



**Is it top-down or bottom-up? An evaluation of processes involved in salience and decision making utilising eye-tracking consumer neuroscience research**

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## **ABSTRACT**

Consumers are exposed to vast amounts of visual stimuli on an everyday basis which, due to the brain's limited processing capacity results in insufficient allocation of attention. This can be seen in terms of product advertising as well as packaging including labelling. Bottom-up and top-down visual attention processing, as well as visual saliency, are measured and analysed in neuromarketing research to aid marketers in understanding consumer attention and decision-making. Bottom-up attention refers to attention in response to external factors such as colour, shape and contrast whereas top-down attention is internally motivated in response to a goal or task. Furthermore, visual salience is said to influence bottom-up control and is used by marketers to influence consumer decision-making. Through the use of eye-tracking, a consumer neuroscience tool commonly used to aid the understanding of consumer behaviour and non-conscious cognitive processes such as decision-making, this study has provided useful insights and findings that can be used to aid future market research. A conceptual framework adapted from Wedel & Pieters (2004) and Casado-Aranda et al. (2023) was created to provide a visualisation of the current research proposal.

The purpose of this research was to identify the role of top-down and bottom-up attentional processes in consumer decision-making as determined by eye tracking, and in particular, to determine whether bottom-up eye tracking alone can explain consumer decision making. The contribution of bottom-up and top-down visual processes to consumer decision making was also examined. Furthermore, this research assessed the effect of salient objects on both bottom-up and top-down attentional processes within the consumer decision-making processes as well as the impact of salience on free and goal-directed visual search. To address the research questions and objectives the study followed a mixed methods approach combining qualitative and quantitative methods. The research included both self-report methods, eye-tracking technology and DeepGaze IIE software to assess the research framework. The combination of traditional market research techniques and consumer neuroscience technology allowed for the analysis of both conscious and subconscious responses. Respondents completed a questionnaire and three eye-tracking experiments including memorisation and decision-making tasks regarding the advertisements. A target sample of 70 people was restricted to individuals between the ages of 18 and 60 residing in the Cape Town Metropolitan area.

Market researchers commonly measure visual attention processes to assess advertisements and packaging. Inconsistent terminology and confusion has provided a need to assess the role of bottom-up and top-down visual attention processes with regard to consumer decision-making. The present study addressed gaps in literature on the role of visual attention in consumer decision-making which can be used by marketers in research and strategy development in respect of the visual attention processes and eye-tracking. The results of this study provided insights into the role of the two visual attention processes and consumer decision making utilising eye-tracking technology. Eye-tracking metrics and heatmaps showed that bottom-up visual attention was not allocated to advertisement features used in decision making. Furthermore, results of both descriptive and inferential statistics indicated top-down visual attention processes plays a significant role in consumer decision-making. Furthermore results of this study operationalised eye-tracking such as Total Fixation Duration (TFD), First Fixation Duration (FFD) and Time to First Fixation (TTFF) with regards to decision-making. Despite the role of the visual attention processes in consumer decision making, eye-tracking and visual attention processes should be used alongside other market research tools to aid understanding of consumer decision-making and navigation of marketing material allowing for a holistic view of eye-tracking and consumer decision making.

**Keywords: Visual attention, Eye-tracking, Consumer decision-making, Salience**

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## **LIST OF ABBREVIATIONS**

AC-TEA: Attention Capture and Transfer to Elements of Print Advertisements
ANOVA: Analysis of Variance
AOI: Areas of Interest
FFD: First Fixation Duration
JASP: Jeffrey's Amazing Statistics Program
N: Fixation Count
TTFF: Time to First Fixation
TFD: Total Fixation Duration
UCT: University of Cape Town

