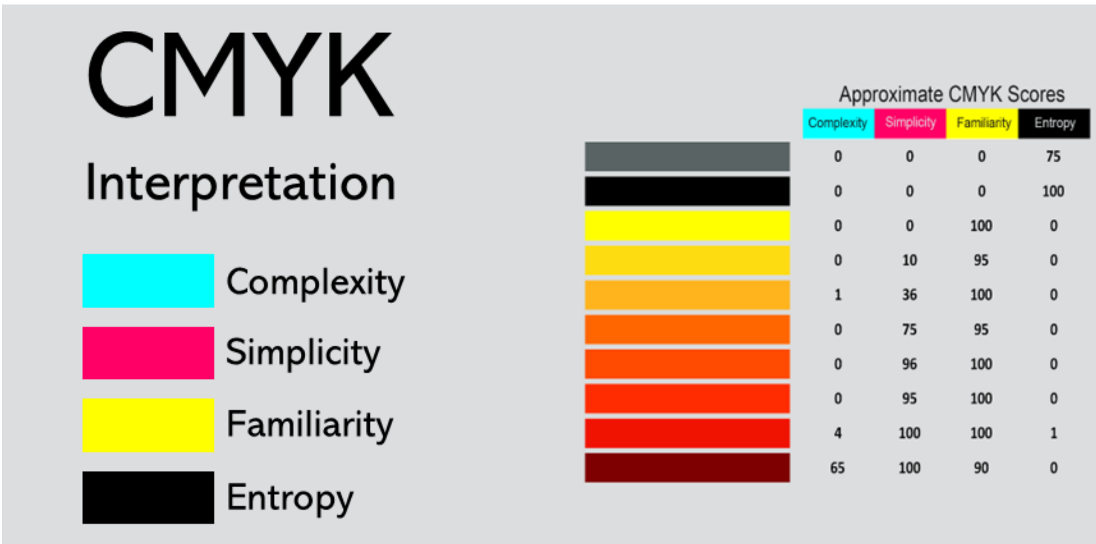


Figure 7.11a: Interpretation chart for the CMYK method

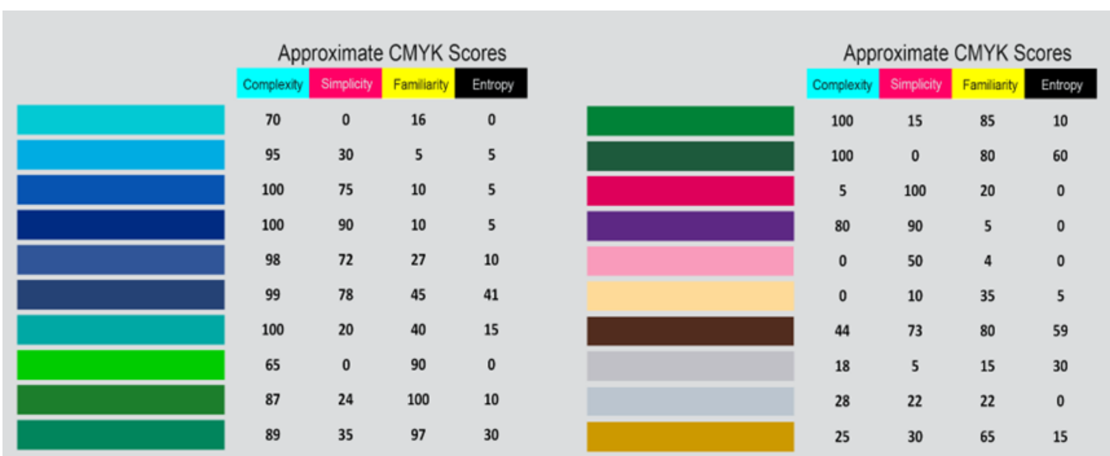


Figure 7.11b: Interpretation chart for the CMYK method

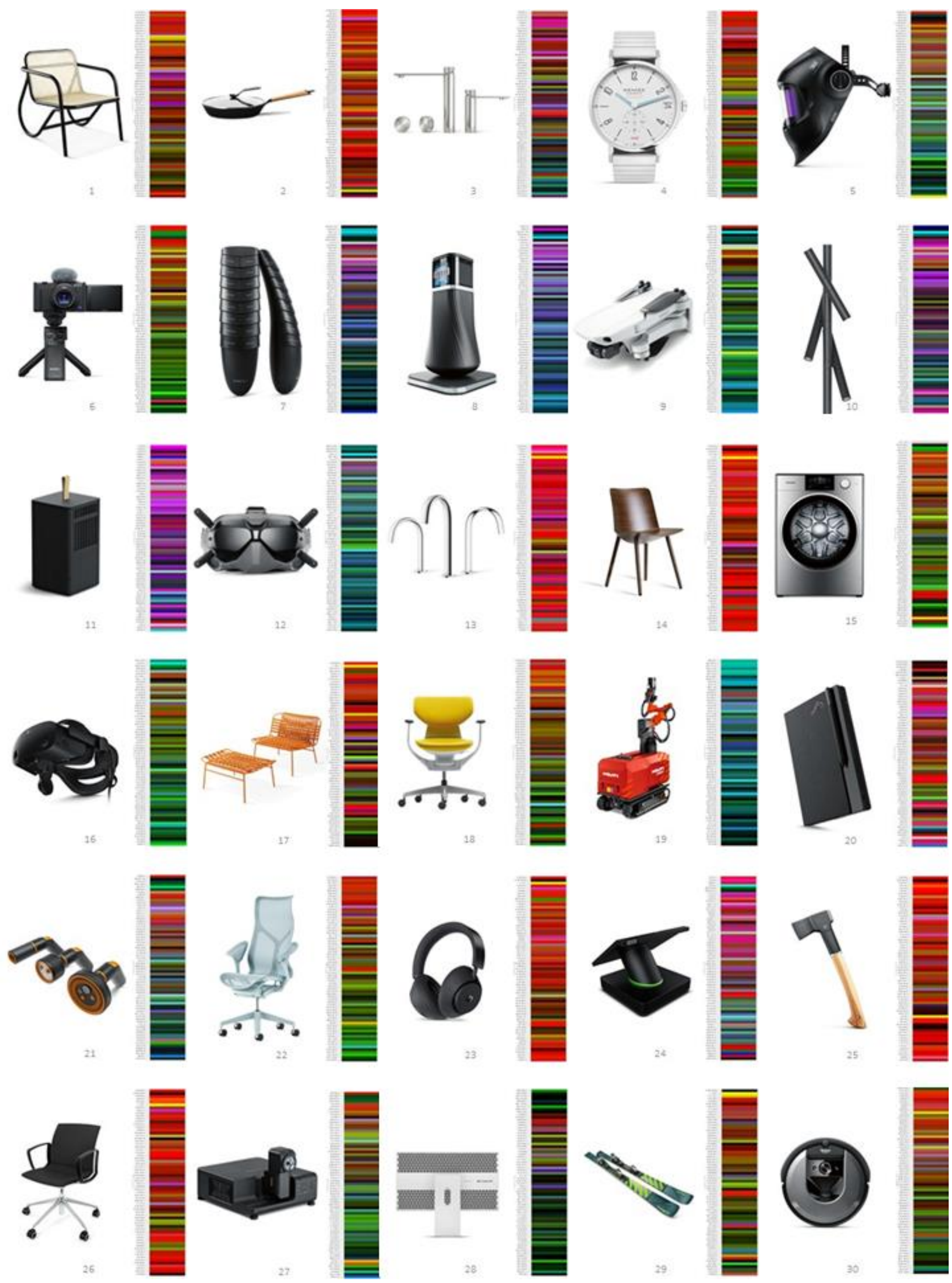


Figure 7.12: Product images from red dot design award

Figure 7.12 is an image collection of products that had been awarded as Best of Best in the Red Dot Product Design Award. The Best of Best is the highest ranking in the Red Dot design award assigned by highly regarded judges around the world. I selected this category for three reasons: 1) avoiding my personal bias, 2) keeping it as objective as possible and 3) having product designs that a general audience can agree on. This study illustrated four findings regarding complexity, simplicity, and familiarity. Arguably, complexity, simplicity, and familiarity are very subjective depending on the participants' background and experience. The CMYK method can reasonably predict the participants' background or experience by looking at CMYK color spectrum and CMYK scores.

Figure 7.13: A Group of design that shows cool colors

First, participants tend to show high scores in complexity while having low scores in familiarity and it is mainly a group of cool colors like blue(CMYK Score 95-30-5-5) (Figure 7.13). It means that users can perceive the product as complex design when they have a little knowledge of the products, or else the products fail to communicate what they do and how they function with the users.

The finding that participants tend to perceive a design as complex while having low scores in familiarity is an important insight that can help designers better understand their audience's perception of their designs. When a design is perceived as complex, it may mean that it is difficult for users to understand or that it requires a certain level of knowledge or expertise to use. This can be a barrier to adoption and can make users feel frustrated or overwhelmed. The fact that cool colors like blue are associated with high complexity CMYK scores and low familiarity CMYK scores suggests that these designs may be perceived as more abstract or technical (Figure 7.14). It is important for designers to understand the target users' background and level of experience to implement visual complexity.

Figure 7.14: A Group of the design that shows a group of green colors

Second, there are products that the participants indicated high scores in both complexity and familiarity, which shows mainly a family of green (CMYK Score 100-15-85-10) (Figure 7.13). The fact that there are products that participants rated highly in both complexity and familiarity is an interesting finding of the CMYK method. The family of green colors in the CMYK color spectrum is that these products suggest that users have a higher tolerance for visual complexity when they are familiar with the product or its function. This means that if a product has a complex design, but the user is already familiar with how it operates, or knows similar, they are more likely to find it understandable and usable despite its complexity. For example, a smartphone can have a complex interface with multiple features and options, but users who are familiar with smartphones in general can quickly adapt and find it usable. On the other hand, a completely new and unfamiliar product with a similar complex interface may be perceived as difficult to use and understand. This finding can be useful for designers, as it suggests that they can incorporate more visual complexity into their designs without sacrificing usability, as long as the users are already familiar with the product or its function. It also emphasizes the importance of considering the user's prior knowledge and experience when designing products or interfaces.

Figure 7.15: A Group of the design that shows warm colors

Third, there is a group of products resulting in mainly warm colors like orange (CMYK score 0-95-100-0) (Figure 7.15). This means that participants placed high scores in simplicity and familiarity when the products had affordances that the user had to understand. The warm color group, including orange, represents products that scored high in simplicity and familiarity according to the CMYK method. This indicates that participants perceived these products as having a clean and clear design, which makes them easy to understand and operate. This is especially true when the products have affordances, meaning that the design of the product suggests how it should be used. When a product has clear and intuitive affordances, users can easily figure out how to interact with it, reducing the need for complicated or confusing design elements. As a result, products in this group tend to have a high yellow score, indicating a strong sense of familiarity, which is important for building trust with users. The high magenta score also suggests a straightforward and uncluttered design, making it easy for users to navigate and use the product. Overall, this group of products demonstrates the importance of simplicity and familiarity in design, especially when combined with affordances to create an intuitive and easy-to-use product.

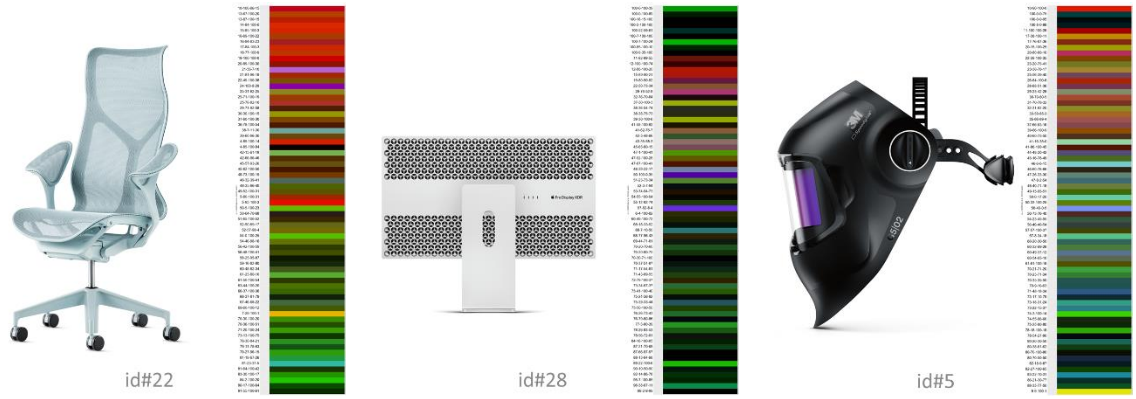


Figure 7.16: A Group of the design that shows mixed colors between cool and warm colors

Fourth, participants placed a high score on familiarity in Figure 7.16, which meant they were aware of its main function that was not necessarily complicated. For example, figure 7.16 (left) is an office chair and it is a product that users can sit on. In terms of affordance, it is pretty clear. However, adding complexity both visually and functionally can add significant value to overall design quality and the user experience. Figure 7.16 (middle) is a computer monitor that does not have any other features besides displaying contents from users' computer. The back of a computer monitor used to have only one feature – that is, dissipating heat from electronic components so designers did not typically pay it much attention. However, adding visual complexity on ventilation holes makes the overall design elevated to different levels and offers something for the users to see.