# 1. CHAPTER ONE: INTRODUCTION

## 1.1. INTRODUCTION

Consumers are exposed to numerous visual stimuli on an everyday basis through packaging, advertising, and other marketing material, resulting in competition for consumers' attention. This large influx of information exceeds the brain's processing capacity resulting in the allocation of attention, and prioritizing, perceiving and even ignoring relevant stimuli (Benoni, 2018) ultimately impacting consumer decision-making. This allocation of attentional control emphasizes the increased interest in the difference between bottom-up and top-down attention for visual attention theories. Bottom-up attention is stimulus-driven, whereas top-down attention is task orientated or goal driven (Motoki, Saito & Onuma, 2021). Despite bottom-up and top-down-attention being generated through different factors, the boundary between the two types of visual attention is not always clear (Benoni, 2018). In addition to this visual salience, an aspect of bottom-up attention is used by marketers to influence decision-making. There is debate in prior literature with regard to the influence of salience on the two attentional controls and confusion due to inconsistent terminology. Bottom-up and top-down control, as well as visual saliency, are measured and analysed in neuromarketing research to aid marketers in understanding consumer attention and decision-making (Cherubino, Martinez-Levy, Caratù, Cartocci, Di Flumeri, Modica, Rossi, Mancini & Trettel, 2019).

Consumer neuroscience, otherwise known by the industry term neuromarketing, applies neuroscience techniques for quantitative evaluation of marketing stimuli to aid in the understanding of consumer behaviour and non-conscious cognitive processes such as decision-making (Harris, Ciorciari & Gountas, 2018). Thus, consumer neuroscience techniques used alongside traditional market research methods that are often subject to bias can be used to improve understanding of consumer behaviour (Harris *et al.*, 2018). Eye-tracking is used in neuroscience and psychology to analyse gaze patterns and generate insights into cognitive processes like memory, learning and attention (Farnsworth, 2017a) Eye-tracking is used for information acquisition as well as choice. Visual attention can thus be assessed using eye-tracking to better understand information processing and consumer choices (Zuschke, 2020) and is commonly used by brands to assess consumer attention to advertising messages (Farnsworth, 2017a). Despite consumers' use of conscious thought to rationalise buying behaviour, 95% of cognitive processes such as purchase decisions and attention to marketing stimuli occur subconsciously (Hamelin & Harcar, n.d.: 163–184). Thus, neuroscience technology, such as eye-tracking, can be utilised to aid marketers and analyse unconscious consumer processes like decision-making (Hamelin & Harcar, n.d.: 163–184). Furthermore, neuromarketing can be used to improve promotional material such as advertisements to improve attention, engagement and other factors leading to decision-making (Hamelin & Harcar, n.d.: 163–184).

Due to the complexity of visual attention, the current study aimed to investigate the role of bottom-up and top-down attention processes in decision-making. Competition for attention generated by constant exposure to advertising and marketing material, numerous alternatives, similar product offerings and stimulus-rich consumer settings emphasizes the need for marketers to understand what captures consumer attention and consumer decision-making. This research has the potential to provide useful insights for marketers that can be used to aid and improve market research. The following sections will provide a comprehensive outline of the background of the study.

## **1.2. BACKGROUND OF RESEARCH**

This section provides an explanation of key constructs and the background to the research study. In particular, the history of consumer neuroscience, otherwise known as neuromarketing, is discussed, followed by consumer decision making and the visual attention process. Furthermore, the conceptual framework will be discussed briefly to provide a visualisation of the study.

### **1.2.1. Consumer Neuroscience and Neuromarketing**

Consumer neuroscience or neuromarketing is a fairly new research field that has been used for around twenty years (Tommi, 2019). Although each term has its own definition, the two are often used interchangeably (Tommi, 2019). Consumer neuroscience refers to the utilisation of neuroscience methods and theories to enhance the understanding of consumer behaviours and psychology, whereas neuromarketing is defined as the commercial and non-commercial use of neuroscience technologies, methods and theories to generate consumer insights and marketing effects (Tommi, 2019). These terms are utilised and interchanged to suit the purpose of the research (Tommi, 2019).

Self-report techniques may be subject to bias such as biases in measuring consumer response to advertising stimuli. This has resulted in the need for more objective and accurate ways of measuring consumer responses (Sánchez-Fernández, Casado-Aranda & Bastidas-Manzano, 2021). Neuroscience technology and psychology allow for a more objective measure of consumer behaviour (Sánchez-Fernández *et al.* , 2021). More traditional marketing techniques such as self-report methods like interviews, surveys and focus groups are often used to understand and predict consumer behaviour in an advertising context (Sánchez-Fernández *et al.* , 2021). However, traditional techniques measure conscious responses from consumers (Sánchez-Fernández *et al.*, 2021). Responses are thus subjective and may be affected by emotions and social desirability, which may lead to bias (Sánchez-Fernández *et al.* , 2021). Furthermore, cognitive and effective processes, as well as moment-by-moment data collection, may not be captured (Sánchez-Fernández *et al.* , 2021). Consumer neuroscience, alongside the use of traditional market research techniques, overcomes most limitations of traditional marketing research methods (Sánchez-Fernández *et al.*, 2021). A brief history of consumer neuroscience and neuroscience technology is discussed in the literature review.

### **1.2.2. VISUAL ATTENTION**

Eye-tracking is a popular tool used by neuromarketers (Tommi, 2019; Zuschke, 2020). Past literature has identified eye-tracking as the most accessible method for capturing advertising responses. This neuroscience technology has competent temporal resolution (60-120HZ) (Tommi, 2019). This study used a screen-based eye-tracker. In particular, the Tobii X-230 was used alongside Tobii Pro Labs software. Advantages of eye-tracking include strong nuanced data with regard to visual advertisements, as well as accurate measurements of attention through eye-tracking metrics (Tommi, 2019).

Attention is referred to as the mental ability to select stimuli, memories and responses (Lee, Liang, Chen, Mahdi & Qin, 2021). Attention should be considered when analysing the consumer decision-making process as it is required for information processing (Lee *et al.*, 2021). Visual attention has become a popular topic of interest for marketing such as advertisements, packaging designs, and labels (Lee *et al.*, 2021). Visual attention can be defined as the distribution of one's attentional processing

capacity to various stimuli in a visual field (Lee *et al.*, 2021). Past literature has stated that visual attention can be captured by both pictorial and textual features (Lee *et al.*, 2021). In particular, it was found that consumers' visual attention can be influenced by a task as well as time spent viewing an advertisement (Lee *et al.*, 2021). Through an understanding of cognitive processes such as attention, marketers can adapt marketing material and activities to be delivered in the most effective way (Sylwester Białowąs, Adrianna Szyszka, 2019).

Moreover, in both cognitive psychology and neuropsychology attention is divided into three forms: bottom-up attention and top-down attention, emotion driven attention, and cognition driven attention (Ramsay, 2019). For the purpose of this research focus is placed on the two main visual attention processes, bottom-up and top-down attention. Attention is not a single process and has multiple causes (Ramsay, 2019). Bottom-up attention is stimulus driven and non-volitional (Ramsay, 2019). Thus, through human senses attention is involuntarily allocated to a salient feature based on external factors and inherent properties relevant to the background (Katsuki & Constantinidis, 2014). Aspects such as colour, contrast, brightness, density, angles and movement are indices for visual salience involved in visual attention (Ramsay, 2019). These factors are critical to consider as they influence the likelihood of a feature or element being seen (Ramsay, 2019). In comparison to bottom-up attention, top-down attention is volitional and task orientated (Ramsay, 2019). Top-down attention is voluntary, using internal factors to generate attention to a specific object or feature. Therefore, top-down attention needs to be mobilised (Ramsay, 2019). Prior research investigated consumers' visual processing behaviour toward advertisements, package design and various products focusing on attention and not prediction (Lee *et al.*, 2021). Furthermore, elements such as pictorial and textual features, task and time allowed for viewing to influence consumers' visual attention (Lee *et al.*, 2021). The role of the two visual attention processes with regards to consumer decision-making has not yet been clearly defined in past and current literature. Consumer decision making and two visual attention processes as well as visual salience are discussed and analysed further in the literature review.