Additionally, by adding functional complexity, such as additional features or capabilities, the product can become more useful to the user and offer a more comprehensive solution to their needs. This can also increase the perceived value of the product and make it more attractive to potential buyers. However, it is important to note that adding complexity for the sake of complexity can be counterproductive and potentially harm the user experience. The complexity should be purposeful and add value to the product in a meaningful way.

7.4 Entropy in the CMYK Method

Although the CMYK Method can be used to visualize intuitively among the variables – complexity, simplicity, familiarity, and entropy – sometimes, entropy can be difficult to visualize because entropy is assigned to black. Also, it may not be easy to visualize the relationship between entropy and other variables like complexity or familiarity. I used R code to generate predictive models by using raw data set as a training set. Then, I created a LOESS curve before applying a linear regression model with an equation. The LOESS method can be applied to a wide range of data sets, including noisy and irregular data, and can be useful for visualizing and exploring relationships between variables. The LOESS curve is particularly useful when the relationship between the variables is not linear, or when there are outliers or other sources of noise in the data. One advantage of the LOESS method is that it is a non-parametric method, meaning that it does not assume a specific functional form for the relationship between the variables, and it can be used to estimate the curve without making any assumptions about the distribution of the data. However, one potential disadvantage of the LOESS method is that the choice of bandwidth can be subjective, and different bandwidths can result in different curve shapes.

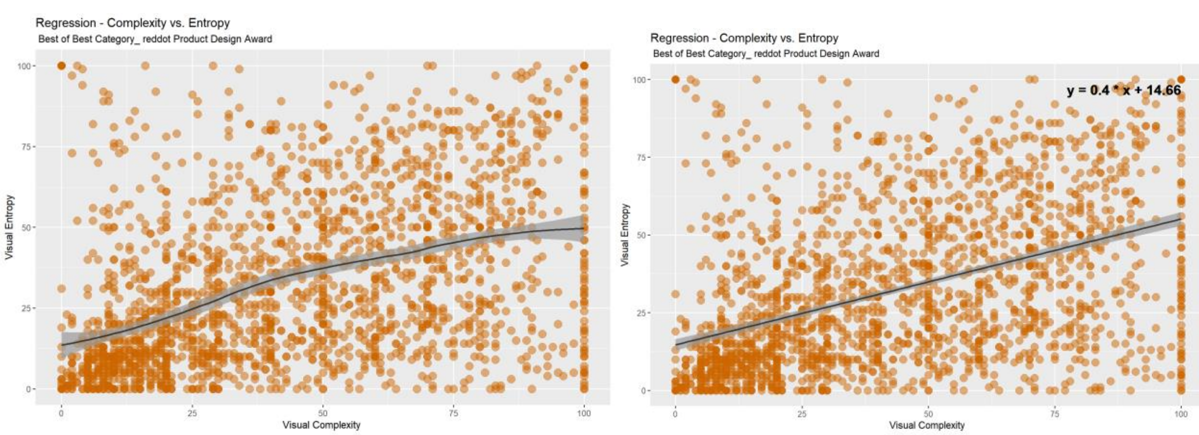


Figure 7.17: The loess curve (left) and linear regression (right) for visual complexity vs. visual entropy

Figure 7.17 (Left) is a LOESS curve and figure 7.17 (Right) is a linear regression model. Visual complexity refers to the level of detail, intricacy, or richness of a visual display or image, while visual entropy refers to the amount of disorder, randomness, or unpredictability in the visual information.

The equation suggests that as visual complexity (x) increases, visual entropy (y) also increases, with a linear relationship between the two variables. The slope of 0.4 indicates that for every one-unit increase in visual complexity, visual entropy increases by 0.4 units, on average. Although it is difficult to say the strength of the relationship between visual entropy and visual complexity without coefficient, generally, it can be expressed as 1:0.4 = visual complexity : visual entropy. The intercept of 14.66 suggests that even when visual complexity is zero, there is still some level of visual entropy in the visual display or image, which may be due to participants' previous experience, familiarity, or knowledge.

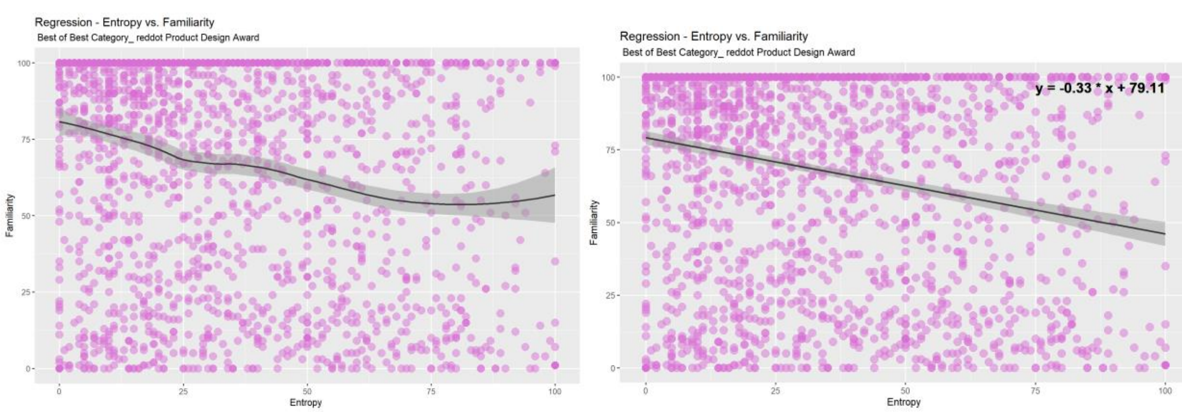


Figure 7.18: The loess curve (left) and linear regression (right) for visual entropy vs. visual familiarity

There is a negative relationship between visual entropy and familiarity (figure 7.18). Figure 7.18 (Right) shows linear regression model with equation, $y = -0.33x + 79.11$. In this linear regression equation, when entropy (x) increases one unit, familiarity (y) decreases 0.33 units, which shows a negative relationship. Again, although it is difficult to say the strength of the relationship without coefficient, the relationship between familiarity and visual entropy is weaker than the relationship between visual entropy and visual complexity. The y-intercept of the equation, 79.11, represents the expected value of familiarity when visual entropy is zero. In practice, this may not be a meaningful value, since it is unlikely that visual entropy would ever be exactly zero in any real-world visual display. The equation can be used to predict the expected value of familiarity for a given value of visual entropy. For example, if visual entropy is measured as x= 20, then the expected value of familiarity would be:

$$y = -0.33(20) + 79.11 = 72.51$$

This suggests that for a visual display or image with a visual entropy score of 20, we would expect the familiarity score to be around 72.51, on average.

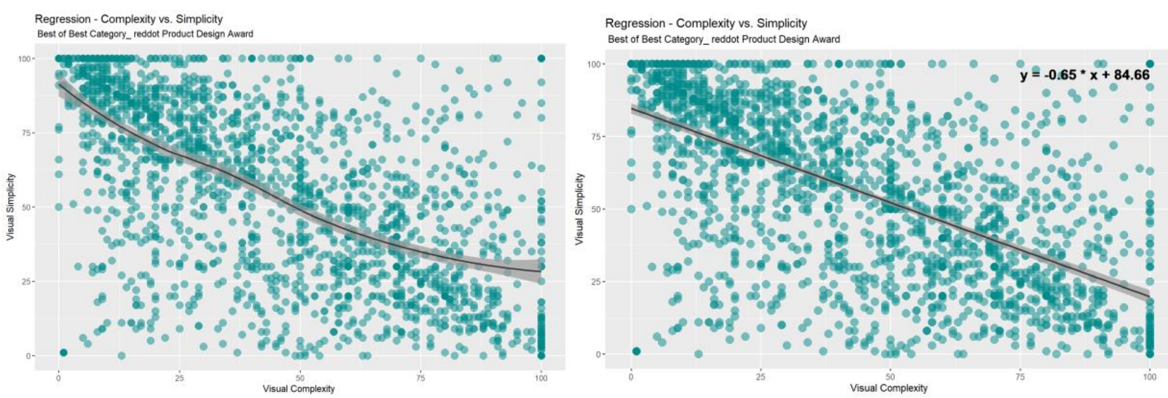


Figure 7.19: The loess curve (left) and linear regression (right) for visual complexity vs. visual simplicity

In this linear regression model (Figure 7.19 right), the dependent variable is visual complexity, and the independent variable is visual simplicity. The equation y = -0.65x + 84.66 represents the relationship between these two variables. Based on the regression equation, we can draw some insights about the relationship between visual complexity and visual simplicity. The coefficient -0.65 indicates that for every unit increase in visual simplicity (x), the visual complexity (y) decreases by 0.65 units. Therefore, as the level of visual simplicity increases, the perceived visual complexity tends to decrease.

When participants believed that the level of complexity was 100% (x = 100), the predicted visual simplicity would be y = -0.65 * 100 + 84.66 = 18.34. This implies that even though participants thought the complexity was at its maximum, there was still about 18.34% simplicity present. In other words, the predictable model suggests that there is no pure visual complexity and no simplicity. Conversely, when participants believed that there was 0% complexity (x = 0), the predicted visual simplicity would be y = -0.65 * 0 + 84.66 = 84.66. This indicates that when participants perceived no complexity, there was still about 84.66% simplicity present, whereas our perception might typically interpret 0% complexity as 100% simplicity, but according to the model, there is still a significant amount of simplicity present. Interestingly, when there was 50% complexity (x = 50), participants believed that there was about 50% simplicity. This aligns with the regression equation, as the predicted visual complexity would be y = -0.65 * 50 + 84.66 = 52.66.

It suggests that there is no pure complexity or simplicity, and even when participants believed that complexity was absent or at its maximum, a certain level of simplicity or complexity was still present, respectively. This linear regression model provides insights into the relationship between visual complexity and visual simplicity and can be utilized to find out the balance between complexity and simplicity. For example, when there is about 25% complexity exist, the rest of design would need to have about 68% simplicity. Also, when there is 75% complexity, the rest of design would need to have about 36% simplicity.

7.5 Familiarity, Remember, and Knowledge

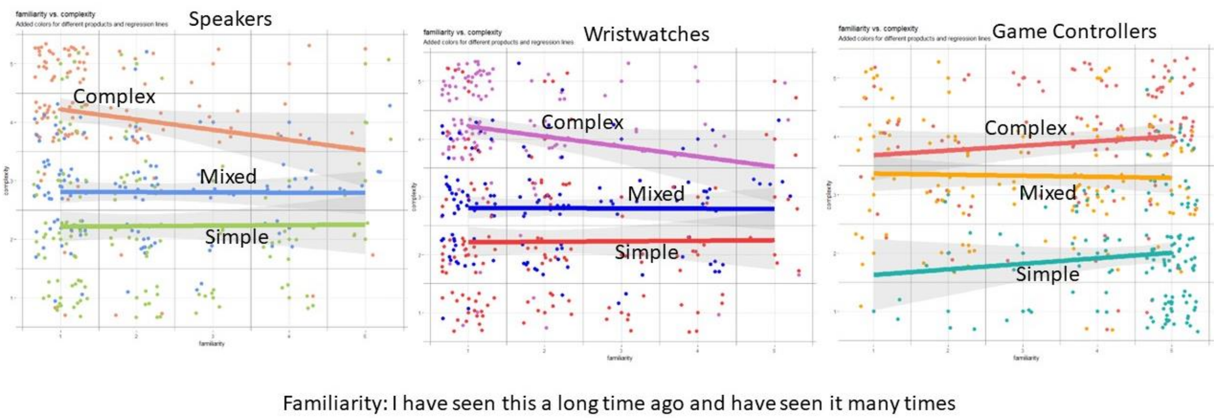


Figure 7.20: Visual complexity vs. familiarity

The study found that there is a relationship between visual complexity and familiarity in sets of speakers and wristwatches, which is inverse (Figure 7.20). Interestingly, this inverse relationship was observed only in products that have complex designs in both sets. However, for products with mixed and simple designs, the relationship between familiarity and visual complexity was almost constant, indicating that familiarity did not significantly impact visual complexity. This suggests that simple and mixed designs have fewer design elements compared to complex designs, and once people see them, they become familiar with them without requiring additional effort to maintain familiarity. Overall, the study highlights the interdependence of visual complexity and familiarity in product design, with simpler designs being more effective in promoting familiarity.