### **1.2.3. Consumer Decision Making**

The digital age has resulted in a change in the needs of both the consumers and advertisers (Royo-Vela & Varga, 2022). This change has resulted in advertising avoidance, making it increasingly difficult for marketers to convey advertising messages effectively (Royo-Vela & Varga, 2022). Thus, market researchers are expected to produce more accurate results and furthermore predict and improve understanding of consumer behaviour in order to combat consumer advertising avoidance (Royo-Vela & Varga, 2022). Advancements in technology have allowed marketers to better understand consumers through consumer neuroscience and neuromarketing (Royo-Vela & Varga, 2022). Marketers need to understand the processes underlying consumer decision-making to ensure the desired response to marketing stimuli (Zuschke, 2020). Vision plays a pivotal role in the acquisition of information (Zuschke, 2020). Eye-tracking is a research method that has been used to understand the cognitive processes behind consumer decision-making (Zuschke, 2020). In particular, eye-tracking research has provided an understanding of cognitive processes between the stimulus onset and decision as well as valuable insight and analysis into underlying cognitive processes (Zuschke, 2020). Decision-making insights generated through eye-tracking can provide improved understanding of contextual influences as well as how to influence decision-making more effectively (Zuschke, 2020). This information is valuable to marketers as insights can be used to improve marketing strategies and convey marketing messages more effectively.

#### **1.2.4. Theoretical and Conceptual Framework**

The present study derived a theoretical framework from key elements shared between this research and literature by (Casado-Aranda, Sánchez-Fernández & Ibáñez-Zapata (2023), Pieters & Wedel (2004) and other current and prior literature. Other key constructs utilised in this research were identified through an analysis of past and current literature.

Furthermore theoretical foundations of the two visual attention processes and visual salience were drawn from past literature. In particular, research by Pieters & Wedel (2004), Linardos, Kümmerer & Bethge (n.d.); Kümmerer, Wallis & Bethge (2016), Kümmerer, Bethge & Wallis (2022). Linardos, Kümmerer & Bethge (n.d.); Kümmerer, Wallis & Bethge (2016) and Kümmerer, Bethge & Wallis (2022) who developed DeepGaze II and IIE visual saliency models that indicate saliency predictions. A comparative analysis of differences between DeepGaze IIE and III output and eye-tracking heatmaps was conducted in this study.

A conceptual framework was developed for this study by combining the AC-TEA (Attention Capture and Transfer to Elements of Print Advertisements) model, areas of future research identified by Casado et al. (2023) and additional constructs from prior literature. The key constructs relevant to this study are visual attention, bottom-up and top-down factors, visual salience, high-level and low-level conceptual features as well as free search and visual search. This conceptual framework provides an adapted visualisation of the visual attention process and consumer decision making. Casado et al. (2023) conducted research to evaluate communication effectiveness by using eye-tracking. The research provided a figure indicating future research areas and application of the eye-tracking technique from past literature. This figure was developed using SciMAT software and identified common research themes amongst neuroscience techniques as well as the classification of relevant social, intellectual and conceptual frameworks used in eye-tracking research (Casado-Aranda et al., 2023). Pieters & Wedel (2004) developed the AC-TEA model for determinants of attention capture and transfer to elements of print advertisements (Pieters & Wedel, 2004).

Overall, a combination of the aforementioned and other prior literature was used to generate the theoretical framework for this research. This study aimed to assess the role of visual attention processes with regard to consumer decision making.

### **1.3. THE PROBLEM STATEMENT, JUSTIFICATION AND CONTRIBUTION OF RESEARCH**

Visual attention aids in the understanding of consumer behaviour by gaining insight into consumer judgement and decision processes through information search, evaluation of alternatives and selection (Ladeira, Nardi, de Oliveira Santini & Jardim, 2019). Through analysis of consumers' physiological behaviours such as eye movements, marketing managers, researchers and other marketing personnel, can use eye-tracking results to gain competitive advantage through making more strategic marketing decisions (Ladeira *et al.*, 2019). Improving the understanding of visual attention with regard to consumer behaviour will allow marketers to develop more efficient communication strategies (Ladeira *et al.*, 2019) and research methods. Eye-tracking has become a popular tool to assess visual attention; however, conflicting results, discrepancies and inconsistent terminology were reported in past literature (Ladeira *et al.*, 2019; Schutt *et al.*, 2019). At present, there is no universal agreement on which of the two visual attention processes is more important and the boundary between bottom-up and top-down attention is blurred (Benoni, 2019; Katsuki & Constantinidis, 2014). There are contrasting views with

some literature arguing for top-down control as opposed to bottom-up control (Vo, 2020). Research suggests that bottom-up factors such as salience are irrelevant in natural environments, implying that attention only uses top-down processes (Orquin, Bagger, Lahm, Grunert, & Scholderer, 2020), thus indicating that consumers should be able to ignore visually salient advertising (Orquin *et al.*, 2020). This gives rise to questions about the involvement of and relationship between the two visual attention processes with salience and decision-making.