Unlike speakers and wristwatches, game controllers showed a positive relationship between visual complexity and familiarity. In addition, the study found that participants in the game controller group had strong and unique personalities, which suggests that game controllers may be more personal than other products are to game controller users. The study found that, with an increased duration of using game controllers, users improve their gameplay skills. This implies that game controllers are a critical factor in improving gaming skills. To speculate a little, users who spend a significant amount of time playing games may also prefer to have game controllers that have a complex design to demonstrate their passion for gaming. The study highlights the importance of game controllers in gaming culture and the unique relationship between visual complexity and familiarity in game controllers as compared to other products.

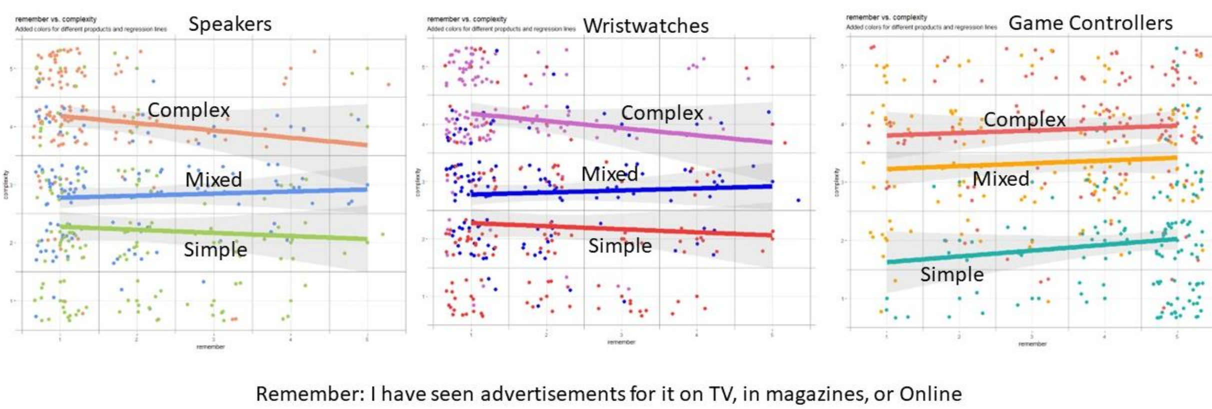


Figure 7.21: Visual complexity vs. remember

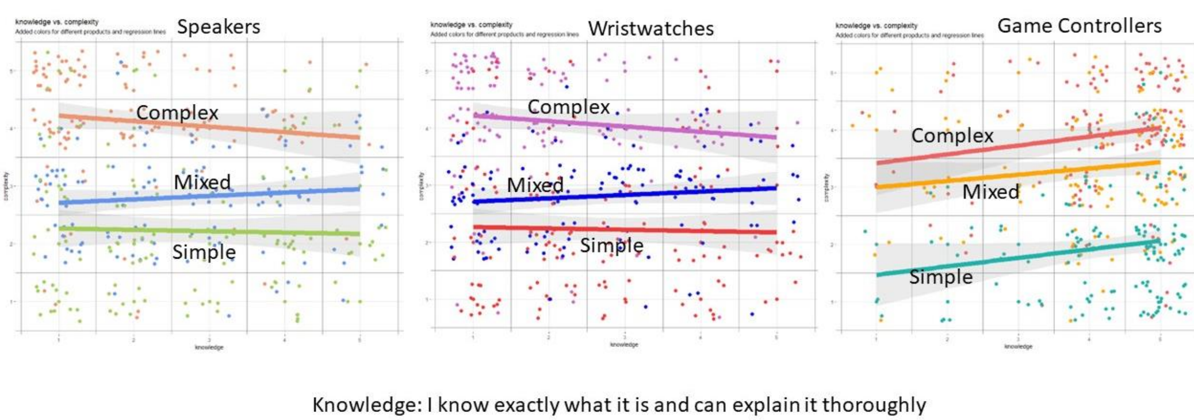


Figure 7.22: Visual complexity vs. knowledge

This analysis was executed and visualized using multi-level modeling with the R package. There is a high concentration of "Strongly Disagree" responses for the predictive regression model for speakers and wristwatches in the graph depicting Visual Complexity vs. Familiarity (Figure 7.20). The graphs representing Figure 7.21 (Visual Complexity vs. Remember) and Figure 7.22 (Visual Complexity vs. Knowledge) exhibit a decreased concentration of "Strongly Disagree" responses compared to the Visual Complexity vs. Familiarity graph (Figure 7.20) in the predictive regression model.

The comparison between familiarity regression and remember/knowledge regression reveals important differences in terms of the density of "strongly disagree" responses and the slopes of each product category (remember and knowledge). In the case of speakers and wristwatches, the slopes are weak, indicating that there may not be a statistically significant relationship between these products and the variables being measured. This suggests that a re-investigation of the predictive regression model may be necessary, or that a larger sample size may be needed to obtain more accurate results. The analysis shows a weak inverse relationship between complex design and both speakers and wristwatches. However, the game controllers exhibit a positive relationship across all categories, including complex, mixed, and simple designs. This pattern is similar to the game controllers in the familiarity regression model, suggesting that there is a consistent trend in the way participants perceive these products. These findings highlight the importance of considering multiple regression models and taking into account different product categories when analyzing survey data of this kind. It also underscores the need for careful interpretation of results and the potential for further investigation to clarify any inconsistencies or unexpected findings.

7.6 Multidimensional Scaling(MDS)

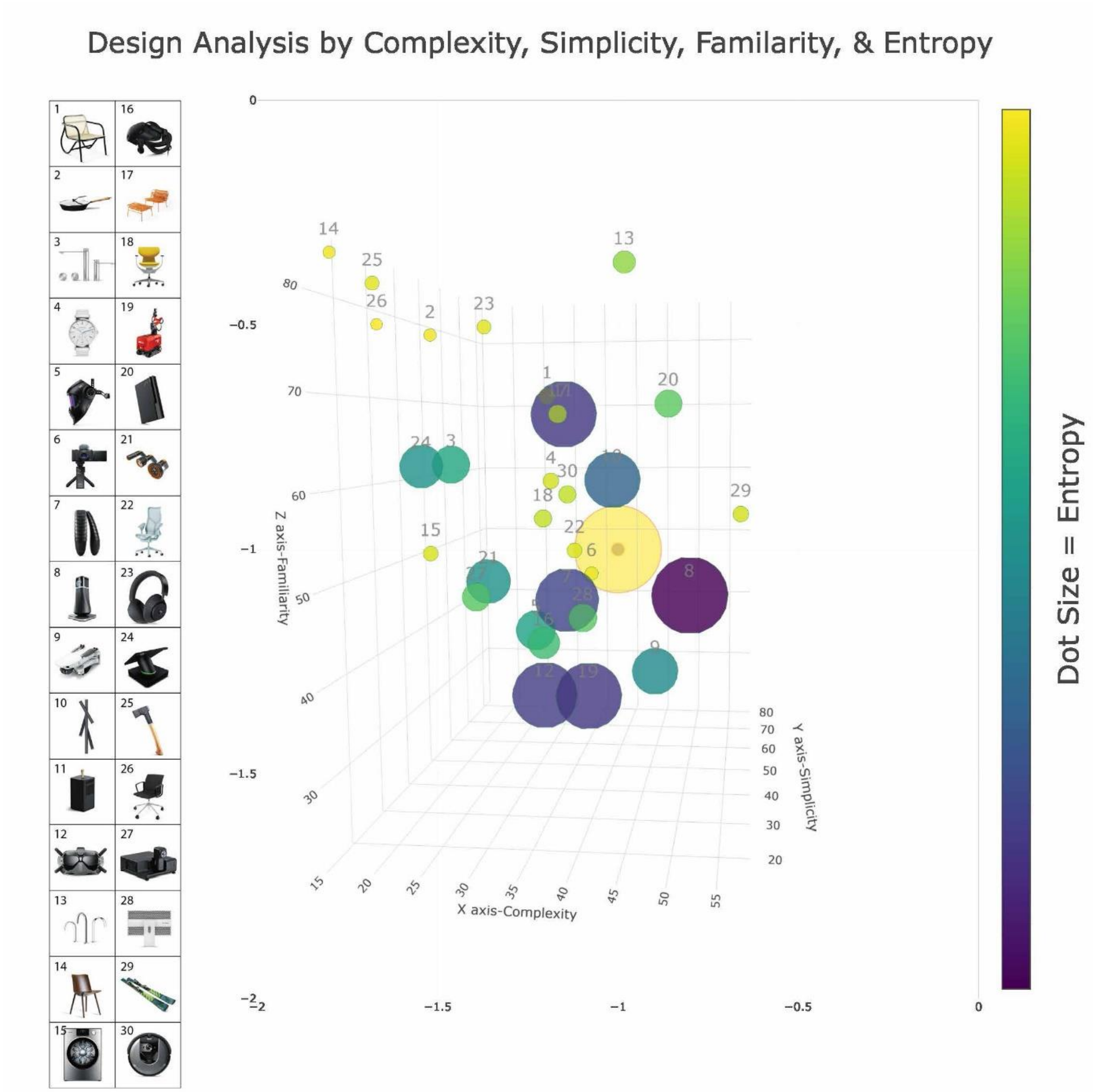


Figure 7.23: Screen capture from 3d interactive MDS

An MDS 3D visualization (Figure 7.23) was used to confirm that participants indicated lower complexity when their answers were placed on high familiarity. The level of visual entropy was also included as an additional dimension, with bigger dots indicating higher visual randomness and smaller dots indicating less visual randomness. Generally, lower entropy is associated with simpler design while higher entropy falls into the category of designs with visual complexity. A design with high entropy can be seen as having a high level of visual complexity or unpredictability, while a design with low entropy can be seen as having a simple and predictable appearance. It is important to note that the concept of entropy can be a little counterintuitive at first glance. For example, many people might assume that a design with a lot of intricate patterns and details would have a higher level of entropy than a simple design with few elements. However, as mentioned earlier, if those patterns are very predictable and repetitive, then the design actually has a low level of entropy. This is because entropy is a measure of the degree of randomness or disorder in a system, rather than the amount of information it contains.

In the context of this study, the inclusion of entropy as an additional dimension in the MDS visualization allows for a more nuanced understanding of the relationship between visual complexity, familiarity, and entropy. The size of the dots in the visualization provides a quick and easy way to see which designs have higher or lower levels of entropy, which can help to clarify the relationship between the various variables being studied. By examining the patterns in the data, researchers can gain insights into the factors that influence people's perceptions of visual complexity and simplicity in design. It is worth noting that participants tended to believe that patterns in design would increase in visual complexity, leading to an increase in entropy when patterns were present in products. However, this may indicate a lack of understanding of the concept of entropy since patterns can be very sequential and predictable, which leads to low entropy. Entropy is defined as a measurement of disorder.

MDS was chosen for this study because it is a flexible technique that can be adapted to different types of data and research questions. One of its key advantages is its ability to reduce the complexity of data by transforming high-dimensional data into a lower-dimensional space while preserving the relationships between data points. In this study, the addition of the entropy dimension as the size of dots makes it easier to visualize and interpret complex data, particularly in understanding the relationships between visual complexity, visual simplicity, familiarity, and entropy. MDS can also analyze a wide range of variables, including numerical, categorical, and ordinal data, and can explore various types of relationships such as similarities, dissimilarities, and preferences.

CHAPTER 8: FINDINGS

8.1 Hypothesis

8.1.1 Participants think that simplicity is 0% when visual complexity becomes 100%. (Hypothesis 2.1)

The hypothesis was tested using a linear regression analysis with a predictive model implemented using the R package. Figure 7.18 displays the results, indicating a negative linear relationship between complexity and simplicity. The predictive model derived a linear equation, $y = -0.65*x + 84.66$, where y represents simplicity and x represents complexity. According to the model, when the level of visual complexity reaches 100%, the corresponding visual simplicity is estimated to be 18.44. Based on these findings, the hypothesis cannot be accepted, as the data suggests that 100% visual complexity becomes 18.44% simplicity.

8.1.2 Participants believe that complexity increases when visual entropy increases. (Hypothesis 2.2)

A linear equation, $y = 0.4*x + 14.66$, where y is visual entropy and x is visual complexity, was populated by predictive model from R Package (Figure 7.16). As the equation from the predictive model suggests, one unit increases in visual complexity, the visual entropy is increased by 0.4 unit of entropy. Since it is a positive correlation, the hypothesis can be accepted.

8.1.3 Visual complexity exhibits significant positive correlations with knowledge, moderate positive correlations with memory, and weak positive correlations with familiarity. (Hypothesis 2.3)

In the study encompassing three categories of products, namely speakers, wristwatches, and game controllers, the findings indicate varying correlations between visual complexity (dependent variable) and the three independent variables (familiarity, remember, and knowledge). Among the game controllers, which encompass complex, mixed, and simple designs, there are moderate positive correlations observed between visual complexity and all three independent variables (Figure 7.21, 7.20, and 7.21). Conversely, for the other products, namely speakers and wristwatches, there exists a weak inverse correlation solely between visual complexity and the three independent variables in products with a complex design (Figure 7.19, 7.20, and 7.21). On the contrary, products with a mixed and simple design demonstrate minimal impact in terms of the slope of the linear regression. Consequently, the visual complexity of products related to performance tends to increase with higher levels of familiarity, remember, and knowledge. In the case of products not linked to performance, an increase in familiarity, remember, and knowledge leads to a decrease in visual complexity, primarily observed in products with a complex design, while the mixed and simple design products exhibit limited effects. Therefore, based on these findings, the hypothesis cannot be accepted.

8.1.4 Visual complexity is an important factor for aesthetic longevity. (Hypothesis 2.4)

Hypothesis 2.4 posits that visual complexity is a crucial factor contributing to aesthetic longevity. In examining the relationship between visual interest (independent variable #2) and aesthetic longevity (dependent variable) across three product categories, it was found that visual interest exhibited strong statistical significance (Table 8.1). Notably, the product samples achieved the highest level of visual interest when designs that were unrelated to performance exhibited a balanced blend of complexity and simplicity. This suggests that the presence of visual complexity contributes to heightened visual interest. As a result, visual complexity emerges as a significant determinant of aesthetic longevity. Therefore, based on the evidence gathered, the hypothesis can be accepted.

Table 8.1: P-values for independent variables #2 visual interest

Product Samples		**P-value for Visual Interest**
	Speaker#1	Coefficients: Estimate Std. Error z value Pr(>|z|) (Intercept) -2.5860 0.5640 -4.585 4.54e-06 *** df5.1$vi_sp1 0.6553 0.1580 4.147 3.37e-05 ***
	Speaker#2	Coefficients: Estimate Std. Error z value Pr(>|z|) (Intercept) -6.0984 1.1605 -5.255 1.48e-07 *** df6.1$vi_sp2 1.8956 0.3403 5.570 2.55e-08 ***
	Speaker#3	Coefficients: Estimate Std. Error z value Pr(>|z|) (Intercept) -6.0984 1.1605 -5.255 1.48e-07 *** df6.1$vi_sp2 1.8956 0.3403 5.570 2.55e-08 ***
	Wristwatch#1	Coefficients: Estimate Std. Error z value Pr(>|z|) (Intercept) -5.0452 0.9815 -5.14 2.74e-07 *** df8.1$vi_wch1 1.2033 0.2555 4.71 2.48e-06 ***
	Wristwatch#2	Coefficients: Estimate Std. Error z value Pr(>|z|) (Intercept) -6.6954 1.2941 -5.174 2.29e-07 *** df9.1$vi_wch2 1.9199 0.3475 5.525 3.30e-08 ***
	Wristwatch#3	Coefficients: Estimate Std. Error z value Pr(>|z|) (Intercept) -2.5140 0.6269 -4.01 6.06e-05 *** df10.1$vi_wch3 0.9409 0.2032 4.63 3.66e-06 ***
	Game Controller#1	Coefficients: Estimate Std. Error z value Pr(>|z|) (Intercept) -4.9337 0.9271 -5.322 1.03e-07 *** df11.1$vi_gc1 1.2254 0.2447 5.008 5.49e-07 ***
	Game Controller#2	Coefficients: Estimate Std. Error z value Pr(>|z|) (Intercept) -4.4117 0.9496 -4.646 3.39e-06 *** df12.1$vi_gc2 1.4369 0.2747 5.231 1.68e-07 ***
	Game Controller#3	Coefficients: Estimate Std. Error z value Pr(>|z|) (Intercept) -1.7104 0.5806 -2.946 0.003221 ** df13.1$vi_gc3 0.7266 0.1872 3.882 0.000104 ***

8.1.5 Increased interaction and closer proximity lead to an increase in aesthetic longevity. (Hypothesis 2.5)

Proximity of interaction for the speakers was most commonly preferred at a distance of 5ft. to 7ft. and 9ft. to 15ft. The study suggested that products placed closer to users may have a higher chance of longevity (Figure 7.5). Regarding wristwatches, participants indicated a strong intention to retain them for the next decade. Frequency of interaction varied, with some participants using the watch several times a day for functional purposes, while others used it less frequently as a decorative item (Figure 7.6). For participants committed to keeping a product for ten years, closer proximity of interaction was preferred, indicating constant interaction. This finding may be attributed to factors such as accessibility, ease of use, better maintenance, and integration into daily life.

Proximity of interaction emerged as an important factor in product longevity, highlighting the need for designers to consider user preferences when designing physical interactions. In the case of game controllers (Figure 7.8 and 7.9), most participants expressed an intention to keep them for ten years, even with infrequent usage. Mixed design controllers received more agreement responses, indicating a preference for that design. Proximity of interaction had a lesser impact on participants' decision to keep their game controllers, with the highest density of responses indicating that the controllers were "out of sight."

The hypothesis in this case is found to be partially true, considering the limitations encountered during the study. Three main factors have contributed to this partial acceptance: time constraints, survey questions, and the sample size.

Time constraints played a role in shaping the outcome of the study. It is possible that the limited time available for conducting the survey and data collection restricted the researchers' ability to thoroughly explore all relevant variables and gather comprehensive data. This constraint could have resulted in a partial acceptance of the hypothesis, as some aspects might not have been adequately addressed or examined within the given time frame.

The design and formulation of the survey questions also played a significant role. If the questions were not effectively designed to capture all relevant aspects of the hypothesis, the responses obtained might have been incomplete or ambiguous. It is crucial to reconfigure the survey questions in a way that comprehensively covers the variables related to the hypothesis. By refining the survey questions, future research can provide a more accurate and conclusive assessment of the hypothesis.

Additionally, the sample size used in the study could have impacted the partial acceptance of the hypothesis. A small sample size limits the generalizability of the findings and increases the risk of sampling bias. Increasing the sample size would provide a broader representation of the population and enhance the reliability and validity of the study's results. Therefore, it is essential to increase the sample size in future research to obtain more robust and representative data.

To address these limitations and improve the validity of the findings, it is recommended to reconfigure the survey questions, allocate more time for data collection, and increase the sample size. By addressing these factors, future research will have a better opportunity to thoroughly investigate the hypothesis and provide more comprehensive and conclusive results.

8.2 Research Question

8.2.1 What is the role of complexity in consumer products that have long-lasting aesthetic longevity?

8.2.2 Main hypothesis: visual complexity plays a significant role in determining aesthetic longevity.

In today's information-rich society, we are constantly exposed to a flood of both controllable and uncontrollable information. As a response to this overwhelming abundance of information, many people seek simplicity in their lives and believe that simplicity is preferable to complexity. This belief has led to simplicity becoming a mainstream trend and a rejection of visual complexity, particularly in products and designs that interact with users. The concept of "less is more" coined by Ludwig Mies van der Rohe (1947), a pioneer of modernist architecture, embodies this preference for simplicity and minimalism. It predates variations of the idea found in different cultures and time periods and has been widely applied in various fields. The principle suggests that ornamental elements are unnecessary in design and architecture. However, the psychologist Berlyne, known for his work on the psychology of aesthetics and human perception, explored the relationship between complexity, interests, and preferences in his research. According to Berlyne's theories, humans have a natural inclination towards moderate levels of complexity and arousal in their environment and stimuli. He proposed that individuals are motivated to seek out and engage with stimuli that fall within an optimal range of complexity, often referred to as the "hedonic zone." Stimuli that are too simple and monotonous or too complex and overwhelming are less appealing.

Berlyne further suggested that individual differences play a role in determining preferences for complexity. Some individuals may have a higher tolerance or preference for more complex stimuli, while others may prefer simpler or less complex environments.

In terms of aesthetic longevity, visual complexity has played a significant role. The artist Jackson Pollock, for example, created visually complex masterpieces that have been highly regarded and appreciated across generations. Despite their complexity, Pollock's pieces have achieved aesthetic longevity because they provide a visual complexity that resonates with audiences. While the mainstream preference leans towards simplicity and minimalism, research supports the idea that visual complexity can have a positive impact on aesthetic longevity. People are naturally drawn to moderate levels of complexity, finding them more interesting and aesthetically pleasing compared to stimuli that are too simple or too complex, which is represented in Berlyne’s complexity curve.

Berlyne's complexity curve, also known as the inverted U-shaped curve of complexity, provides further insight into people's preferences for complexity. When stimuli are too simple, they may lack the necessary elements to engage our attention and interest. Simple stimuli can be monotonous and predictable, leading to a sense of boredom or disinterest. On the other hand, when stimuli are overly complex, they can become overwhelming and difficult to comprehend. Complex stimuli may require significant cognitive effort to process, leading to a sense of confusion or cognitive overload. Stimuli of moderate complexity strike a balance between being engaging and comprehensible. They offer enough elements and variability to capture our attention and maintain interest, while still being within our cognitive capacity to understand and appreciate.

This research demonstrates the practical application of the complexity curve in the context of product design. It suggests that finding the optimal balance between simplicity and complexity can enhance the longevity and desirability of products. By considering the aesthetic preferences and cognitive capacities of a diverse range of individuals, designers can create experiences that are visually appealing, intellectually stimulating, and capable of enduring relevance over time. The study provides empirical evidence that supports the notion of balancing simplicity and complexity in design to create aesthetically pleasing and enduring products. It reinforces the idea that finding the sweet spot within the complexity curve can lead to experiences that are valued and appreciated by users for the long term. In the study, participants were presented with product samples from three different categories: speakers, wristwatches, and game controllers. There are product samples that were designed with a combination of both visual simplicity and complexity.

After evaluating the samples by participants, the participants rated their willingness to keep the products for the next 10 years.

The results of the study revealed that the product samples that incorporated a mixture of visual complexity and simplicity received the highest scores in terms of participants' willingness to keep them for the next decade. This finding aligns with Berlyne's complexity curve, which suggests that stimuli of moderate complexity are often preferred over stimuli that are too simple or too complex (Figure 8.1).