Furthermore, visual attention in decision-making can be influenced by both how information is presented as well as the relevance of the information. A study by Orquin, Lahm and Stojic in (2021) presentation of information is more important to get attention than the relevance of the information. Thus, by leveraging visual factors marketers can attempt to guide attention to relevant information (Orquin *et al.*, 2021). Current models for visual attention such as the sequential sampling model, assume that information is attended to equally, thus assuming that attention is controlled neither by goals nor visuals (Orquin *et al.*, 2021). Current saliency models only predict bottom-up attention; however, high-level semantic features such as faces, text and symbols are not always represented by bottom-up saliency and may not involve attention due to familiarity, culture, and learning (Takano *et al.*, 2021). By gaining further understanding of the role of bottom-up and top-down visual attention processes on consumer decision making, marketers can better create and establish marketing strategies to generate consumer attention.

In addition, a meta-analysis study by Bhatnagar & Orquin (2022) analysed various stimuli categories, types, valences and positions (Bhatnagar & Orquin, 2022). These are factors which may moderate attention and choice (Bhatnagar & Orquin, 2022), thus, introducing a need for further research quantifying the impact of the environment and context of the decision. This research study assessed the impact of visuals as well as context on complex decision-making by analysing the two attentional processes and saliency during both free search and primed information search.

According to Ramsay (2019), context, time, emotions and cognitive responses are necessary to understand what people are paying attention to as well as why their attention was captured (Ramsay, 2019). Through causal understanding marketers can develop a better understanding of how they can direct consumer attention to the information and advertising elements they want prioritised (Ramsay, 2019). Moreover, definitions for various aspects of consumer neuroscience and neuromarketing are unclear resulting in conceptual confusion (Ramsay, 2019). There is a need to develop clear definitions of concepts in this field (Ramsay, 2019). At present, there is confusion about and blurred definitions of top-down and bottom-up attention. Thus, this research attempted to define the role of the two attentional processes in decision making and generate operational definitions using eye-tracking.

The aim of the study was to improve the understanding of the role of visual attention as well as saliency allowing for better and more robust neuromarketing research. Past literature has discussed and analysed the effects of top-down visual attention, bottom-up visual attention and saliency on decision-making (Ladeira *et al.*, 2019); however, the role of the two attentional processes in decision-making through eye-tracking had not yet been defined. Thus, the research question and objectives outlined in the following section were formulated.

## **1.4. RESEARCH QUESTIONS AND OBJECTIVES**

### **1.4.1. Research Question**

- What is the role of top-down and bottom-up attentional processes in consumer decision-making as determined by eye-tracking?

### **1.4.2. Research Objectives**

Through the investigation of the aforementioned research question this study addressed the following primary objective:

To ascertain the role of top-down and bottom-up attentional processes in consumer decision-making as determined by eye-tracking

As well as the following secondary objectives:

- To determine whether bottom-up eye-tracking alone can explain consumer decision-making
- To examine the contribution of bottom-up and top-down visual processes in consumer decision-making
- To assess the effect of salient objects on both bottom-up and top-down attentional processes within the consumer decision-making processes
- To identify the effect of visual salience on goal-directed and free-search fixation maps within the consumer decision making process
- To explore the effect of salience on goal-directed visual search
- To compare the difference in eye-tracking data between bottom-up features (contrast, brightness, colour) and context (faces, text and symbols)

## **1.5. RESEARCH METHODOLOGY**

This section outlines the research methodology and process through which the current research was conducted. This section discusses the research design, target population, sampling design, data collection and analysis utilised in this research. The methodology is discussed further in Chapter 4: Methodology.