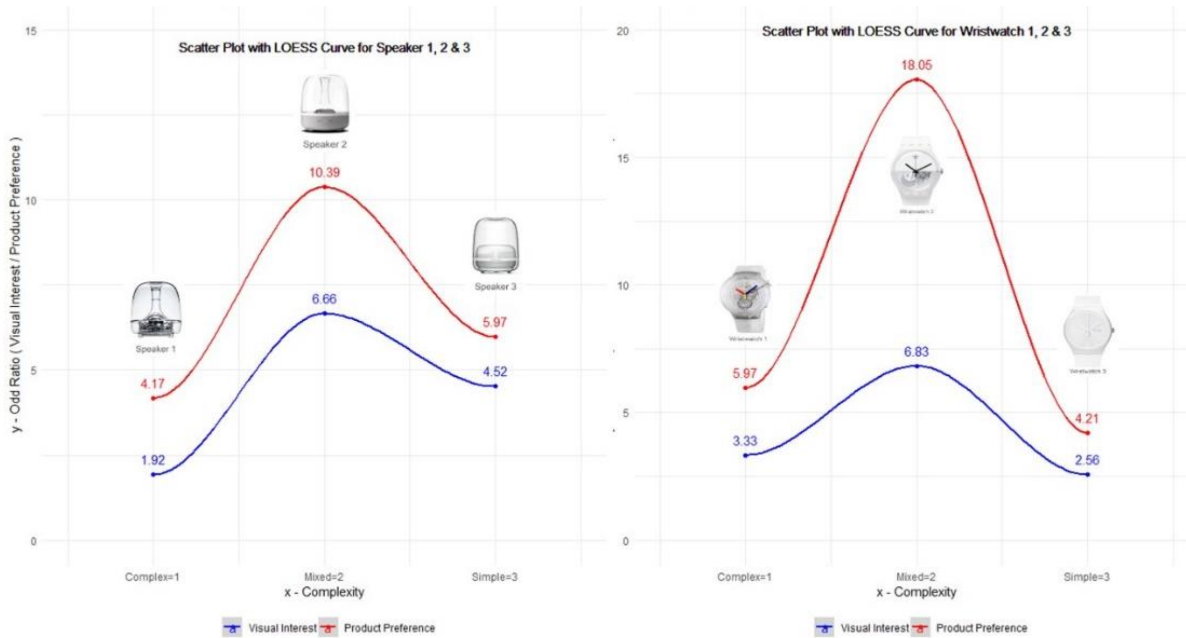


Figure 8.1: Aesthetic longevity vs product preference- speaker (left) and wristwatch (right)

Another noteworthy statistically significant outcome was identified through logistic regression analysis of survey data, indicating a relationship between visual interest and product longevity, as well as between product preferences and product longevity. Among three product categories with three different levels of visual complexity, the product category that has mixed design between visual complexity and simplicity shows strong statistical significance to aesthetic longevity, although there were no related insights. However, upon examining the odds ratio for each product category based on their visual complexity, it yields several findings from qualitative research.

First, participants who expressed a strong preference for simple design demonstrated lower scores when evaluating product samples that exhibited high levels of visual complexity. Conversely, the products with simple designs, which were characterized by good affordance (the ease with which they can be understood and used), tended to receive higher ratings from these participants.

For example, participant id#100 demonstrated a strong preference for product samples with a simple design, rating them highly. Their positive response was accompanied by a comment indicating a personal connection to the product, stating, "I own one of these. It feels like a third hand." However, when evaluating product samples with high visual complexity, participant id#100 expressed a contrasting sentiment, describing them as "a bit creepy." This suggests that the participant finds comfort and familiarity in simple designs but may feel unsettled or overwhelmed by visually complex ones.

Similarly, participant id#14 responded to product samples with a simple design by stating, "simple," implying an appreciation for the straightforwardness and minimalism of the design. On the other hand, when presented with visually complex samples, they expressed the opinion that there was "too much going on," suggesting a preference for designs that are less visually cluttered and more easily comprehensible. Participant id#134 also favored product samples with a simple design, describing them as having a "classic and clean design" that is "easy on the eyes." However, when faced with visually complex samples, they expressed a negative viewpoint, stating that it "doesn't look very good." This indicates a preference for designs that are aesthetically pleasing and visually harmonious, rather than ones that may appear visually chaotic or overwhelming.

This suggests that individuals who appreciate simplicity may find products with excessive visual complexity less appealing or challenging to comprehend. One interesting finding from the study is that participants exhibited a tendency to assign higher scores to products with higher levels of complexity, despite those products having low affordance. This means that participants found these complex products appealing, even though they initially had difficulty identifying their purpose or use. Participant id#129's comment, "*It's hard to identify its use at first and it's cute*," exemplifies this pattern. Despite the initial challenge in understanding the product's functionality, the participant found it aesthetically pleasing or attractive. This suggests that participants may be drawn to the novelty or uniqueness associated with visually complex designs, even if they initially struggle to comprehend their practical utility.

This could be interpreted as a result of unfamiliarity or a lack of knowledge about such products. In these cases, participants may perceive the increased complexity as indicative of sophistication or novelty, which may be appealing even if the ease of use or familiarity is compromised. These findings shed light on how individuals' preferences for simplicity or complexity in design can influence their evaluations of products. The participants' inclination to favor simple designs with good affordance suggests a preference for intuitive and user-friendly products. On the other hand, their willingness to assign higher scores to complex designs with low affordance, albeit in specific contexts, highlights the role of novelty and perceived sophistication in attracting interest. It is important to consider that these observations are specific to the context of the study and the preferences of the participants involved.

Second, participants who exhibited a strong preference for visual complexity did not appear to appreciate the beauty or value of simplicity in design. This was evident in their responses to product samples with different levels of visual complexity. For instance, participant id#67 showed a strong preference for product samples with high visual complexity and expressed enthusiasm, stating, "*The look is new and fantastic*." This suggests that they found the intricate and visually stimulating aspects of the product appealing. On the other hand, participant id#84, who also favored high visual complexity, described the same product samples as "normal," indicating a lack of excitement or interest in simpler designs. Interestingly, participant id#84 showed a preference for high visual complexity but provided a different rationale, stating, "I like the clear look (so I could see what's inside)." In this case, the participant seemed to associate the visual complexity with transparency and the ability to see the product's contents, rather than focusing on the aesthetic appeal of simplicity.

Conversely, participant id#85 expressed a rather dismissive response, describing product samples with simple design as "plain," implying a lack of appreciation for the elegance and understated beauty of simplicity. Also, participant id#2 made a significant observation, stating, "*I feel like you can spend half an hour looking at this product*." This comment suggests that the participant found the product sample intriguing and visually engaging. It implies that the complexity of the design captured their attention and held their interest for an extended period. This response indicates a positive association with visual complexity, as it provided a rich and captivating experience for the participant. On the other hand, participant id#68 described the product sample as "*it looks exotic*." This comment suggests that the visual complexity of the product evoked a sense of uniqueness or unfamiliarity. The use of the term "*exotic*" indicates that the participant perceived the design as distinctive and visually intriguing. This suggests that visual complexity can have an allure that goes beyond traditional notions of simplicity or familiarity. These responses highlight the subjective nature of aesthetic preferences and how individuals can differ significantly in their perceptions and evaluations of design complexity. While some participants found novelty and visual stimulation in complex designs, others did not perceive the value or appeal in simpler designs. These differences suggest that personal taste, prior experiences, and individual interpretations play crucial roles in shaping preferences for visual complexity or simplicity.

Third, the odds ratios were examined for product samples with mixed designs that combined elements of both visual complexity and simplicity. Interestingly, these product samples exhibited the highest odds ratio, resulting in an inverted U-shaped curve when comparing the odds ratios across different levels of visual complexity.

For example, participant id#44, id#54, and id#84 expressed their observations and opinions regarding the mixed design samples. Participant id#44 stated, "*It seems to have the best of both worlds in terms of design. It has some complicated features but also carries simplicity*." This comment suggests that the participant perceived the mixed design as a harmonious combination of both complexity and simplicity, highlighting the positive attributes of each. Participant id#54 remarked, "*It is simple but shows the complexity*," indicating an appreciation for the subtleties and intricate details within the seemingly simple design. This response suggests that the participant recognized the hidden complexity within the overall simplicity of the product. Participant id#84 commented, "*A very nice contrast of complexity and simplicity for a timeless garment/product*." This statement implies an understanding of how the interplay between complexity and simplicity can contribute to the overall aesthetic appeal and enduring quality of the product. The participant perceived the mixed design as striking a balance between the two elements, resulting in a design that is timeless and visually pleasing. These participant comments reinforce the notion that the mixed design samples, which incorporated both complexity and simplicity, were viewed positively. The participants recognized and appreciated the synergy between the contrasting elements, perceiving it as an attractive and appealing feature. The inverted U-shaped curve of the odds ratio suggests that there is an optimal level of visual complexity and simplicity in design that elicits the most favorable responses from participants. Too much simplicity or too much complexity may result in diminished appeal, whereas a balanced integration of both aspects can lead to a more favorable perception of the product.

Also, the comments from participant id#99 and id#129 provide an interesting insight into their perceptions of the product samples. Both participants expressed positive sentiments towards the complex designs, using terms like "futuristic," "advanced," and "sophisticatedly appealing" to describe their impressions. Participant id#99's comment, "It looks very futuristic and advanced," suggests that the visual complexity of the product sample conveyed a sense of innovation and forward-thinking design. The participants associated the complexity with a futuristic aesthetic, perceiving it as a visual representation of advanced technology or cutting-edge design elements. Similarly, participant id#129 remarked, "It looks sophisticatedly appealing." This comment indicates an appreciation for the sophistication and visual appeal of the complex design. The participant perceived the intricacies and intricately detailed aspects of the product sample as contributing to its overall allure and attractiveness. These comments highlight the perception of complexity as a signifier of sophistication, advancement, and aesthetic appeal. The participants recognized visual complexity as a positive attribute, attributing qualities of futurism, sophistication, and appeal to the design. This finding underscores the importance of considering the cultural and contextual factors that influence participants' interpretations of complexity in design. In certain contexts, complexity can be associated with positive attributes such as innovation, sophistication, and attractiveness. These associations can have an impact on participants' evaluations and preferences for visually complex products.

When participants were asked to consider the product in the context of the next 10 years, it triggered a shift in their perspective. Instead of solely focusing on the immediate features and qualities of the product, they began to think about its broader context and long-term implications. This change in perspective had a notable influence on their decision-making process. For instance, when Participant id#1015 and Participant id#1078 mentioned, “visually fits well into home environments” and “Looks like it is good quality and can be used as a display piece as well.” It indicated that they were considering more than just the product's immediate visual appeal. They recognized that the product's design and aesthetics were suitable for integration into their home environments, suggesting that they were envisioning how the product would fit within their living spaces over an extended period.

Moreover, their observations about the product's potential as a display piece indicated that they were thinking beyond its primary function. By recognizing its versatility and aesthetic value, they were considering the long-term usability of the product and its ability to enhance the overall ambiance of their homes. This indicates a more comprehensive evaluation process that goes beyond the product's immediate visual appeal and extends into its potential as a long-term investment. By zooming out and considering the product in a broader context, participants were able to evaluate it from a more holistic perspective. They took into account factors such as the compatibility of the product with its surroundings and its potential impact on their living spaces over the course of several years.

This approach demonstrates that considering the visual aspects of a product in relation to its future use and impact can significantly influence individuals' impressions and decisions. Overall, the participants' shift in perspective, prompted by considering the product in the context of the next 10 years, allowed them to assess the product from a more comprehensive standpoint. They considered not only the immediate visual appeal but also its long-term compatibility, aesthetic value, and potential as a lasting investment. This broader evaluation process influenced their decision-making process and led them to make more informed judgments about the product.

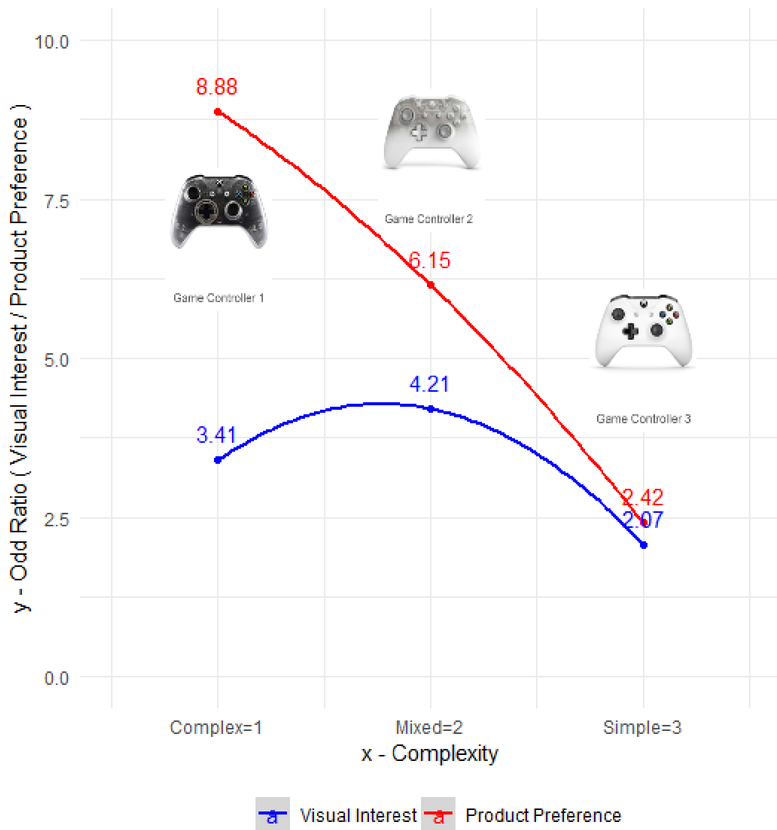


Figure 8.2: Aesthetic longevity vs. visual interest for game controllers

Fourth, as I mentioned in the previous chapter, the game controllers showed different behavior from the set of speakers and a set of wristwatches. Although the odds ratio of visual interest for the game controller showed an inverted U-shaped curve like the odds ratio curve of the set of wristwatches, the odds ratio curve of product preference for the game controllers showed a negative and linear relationship, whereas the odds ratio of visual interest for the game controllers that has the mixed design showed the highest (Figure 8.2). In other words, although game controllers with a mixed design, combining visual complexity and simplicity were considered the most visually appealing, they may not be the users' first choice when it comes to actually playing video games. This suggests that game controller users prioritize gaming performance over visual appeal. The statements from participants further support this notion. Participant id#1010 expressed on the game controller that has mixed design, "*very visually unique and aesthetically beautiful"* , indicating a high level of visual interest. However, participant id#1014 stated for the game controller that has simple design, " *Looks simple. The visible components are only necessary components that are needed for gaming*" emphasizing the importance of functionality. This suggests that users perceive the necessary components as crucial for an optimal gaming experience. Another participant, id#10115, commented that the visually complex product samples appeared "advanced" and "robust." This interpretation suggests that visual complexity can convey the passion and seriousness of the game player. It implies that some users may perceive visually intricate designs as a representation of their dedication and enthusiasm for gaming.

Participant id#2 commented on the game controller that was an example of simple design, "I feel like there is nothing super special with the design. Looks cool, but I can see myself buying another one and throwing out this one." While the same participant commented on the speaker that had the most visual complexity, "I think this is a cool piece that probably won't go out of style for quite a long time. I can see it not being thrown away for the next ten years." In other words, The participant's comment on the game controller with a simple design suggests that while it looks cool, it lacks a sense of uniqueness or special features. This implies that for game controllers, participants may be more inclined to seek out controllers with distinctive design elements or additional features that make them stand out. A simple design alone may not be enough to create a lasting impression or foster a sense of attachment to the product.
In contrast to the game controller, the participant's comment on the speaker with visual complexity indicates a perception of long-lasting appeal. The participant suggests that the

speaker's design is cool and unlikely to go out of style for a significant period, potentially ten years. This insight suggests that visual complexity, in the case of speakers, can contribute to a perception of durability and timelessness. Participants may see visually intricate designs as more likely to withstand changing trends and remain appealing over an extended period. Visual complexity, in this context, refers to the presence of intricate or elaborate design elements that catch the viewer's attention and create a sense of visual interest. In the case of the speaker, the participant believes that the visually complex design is not likely to go out of style over the next ten years. This implies that the intricate design elements of the speaker are perceived as enduring and timeless, capable of maintaining their attractiveness and appeal even as trends and styles evolve.

The participant's comment aligns with the idea that visual complexity can contribute to aesthetic longevity. Visually complex designs often possess unique and intricate details that can transcend passing trends and fads. They have the potential to capture attention, evoke a sense of admiration, and create a lasting impression on viewers. By offering a visually captivating and engaging experience, visually complex designs can stand the test of time, remaining visually appealing and relevant for a longer duration. These comments support the idea that visual complexity can contribute to aesthetic longevity. Visually complex designs are often regarded as "too complicated" or "too much" whereas simple designs are regarded as "more enduring" and "less likely to go out of style" compared to designs that have visual complexity. However, visual complexity can potentially create a lasting impression and maintain their appeal over an extended period, aligning with the participant's belief that the visual complexity can remain desirable for the next ten years. Therefore, the main hypothesis can be accepted.

CHAPTER 9: CONCLUSION

Revisiting the five hypotheses is crucial for establishing the basis of the main research question. The first hypothesis, suggesting that simplicity is perceived as 0% when visual complexity reaches 100%, is found to be false. Contrary to popular belief, the study reveals that visual complexity corresponds to approximately 18.44% of visual simplicity.

The second hypothesis can be accepted, asserting that complexity increases with visual entropy. Regression analysis demonstrates a positive linear relationship with a coefficient of 0.4, supporting this hypothesis.

The third hypothesis is not supported, which proposes significant positive correlations between visual complexity and knowledge, moderate positive correlations with memory, and weak positive correlations with familiarity. The study finds no strong correlations between aesthetic longevity and subjective experiences. Further exploration is required to examine the relationship between aesthetic longevity and subjective experience, necessitating a larger sample size and more focused survey questions.

On the other hand, the data analysis supports the fourth hypothesis, highlighting the importance of visual complexity for aesthetic longevity. The findings affirm that visual complexity does play a significant role in determining aesthetic longevity.

Regarding the fifth hypothesis, asserting that increased interaction and closer proximity lead to increased aesthetic longevity, partial acceptance is warranted due to constraints such as limited time, survey question scope, and sample size. However, it still holds true that increased interaction and closer proximity can positively influence aesthetic longevity.

Investigating and testing the five (5) hypotheses can provide me with supporting evidence to test the hypothesis of the main research question, “visual complexity plays a significant role in determining aesthetic longevity,” which holds true.

The preference for simplicity and minimalism in design is a recurring trend rooted in modernist design theories of the mid-20th century. However, this research and empirical evidence suggest that visual complexity plays a crucial role in aesthetic longevity and the overall appeal of products. Berlyne's complexity curve provides insights into people's preferences for complexity, indicating that stimuli of moderate complexity are often more engaging and aesthetically pleasing than stimuli that are too simple or too complex. Individual differences in preferences for complexity also play a role, with some individuals having a higher tolerance or preference for more complex stimuli.

The study discussed in this research further supports the idea that finding the optimal balance between simplicity and complexity in design enhances the longevity and desirability of products. The results of the study indicated that product samples with a mixed design incorporating elements of both visual complexity and simplicity received the highest ratings in terms of participants' willingness to keep them for the next decade. This finding aligns with Berlyne’s inverted U-shaped curve of complexity, suggesting that stimuli with a moderate level of complexity are often preferred over stimuli that are too simple or too complex. The study also shed light on the different preferences and interpretations individuals have regarding visual complexity and simplicity in design. Some participants favored simplicity, appreciating the elegance and understated beauty it brings, while others found visual complexity appealing, associating it with novelty, sophistication, and visual stimulation. The mixed design samples were particularly well-received, as they struck a balance between complexity and simplicity, highlighting the positive attributes of each.

Furthermore, the study revealed that participants' evaluations and preferences for visually complex products were influenced by factors such as their perception of futurism, sophistication, and aesthetic appeal. Complexity was seen as a signifier of innovation and advanced design elements, contributing to the overall allure and attractiveness of the products.

Considering the long-term implications and compatibility of products with their environments also influenced participants' decision-making processes. Evaluating the products in the context of the next ten years allowed participants to consider factors beyond immediate visual appeal, such as long-term usability and the potential for integration into their living spaces. It is important to note that aesthetic preferences and interpretations of complexity are subjective and can vary among individuals. Contextual factors, for example, the participants who were experienced design students vs. the participants who were non-design students, also influenced participants' perceptions of complexity in design. Therefore, designers should consider a diverse range of individuals' preferences and cognitive capacities when creating products that strike the right balance between simplicity and complexity.

In conclusion, while simplicity and minimalism remain popular trends, visual complexity has a significant role to play in aesthetic longevity and the appeal of products. Finding the optimal balance between simplicity and complexity can create visually appealing and enduring designs that resonate with users over time. By considering the preferences and cognitive capacities of individuals, designers can create experiences that are visually engaging, intellectually stimulating, and capable of standing the test of time.

CHAPTER 10: FUTURE RESEARCH

10.1 Overview

The journey of research is often characterized by a continuous cycle of discovery and curiosity. As I delve deeper into a particular subject or field, each answer I find seems to unearth new layers of knowledge and ignite further intellectual curiosity within myself. This process not only expands my understanding but also opens up a world of exciting research questions waiting to be explored. The initial research I conducted has undoubtedly provided me with valuable insights and answers to the questions I had at the outset. However, as I get into the details, I begin to realize that the more I know, the more there is to discover. The acquired knowledge serves as a foundation upon which I can build new inquiries and move into uncharted territories.

10.2 Future Research Questions

As I embrace this bigger intellectual curiosity, I find myself formulating more research questions that encompass broader aspects of the topic. The research questions below may explore the underlying mechanisms, extend the boundaries of existing theories, or seek to apply the acquired knowledge in innovative ways.

10.2.1 Investigating the optimal balance between visual complexity and simplicity

The exploration of the optimal balance between visual complexity and simplicity is the current research avenue that has gained significant attention in fields such as user interface design and cognitive psychology. This research aims to understand how visual stimuli can effectively convey information while maintaining clarity and ease of comprehension for the intended audience.

One aspect of this research involves examining the impact of visual complexity on attention and cognitive load. Studies have shown that excessively complex visuals can overwhelm individuals, leading to cognitive overload and reduced information processing capacity. On the other hand, overly simplistic visuals may fail to capture attention or convey the desired message effectively. Therefore, researchers strive to find the sweet spot where visuals strike the right balance between complexity and simplicity to optimize information processing and comprehension. This can lead to collaboration among cognitive psychology, industrial design, and information science.

Psychological experiments and surveys are also valuable tools for examining individuals' perceptions and preferences regarding visual complexity and simplicity. Participants can be presented with different visual designs, ranging from highly complex to extremely simple, and their responses can be collected through questionnaires, rating scales, or interviews. This data can shed light on how individuals perceive and interpret visual information, helping researchers identify optimal levels of complexity for different contexts and target audiences.

The findings from research on the optimal balance between visual complexity and simplicity have practical implications across various domains. For instance, in graphic design, understanding the ideal level of complexity can guide the creation of visually appealing and communicative materials, such as logos, advertisements, and infographics. In user interface design, optimizing the balance between complexity and simplicity can enhance the usability and user experience of digital interfaces, leading to improved engagement and satisfaction.

Overall, investigating the optimal balance between visual complexity and simplicity is a multidisciplinary endeavor that draws from fields such as design, psychology, and neuroscience. By employing diverse research methodologies, researchers can gain a comprehensive understanding of how visual stimuli can effectively convey information while considering the cognitive processes and preferences of the intended audience. Ultimately, this research will contribute to the development of guidelines and principles that can inform the creation of visually engaging and comprehensible materials in various domains.

10.2.2 How could the level of visual complexity be changed by users' backgrounds?

The influence of users' backgrounds on the perception and interpretation of visual complexity is an intriguing area of research within the field of visual communication and design. This line of inquiry recognizes that individuals' backgrounds, such as cultural, educational, and experiential factors, can shape their visual preferences, cognitive processes, and overall understanding of visual stimuli.

Culture plays a significant role in shaping individuals' perceptions and preferences regarding visual complexity. Different cultures may have distinct aesthetic values and visual norms that influence how complexity is perceived and evaluated. For example, some cultures may prefer intricate and detailed visuals, while others may value simplicity and minimalism. Researchers have conducted cross-cultural studies to explore these variations in visual preferences and to understand how cultural background impacts individuals' perception of complexity.

Moreover, users' educational backgrounds can also influence their perception of visual complexity. People with a higher level of education or expertise in a particular domain may possess a greater familiarity with complex visual representations and may be more adept at processing intricate information. As a result, their tolerance for visual complexity may differ from that of individuals with less specialized knowledge. Researchers have examined the impact of educational background on visual complexity perception to gain insights into how expertise and knowledge shape individuals' preferences and processing abilities.

Furthermore, individuals' prior experiences and exposure to visual stimuli can also impact their perception of complexity. For instance, someone with extensive experience in a specific field or profession may have developed a mental model that allows them to perceive and comprehend complex visuals more efficiently. On the other hand, individuals with limited exposure to complex visuals may find them more challenging to understand and may prefer simpler representations. Research has explored how prior experiences and familiarity with specific visual domains influence individuals' perception and evaluation of complexity.