### **1.6. Research Philosophy and strategy**

#### **1.6.1. Research Design**

A conclusive research design through experimentation was used in this study to provide insight into managerial decision-making on visual attention by examining the relationships between the two visual attention processes and consumer decision-making. Furthermore, the conclusive research design follows a formal structured approach using large representative sample and quantitative data analysis (Nunan, Birks and Malhotra, 2020). Quantitative data was collected using eye-tracking to gain insight into consumers' visual attention to advertisements and how this influences consumer decision-making. Qualitative data was recorded through a questionnaire, self-report data and DeepGaze IIE outputs.

### **1.6.2. Target Population and Sampling Design**

The target population consisted of individuals between the age of 18 and 60, who reside in the Cape Town metropolitan area and are familiar with the telecommunications brands: MTN, Vodacom, Cell-C and Telkom. The target population's age range was chosen in line with the research instrument. Eye-tracking technology was used in this study therefore participants needed to be above the age of 18 in order to avoid any developmental effects and below 60 to avoid the increased possibility of eye-drooping and other eye problems which may have impacted the quality of the eye-tracking data.

The target sample consisted of 70 respondents. This sample size was suitable due to the nature of the research and was in line with other studies of a similar nature. Participation in this study was voluntary. The sampling technique used in the study was convenience and random sampling. Participants were recruited through the UCT DSA invitation list as well as Neural Sense, a neuromarketing consultancy based in Cape Town. Recruitment of participants through Neural Sense allowed for access to the general public resulting in a more robust sample. A list of willing participants was compiled based on response to the research invitation and participants were randomly selected to partake in this study. Random sampling was used to allow for equal probability of participation in the study (Nunan, Birks and Malhotra, 2020).

### **1.6.3. Data Collection and Analysis**

The data collection process for the present study consisted of self-report data, data generated through consumer neuroscience technology and DeepGaze IIE output. Self-report data was recorded through a questionnaire and typed responses during the eye-tracking experiment. A questionnaire was provided to respondents through Qualtrics. A screen-based eye tracker, the Tobii X-230, was used to record participants' eye movements. Consumer neuroscience technology was used to avoid bias. Eye-tracking was used to record consumers' visual attention through eye-tracking metrics such as first fixation duration, time to first fixation, and total fixation duration, as well as fixation-based heatmaps.

DeepGaze II is a highly ranked saliency model developed by Matthias Kummerer that was used to generate predicted fixations in an image. Saliency models are image computable thus using software such as DeepGaze II, saliency maps can be formulated providing a visual representation of the likelihood of fixation at locations across stimuli (Kümmerer, Wallis & Bethge, 2016). A more recent version of DeepGaze II, DeepGaze IIE was used in this study to generate saliency maps using Jupyter software. Quantitative data Analysis was conducted using JASP, a software used for statistical analysis and hypothesis testing.

## **1.7. ORGANISATION OF THE STUDY**

**Chapter 1: Introduction** – Chapter One presents an overview of the entire study, providing an overview of the research problem, the research question as well as primary and secondary research objectives through context and relevant literature.

**Chapter 2: Literature Review** – Relevant literature is discussed and analysed in this chapter to provide insight into the current research project. Visual attention processes, visual salience as well as eye-tracking and consumer neuroscience or neuromarketing tools and research avenues are explored.

**Chapter 3: Conceptual Framework** – A conceptual model was created by adapting the ACT-TEA model by Pieters & Wedel (2004) and prospective research areas highlighted by Casado-Aranda *et al.* (2023). The conceptual framework provided a visualisation of the current study.

**Chapter 4: Methodology** – The research methodology is discussed in this chapter. In particular, the research design, research methodology, sampling design, target population, measurement instrument, data collection and analysis, as well as ethical considerations.

**Chapter 5: Presentation and Interpretation of Findings** –An overview of the findings is discussed in Chapter five. In particular, descriptive and inferential statistics are analysed and discussed.