To investigate the influence of users' backgrounds on visual complexity, researchers often employ a combination of qualitative and quantitative methods. Surveys, interviews, and focus groups can help gather subjective insights and preferences related to visual complexity. Researchers can ask participants about their cultural background, educational experiences, and visual preferences to understand how these factors shape their perception of complexity. Additionally, psychophysical experiments can be conducted to measure individuals' sensitivity to changes in visual complexity based on their backgrounds. By exploring the relationship between users' backgrounds and the perception of visual complexity, researchers can gain a more nuanced understanding of how individual differences influence visual communication and design. This knowledge can inform the development of tailored visual materials that resonate with diverse audiences, considering their cultural backgrounds, educational levels, and prior experiences. It can also help designers create inclusive and accessible visuals that effectively convey information to a wide range of users, accounting for their varied perceptions and preferences regarding complexity.

10.2.3 How will users perceive the visual complexity between good affordance and no affordance?

The concept of affordance, introduced by psychologist James J. Gibson, refers to the perceived action possibilities or functionalities of an object or environment. In the context of visual design, the level of affordance refers to the degree to which visual elements suggest their intended interactions or functions. Understanding how users perceive visual complexity in relation to the level of affordance is a crucial area of research that explores how design cues influence users' interactions and interpretations.

When visual elements exhibit a high level of affordance, they provide clear and intuitive cues about their functionality or purpose, making it easier for users to understand how to interact with them. In this context, the level of visual complexity can influence users' perception and interpretation of affordance.

Research (Hartson & Pyla, 2012) has shown that in some cases, “*the amount of visual complexity can increase affordances or perceived cues for engagement*.” When visual elements display subtle cues, such as gradients, shadows, or texture, users may perceive them as more tangible and interactive. This moderate level of complexity adds visual richness and depth to the design, conveying a sense of functionality and interactivity.

However, there is a limit to the beneficial impact of visual complexity on affordance perception. When the complexity surpasses a certain threshold, it can lead to confusion or cognitive overload, hindering users' ability to recognize and understand the affordances of the visual elements. Excessive complexity may obscure the intended functionality or create visual noise, making it difficult for users to discern the affordance cues amidst the clutter.

To investigate the relationship between the level of affordance and users' perception of visual complexity, researchers employ a range of methodologies. User studies and usability tests can be conducted to assess how users perceive and interpret visual elements with different levels of affordance and complexity. By collecting qualitative and quantitative data, researchers can gain insights into users' preferences, comprehension, and ease of interaction with visually complex elements that exhibit varying levels of affordance. Understanding how users perceive visual complexity in relation to the level of affordance is essential for effective design practices. Designers can leverage this knowledge to create visually appealing and user-friendly interfaces or products by carefully balancing the complexity and affordance of visual elements. By providing clear and intuitive cues while considering the users' cognitive load, designers can enhance users' perception of affordance, improving the usability and user experience of their designs.

Overall, research on the relationship between users' perception of visual complexity and the level of affordance provides valuable insights into the interplay between design cues and users' interpretations. By understanding how visual elements with varying levels of complexity influence affordance perception, designers can create more intuitive and engaging visual experiences that facilitate users' interactions and understanding.

REFERENCES

Ainsworth, M. D. S. (1969). Object relations, dependency, and attachment: A theoretical review of the infant-mother relationship. *Child development*, 969-1025.

Aldwin, C. M., Park, C. L., & Spiro, A. (2007). *Handbook of health psychology and aging*: Guilford Press.

Anderson, R. E., & Jolson, M. A. (1980). Technical wording in advertising: implications for market segmentation. *Journal of Marketing, 44*(1), 57-66.

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.

Arnheim, R. (1954). Art and visual perception. Berkeley. *University of California Press, Ltd, 197*(4), 96-161.

Arnheim, R. (1974). *Entropy and art: An essay on disorder and order*: Univ of California Press.

Babri, M., Corvellec, H., & Stål, H. I. (2021). Material affordances in circular products and business model development: for a relational understanding of human and material agency. *Culture and Organization*, 1-18.

Bandt, C., & Pompe, B. (2002). Permutation entropy: a natural complexity measure for time series. *Physical review letters, 88*(17), 174102.

Barbiroli, G. (2008). Profile of products enduring quality over long periods as strategic factor to increase their utilisation rate. *International Journal of Product Development, 6*(3-4), 450-467.

Barnsley, M. F. (2014). *Fractals everywhere*: Academic press.

Bennett, C. H. (1995). Logical depth and physical complexity. *The Universal Turing Machine A Half-Century Survey*, 207-235.

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

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.

Bogg, T., & Roberts, B. W. (2004). Conscientiousness and health-related behaviors: a meta-analysis of the leading behavioral contributors to mortality. *Psychological bulletin, 130*(6), 887.

Bogg, T., & Roberts, B. W. (2013). The case for conscientiousness: Evidence and implications for a personality trait marker of health and longevity. *Annals of Behavioral Medicine, 45*(3), 278-288.

Bonner, J. T. (2004). Perspective: the size-complexity rule. *Evolution, 58*(9), 1883-1890.

Braathen, N. A. (2004). *Addressing the Economics of Waste*.

Burall, P. (1991). *Green design*: Gower Publishing Company, Limited.

Carroll, T., & Burton, R. M. (2000). Organizations and complexity: Searching for the edge of chaos. *Computational & Mathematical Organization Theory, 6*(4), 319-337.

Chapman, J. (2009). Design for (Emotional) Durability. *Design Issues, 25*(4), 29-35. Retrieved from http://www.jstor.org/stable/20627827

Charter, M., & Tischner, U. (2001). *Sustainable solutions: developing products and services for the future*: Routledge.

Chase, W. G., & Simon, H. A. (1973). Perception in chess. *Cognitive psychology, 4*(1), 55-81.

Coggins, C. (2001). Waste prevention—an issue of shared responsibility for UK producers and consumers: policy options and measurement. *Resources, Conservation and Recycling, 32*(3-4), 181-190.

Cooper, T. (1994 a). The durability of consumer durables. *Business Strategy and the Environment, 3*(1), 23-30.

Cooper, T. (1994 b). Beyond recycling: The longer life option.

Cooper, T. (2012). *The value of longevity: product quality and sustainable consumption.* Paper presented at the Proceedings: Global Research Forum on Sustainable Consumption and Production, June.

Cover, T. M. (1999). *Elements of information theory*: John Wiley & Sons.

Cutting, J. E. (1982). Two ecological perspectives: Gibson vs. Shaw and Turvey. *The American Journal of Psychology, Vol. 95*(No. 2), 199-222.

De Young, R., Duncan, A., Frank, J., Gill, N., Rothman, S., Shenot, J., . . . Zweizig, M. (1993). Promoting source reduction behavior: The role of motivational information. *Environment and Behavior, 25*(1), 70-85.

Deicher, S. (1999). *Piet Mondrian, 1872-1944: structures in space*: Taschen.

Donaldson, W., MAcKENZIE, T. M., & Underhill, C. F. (1996). A comparison of recollective memory and source monitoring. *Psychonomic Bulletin & Review, 3*, 486-490.

Edell, J. A., & Mitchell, A. A. (1978). An information processing approach to cognitive responses. *Research frontiers in marketing: Dialogues and directions*, 178-183.

Eunomia, T. E. C., Öko-Institut, TNO, & Consulting, A. (2007). WR0103: Household Waste Prevention Policy Side Research Programme. A project for Defra's WREP. In.

Faber, N., Jorna, R., & Van Engelen, J. (2010). The sustainability of "sustainability"—A study into the conceptual foundations of the notion of "sustainability". In *Tools, techniques and approaches for sustainability: Collected writings in environmental assessment policy and management* (pp. 337-369): World Scientific.

Falconer, K. J. (2013). *Fractals: A very short introduction* (Vol. 367): Oxford University Press.

Feldman, D. P., & Crutchfield, J. P. (1998a). Measures of statistical complexity: Why? *Physics Letters A, 238*(4-5), 244-252.

Feldman, D. P., & Crutchfield, J. P. (1998b). Measures of statistical complexity: Why? *Physics Letters-Section A, 238*(4), 244-252.

Fibuch, E., & Van Way III, C. W. (2012). Sustainability: a fiduciary responsibility of senior leaders? *Physician executive, 38*(2), 36-42.

Fiksel, J. (1996). Achieving eco-efficiency through design for environment. *Environmental Quality Management, 5*(4), 47-54.

Forsythe, A., Nadal, M., Sheehy, N., Cela-Conde, C. J., & Sawey, M. (2011). Predicting beauty: fractal dimension and visual complexity in art. *British journal of psychology, 102*(1), 49-70.

Friedman, H. S. (2000). Long-term relations of personality and health: Dynamisms, mechanisms, tropisms. *Journal of personality, 68*(6), 1089-1107.

Gell-Mann, M. (2002). Plectics: The study of simplicity and complexity. *Europhysics news, 33*(1), 17-20.

Geraci, L., McCabe, D. P., & Guillory, J. J. (2009). On interpreting the relationship between remember–know judgments and confidence: The role of instructions. *Consciousness and cognition, 18*(3), 701-709.

Ghim, Y.-G., & Shin, C. (2021). *Ageless design: Interdependency between complexity and simplicity in visual perception of product aesthetics for product longevity.* Paper presented at the Advances in Industrial Design: Proceedings of the AHFE 2021 Virtual Conferences on Design for Inclusion, Affective and Pleasurable Design, Interdisciplinary Practice in Industrial Design, Kansei Engineering, and Human Factors for Apparel and Textile Engineering, July 25-29, 2021, USA.

Gibson, J. J. (1979). The Ecological Approach to Visual Perception: Classic Edition.

Harte, J. (1985). Consider a spherical cow: a course in environmental problem solving.

Hartmanis, J., & Hopcroft, J. E. (1971). An overview of the theory of computational complexity. *Journal of the ACM (JACM), 18*(3), 444-475.

Hartson, R., & Pyla, P. S. (2012). *The UX Book: Process and guidelines for ensuring a quality user experience*: Elsevier.

Heimbach, A. E., Johansson, J. K., & MacLachlan, D. L. (1989). Product familiarity, information processing, and country-of-origin cues. *ACR North American Advances*.

Hekkert, P., Snelders, D., & Van 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.

Jessor, R. (1998). *New perspectives on adolescent risk behavior*: Cambridge University Press.

Johnson, E. J., & Russo, J. E. (1981). Product Familiarity and Learning New Information. *ACR North American Advances*.

Johnson, E. J., & Russo, J. E. (1984). Product familiarity and learning new information. *Journal of consumer research, 11*(1), 542-550.

Kauffman, S. A. (1993). *The origins of order: Self-organization and selection in evolution*: Oxford University Press, USA.

King, A. M., Burgess, S. C., Ijomah, W., & McMahon, C. A. (2006). Reducing waste: repair, recondition, remanufacture or recycle? *Sustainable development, 14*(4), 257-267.

Kuznetsov, B. (1987). Dynamism and the Critique of Stationary Being. In *Reason and Being* (pp. 239-275): Springer.

Langton, C. G., Taylor, C., Farmer, J. D., & Rassmussen, S. (1992). *Artificial life 2: Santa Fe Institute studies in the sciences of complexity.* Paper presented at the Proc.

Lewis, H., Gertsakis, J., Grant, T., Morelli, N., & Sweatman, A. (2001). Design plus Environment.

Lidwell, W., & Manacsa, G. (2011). *Deconstructing product design: exploring the form, function, usability, sustainability, and commercial success of 100 amazing products*: Rockport Pub.

Lloyd, S., & Pagels, H. (1988). Complexity as thermodynamic depth. *Annals of physics, 188*(1), 186-213.

Lombrozo, T. (2007). Simplicity and probability in causal explanation. *Cognitive psychology, 55*(3), 232-257.

Mandelbrot, B. B. (1982). *The fractal geometry of nature* (Vol. 1): WH freeman New York.

McGrenere, J., & Ho, W. (2000). *Affordances: Clarifying and evolving a concept.* Paper presented at the Graphics interface.

McWhinnie, H. J. (1993). Response time and aesthetic preference. *Perceptual and motor skills*.

Mitchell, M. (2009). *Complexity: A guided tour*: Oxford University Press.

Mittelstrass, J. (2014). Complexity, reductionism, and holism in science and philosophy of science. *Complexity and analogy in science: theoretical, methodological and epistemological aspects*, 45.

Mont, O. (2008). Innovative approaches to optimising design and use of durable consumer goods. *International Journal of Product Development, 6*(3-4), 227-250.