**Chapter 6: Conclusions and Recommendations** – Conclusions and recommendations are summarised in this chapter. Furthermore, managerial implications, limitations of this research and future research avenues are outlined in this section.

## **2. CHAPTER TWO: LITERATURE REVIEW**

### **2.1. INTRODUCTION**

To investigate bottom-up and top-down attentional processes and their effect on visual salience and decision-making processes based on eye-tracking metrics, past and current literature was reviewed and analysed to define and outline relevant constructs. Firstly, an overview of consumer neuroscience and the history of consumer neuroscience and eye-tracking are discussed. This is followed by a discussion on the visual attention processes and salience in relation to consumer decision-making and eye-tracking. Lastly, the conceptual framework used to provide a visualisation of the study is presented and discussed.

### **2.2. CONSUMER NEUROSCIENCE**

An objective of market research is to obtain information that supports commercial decision-making that will guide marketing actions, and communicate findings and implications, as well as information collection methods and data collection processes (Royo-Vela & Varga, 2022). Thus, by utilising consumer neuroscience technology and resources alongside traditional market techniques, marketers may enhance their marketing strategies and actions. An outline of consumer neuroscience and neuromarketing, consumer neuroscience methods and metrics, eye-tracking metrics as well as the visual system and eye-tracking is provided in this section.

#### **2.2.1. Consumer Neuroscience and Neuromarketing**

Consumer neuroscience combines the study of mental processes and the physiological functioning of the brain and body in response to marketing stimuli (Royo-Vela & Varga, 2022). In other words, consumer neuroscience is a term used and understood as academic research combining neuroscience, biology and psychology to understand human behaviours (Royo-Vela & Varga, 2022). Although there are specific definitions for each term, consumer neuroscience and neuromarketing are used synonymously or interchangeably (Casado-Aranda & Sanchez-Fernandez, 2022; Royo-Vela & Varga, 2022). However, the two fields differ conceptually (Casado-Aranda & Sanchez-Fernandez, 2022). Neuromarketing is more commonly used as an industry term for the practical and industry application of theory and knowledge generated through consumer neuroscience (Casado-Aranda & Sanchez-Fernandez, 2022; Royo-Vela & Varga, 2022).

Neuromarketing is defined as the application of neuroscience techniques to improve understanding of the effect of marketing material such as products, brands and advertising stimuli on consumers, consumer behaviour and purchasing processes. In other words, neuromarketing is defined as a science investigating and analysing brain processes to explain actions and decision-making processes of consumers (Royo-Vela & Varga, 2022). Through the use of neuroscience tools, marketers can gain insight into consumer responses to advertisements, logos, images, packaging, branding, websites and more (Royo-Vela & Varga, 2022). Thus the combination of neuroscience and marketing allows for a better understanding of the unconscious and subconscious mind of consumers (Royo-Vela & Varga, 2022). Neuromarketing provides a means for companies to predict, analyse and comprehend consumer responses to specific brands and products related to marketing campaigns (Royo-Vela & Varga, 2022). This allows marketers to generate insights into consumer decision-making processes, and how marketing elements impact the individual, their thinking and emotions (Royo-Vela & Varga, 2022).

Neuromarketing uses cognitive psychology, neurology, neurophysiology and marketing methods to understand responses to external stimuli providing an understanding of consumer behaviours as well as their buying and decision processes (Royo-Vela & Varga, 2022). This combines the study of mental processes and the physiological functioning of the brain and body in response to marketing stimuli (Royo-Vela & Varga, 2022), allowing for objective and unbiased information to be collected with regard to consumers' memory, feelings, perception and learning throughout the consumer journey (Royo-Vela & Varga, 2022).

The overall goal of consumer neuroscience, or neuromarketing is to complement traditional marketing models (Tommi, 2019). Popular research methods are fMRI, eye-tracking, EEG (Electroencephalography), facial coding as well as GSR (Galvanic Skin Response) (Royo-Vela & Varga, 2022). According to literature by Casado-Aranda & Sanchez-Fernandez (2021), there is an increased need to highlight the contribution of neurophysiological tools used in marketing in relation to consumer decision-making. This is advantageous for market researchers as neurophysiological and psychological responses can be used to inform marketing phenomena (Casado-Aranda & Sanchez-Fernandez, 2022). This research study has contributed to this need by assessing the role of top-down and bottom-up attentional processes in consumer decision-making using eye tracking technology.