Norman, D. A. (1988). *The psychology of everyday things*: Basic books.

Norman, D. A. (1999). Affordance, conventions, and design. *interactions, 6*(3), 38-43.

Norman, D. A. (2016). *Living with complexity*: MIT press.

Packard, N. H. (1988). Adaptation toward the edge of chaos. *Dynamic patterns in complex systems, 212*, 293-301.

Paola, C., & Leeder, M. (2011). Simplicity versus complexity. *Nature, 469*(7328), 38-39.

Peitgen, H.-O., Jürgens, H., Saupe, D., & Feigenbaum, M. J. (2004). *Chaos and fractals: new frontiers of science* (Vol. 106): Springer.

Reason, P., & Goodwin, B. (1999). Toward a science of qualities in organizations: lessons from complexity theory and postmodern biology. *Concepts and Transformation, 4*(3), 281-317.

Rescher, N. (2020). *Complexity: A philosophical overview*: Routledge.

Rosso, O. A., De Micco, L., Larrondo, H. A., Martín, M. T., & Plastino, A. (2010). Generalized statistical complexity measure. *International Journal of Bifurcation and Chaos, 20*(03), 775-785.

Runkel, M. (2003). Product durability and extended producer responsibility in solid waste management. *Environmental and Resource Economics, 24*(2), 161-182.

Sandau, K., & Kurz, H. (1997). Measuring fractal dimension and complexity—an alternative approach with an application. *Journal of microscopy, 186*(2), 164-176.

Sanders, J. T. (1997). An ontology of affordances. *Ecological psychology, 9*(1), 97-112.

Scarantino, A. (2003). Affordances explained. *Philosophy of science, 70*(5), 949-961.

Schooler, R. D. (1965). Product bias in the Central American common market. *Journal of marketing research, 2*(4), 394-397.

Schultz, M., & Joachims, T. (2003). Learning a distance metric from relative comparisons. *Advances in neural information processing systems, 16*.

Shaw, R., Turvey, M., & Mace, W. (1982). Ecological psychology. The consequence of a commitment to realism. In W. Weimer & D. Palermo (Eds.) Cognition and the symbolic processes. Vol. 2 Pages 159–226.

Shelley, C. (2015). The nature of simplicity in Apple design. *The Design Journal, 18*(3), 439-456.

Sigaki, H. Y., Perc, M., & Ribeiro, H. V. (2018). History of art paintings through the lens of entropy and complexity. *Proceedings of the National Academy of Sciences, 115*(37), E8585-E8594.

Skogen, M. (2017). Do You See What I See? Investigations into the Underlying Parameters of Visual Simplicity.

Smith, L. F., Bousquet, S. G., Chang, G., & Smith, J. K. (2006). Effects of time and information on perception of art. *Empirical Studies of the Arts, 24*(2), 229-242.

Smuts, J. (1927). Holism and Evolution. *International Journal of Ethics, 37*(3).

Stahel, W. (2010). *The performance economy*: Springer.

Stahel, W. R., & Jackson, T. (1993). Optimal utilisation and durability: towards a new definition of the service economy In T. Jackson (Ed.), *Clean Production Strategies, developing*

preventive environmental management in the industrial economy (1st Edition ed., pp. 261-294): CRC Press.
Stoffregen, T. A. (2003). Affordances as properties of the animal-environment system. *Ecological psychology, 15*(2), 115-134.
Tame, J. R. (2019). *Approaches to Entropy*: Springer.
Taylor, R., Micolich, A., & Jonas, D. (2002). The construction of Pollock's fractal drip paintings, to be published in. *Leonardo*.
Taylor, R. P., Spehar, B., Wise, J., Clifford, C., Newell, B., & Martin, T. (2005). Perceptual and physiological responses to the visual complexity of Pollock's dripped fractal patterns. *Journal of Non-linear Dynamics, Psychology and Life Sciences*.
Taylor, R. P., Spehar, B., Wise, J. A., Clifford, C., Newell, B. R., Hagerhall, C. M., . . . Martin, T. P. (2005). Perceptual and physiological responses to the visual complexity of fractal patterns. *Nonlinear Dynamics Psychol. Life. Sci, 9*, 89-114.
Tinsley, B. J. (1992). Multiple influences on the acquisition and socialization of children's health attitudes and behavior: An integrative review. *Child development, 63*(5), 1043-1069.
Turvey, M. T. (1992). Affordances and prospective control: An outline of the ontology. *Ecological psychology, 4*(3), 173-187.
Van der Helm, P. A. (2000). Simplicity versus likelihood in visual perception: From surprisals to precisals. *Psychological Bulletin, 126*(5), 770.
Varnedoe, K., & Karmel, P. (1998). *Jackson Pollock*: Abrams.
Wahl, D. C. (2006). *Design for Human and Planetary Health: A Holistic and Integral Approach to Complexity and Sustainability.* University of Dundee,
Wallner, T. S., Magnier, L., & Mugge, R. (2020). An exploration of the value of timeless design styles for the consumer acceptance of refurbished products. *Sustainability, 12*(3), 1213.
Weaver, P. M. (2008). Incentives and frameworks for increasing the capital value, service value and use rates of durable goods. *International Journal of Product Development, 6*(3-4), 310-333.
Williams, H. L., Conway, M. A., & Moulin, C. J. (2013). Remembering and knowing: Using another's subjective report to make inferences about memory strength and subjective experience. *Consciousness and Cognition, 22*(2), 572-588.
Williams, H. L., & Moulin, C. J. A. (2015). Know versus Familiar: Differentiating states of awareness in others' subjective reports of recognition. *Memory, 23*(7), 981-990. doi:10.1080/09658211.2014.945460
Williams, R., Kuhn, C., Helms, M., Siegler, I., Barefoot, J., & Ashley-Kocy, A. (2004). *Central nervous system (CNS) serotonin function and NEO-PI personality profiles.* Paper presented at the 62nd annual meeting of the American Psychosomatic Society, Orlando, FL.
Wright, P. (1975). Consumer choice strategies: Simplifying vs. optimizing. *Journal of marketing research, 12*(1), 60-67.
Zenil, H., Kiani, N. A., & Tegnér, J. (2018). A review of graph and network complexity from an algorithmic information perspective. *Entropy, 20*(8), 551.

APPENDIX A: CONSENT FORM FOR MEDIA RELEASE

Media Consent & Release

I understand that I will be recorded by the University of Illinois at Urbana-Champaign arising out of

STUDY OF INTERDEPENDENCY BETWEEN COMPLEXITY AND LONGEVITY

(Program and/or Activity)

I understand that this content may be used for educational and/or promotional purposes and distributed in various formats including, but not limited to, the classroom, online, and any other communications medium currently existing or later created.

I give my permission and authorize the University of Illinois at Urbana-Champaign to record, photograph, edit, or otherwise reproduce this content, and the associated image, voice, likeness, and other materials, and to use it in the formats and for the purposes stated above.

I agree to hold harmless the University of Illinois at Urbana-Champaign, and their employees and representatives, against any and all claims arising out of the recording, including, but not limited to, claims of copyright infringement. I warrant that I have the full right and authority to grant this consent.

I declare that I have read the above, fully understand its meaning and effect, and agree to be bound by it.

NAME: ____________________

DATE: ____________________

SIGNATURE: ____________________

APPENDIX B: CONSENT FORM FOR SOCIAL BEHAVIOR RESEARCH

Social Behavioral Research Consent Form

INTERDEPENDENCY BETWEEN COMPLEXITY AND LONGEVITY

You are being asked to participate in a voluntary research study. The purpose of this study is to find out relationship between aesthetic complexity and product longevity. Participating in this study will involve examining each consumer electronics and your participation will last 30 min ~ 45 min. There is no known Risks related to this research; benefits related to this research include finding out own aesthetic preferences. The alternative to participating in this study is to withdraw this participation.

Principal Investigator Name and Title: Cliff Shin, Associate Professor of Industrial Design
Department and Institution: School of Art and Design
Contact Information: thecliff@illinois.edu
Sponsor: None

Why am I being asked?
You are being asked to be a participant in a research study about Interdependency Between complexity and longevity. The purpose of this study is to find out relationship between aesthetic complexity and product longevity. You have been asked to participate in this research because you would be able to use Bluetooth speakers and game controllers. Approximately 90 participants will be involved in this research at the University of Illinois at Urbana-Champaign.

Your participation in this research is voluntary. Your decision whether or not to participate will not affect your current or future dealings with the University of Illinois at Urbana-Champaign. If you decide to participate, you are free to withdraw at any time without affecting that relationship.

What procedures are involved?
The study procedures are to examine the consumer electronic products – Bluetooth Speakers, Game Controllers, and Wristwatches – and to answer the questions.

This research will be performed at School of Art & Design, SCD, and BIF. You will need to come to any sites based on your preference at least one time over the fall semester. Each of those visits will last 30min ~ 45min.

What are the potential risks and discomforts?
There is no known risk or discomfort.

Are there benefits to participating in the research?
Participants may learn their own aesthetic preferences. By participating in this research, researchers analyze and investigate the date if there is a relationship between aesthetic complexity and product longevity. At the same time, the researchers will investigate relationship between familiarity and complexity.

What other options are there?
You have the option to not participate in this study.

Will my study-related information be kept confidential?

1

Faculty, staff, students, and others with permission or authority to see your study information will maintain its confidentiality to the extent permitted and required by laws and university policies. The names or personal identifiers of participants will not be published or presented.

Will I be reimbursed for any expenses or paid for my participation in this research?
You will not be offered payment for being in this study.

Can I withdraw or be removed from the study?
If you decide to participate, you are free to withdraw your consent and discontinue participation at any time. The researchers also have the right to stop your participation in this study without your consent if they believe it is in your best interests, you were to object to any future changes that may be made in the study plan.

Will data collected from me be used for any other research?
Your de-identified information and/or biospecimens could be used for future research without additional informed consent.

Who should I contact if I have questions?
Contact the researchers Cliff Shin, Associate Professor of Industrial Design at thecliff@illinois.edu if you have any questions about this study or your part in it, or if you have concerns or complaints about the research.

What are my rights as a research subject?
If you have any questions about your rights as a research subject, including concerns, complaints, or to offer input, you may call the Office for the Protection of Research Subjects (OPRS) at 217-333-2670 or e-mail OPRS at irb@illinois.edu. If you would like to complete a brief survey to provide OPRS feedback about your experiences as a research participant, please follow the link here or through a link on the OPRS website: https://oprs.research.illinois.edu/. You will have the option to provide feedback or concerns anonymously or you may provide your name and contact information for follow-up purposes.

I have read the above information. I have been given an opportunity to ask questions and my questions have been answered to my satisfaction. I agree to participate in this research. I will be given a copy of this signed and dated form.

______________________________ ____________
Signature Date

____
Printed Name

______________________________ ____________
Signature of Person Obtaining Consent Date (must be same as subject's)

Cliff Shin
Printed Name of Person Obtaining Consent

APPENDIX C: IRB APPROVAL LETTER

UNIVERSITY OF ILLINOIS URBANA-CHAMPAIGN

Office of the Vice Chancellor for Research & Innovation
Office for the Protection of Research Subjects
805 W. Pennsylvania Ave., MC-095
Urbana, IL 61801-4822

Notice of Approval: New Submission

August 22, 2022

Principal Investigator	Cliff Shin
Protocol Title	*INTERDEPENDENCY BETWEEN COMPLEXITY AND LONGEVITY*
Protocol Number	23250
Funding Source	Unfunded
Review Type	Expedited 6, 7
Risk Determination	No more than minimal risk
Status	Active
Amendment Approval Date	August 19, 2022
Expiration Date	August 18, 2027

This letter authorizes the use of human subjects in the above protocol. The University of Illinois at Urbana-Champaign Institutional Review Board (IRB) has reviewed and approved the research study as described.

The Principal Investigator of this study is responsible for:

- Conducting research in a manner consistent with the requirements of the University and federal regulations found at 45 CFR 46.
- Using the approved consent documents, with the footer, from this approved package.
- Requesting approval from the IRB prior to implementing modifications.
- Notifying OPRS of any problems involving human subjects, including unanticipated events, participant complaints, or protocol deviations.
- Notifying OPRS of the completion of the study.

UNIVERSITY OF ILLINOIS URBANA-CHAMPAIGN

IORG0000014 • FWA #00008584
217.333.2670 • irb@illinois.edu • oprs.research.illinois.edu