Furthermore, the digital age has resulted in a change in consumer needs. A constant influx of information has resulted in intense competition for consumers' attention. However, this has resulted in consumer avoidance of advertising material, thus more accurate market research is necessary (Royo-Vela & Varga, 2022). Moreover, understanding and predicting consumer behaviour for relevant markets has become increasingly important. Due to the ability of neuroscience technology to produce accurate results, methodologies have been adapted to specific marketing needs to help understand consumer purchasing processes and moreover tap into both unconscious and subconscious processes (Royo-Vela & Varga, 2022). The majority of consumer purchase decisions (85-90%) are made unconsciously. Traditional market research techniques cannot provide insight into the subconscious feelings, reasoning, and desires of consumers' decisions to purchase. Thus, neuromarketing has both methodological and theoretical application (Royo-Vela & Varga, 2022).

Using cognitive and affective neuroscience, neuromarketers can generate direct subconscious responses to marketing stimuli. Furthermore, through theoretical understanding of the brain and psychological responses, insights and patterns of consumer behaviour can be better understood (Royo-Vela & Varga, 2022). Studying subconscious decision-making processes is important due to the influence of the subconscious on decision-making and explanations of decisions and emotions impacting consumer judgement and choices as well as decisions often occurring based on partial information (Royo-Vela & Varga, 2022).

### **2.2.2. Consumer Neuroscience Methods and Metrics**

Neuromarketing tools have been divided into three subcategories: (1) Metabolic brain activity (e.g., functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG) or positron emission tomography (PET)); (2) Electrical activity of the brain (e.g., electroencephalography (EEG)); and (3) Physiological measures relating to neural activities (e.g. Eye-tracking, Galvanic Skin Response (GSR), and heart rate (ECG)). For the purpose of this research focus was placed on eye-tracking and the visual attention processes involved in consumer decision-making. These methods are often used alongside

traditional market research to enhance marketing activities and improve understanding of consumer behaviour and decision making.

Traditional market research utilises explicit measures such as questions and comparative and non-comparative statistical measures and quantitative analysis (Royo-Vela & Varga, 2022). Traditional market research is used to provide insight and predictions of relationships through the use of self-report tools such as surveys, interviews, and focus groups (Casado-Aranda & Sanchez-Fernandez, 2022). This type of research allows marketers to evaluate constructs such as attitudes, preferences, and advertising effectiveness as well as communication and distribution strategies (Casado-Aranda & Sanchez-Fernandez, 2022). However, traditional marketing techniques can be subjected to various forms of bias such as social desirability, subjectivity, and error due to language barriers (Casado-Aranda & Sanchez-Fernandez, 2022).

In contrast, neuromarketing measures implicit responses through physiological changes (Royo-Vela & Varga, 2022). Due to the complex nature of the brain, neuromarketing utilises computational models (Royo-Vela & Varga, 2022). How information is measured is dependent on the type of information received by the brain. For example, visual and auditory information will be processed differently (Royo-Vela & Varga, 2022).

Neuroscience is defined as the study of mental activities through the coordination and integration of incoming sensory messages and outgoing motor responses (Casado-Aranda & Sanchez-Fernandez, 2022). Both, cognitive and affective neuroscience have stimulated increased interest regarding the understanding of neural mechanisms and mental processes used when making decisions (Casado-Aranda & Sanchez-Fernandez, 2022). This has resulted in the development of neuroeconomics followed by consumer neuroscience (Casado-Aranda & Sanchez-Fernandez, 2022). Cognitive neuroscience provides an understanding of decision-making based on physiological responses (Casado-Aranda & Sanchez-Fernandez, 2022). The development of consumer neuroscience resulted in the use of cognitive and affective neuroscience theories by marketing academics to inform marketing tools and strategies. The use of neurophysiological tools and theories provided insight into and understanding of marketing strategies (Casado-Aranda & Sanchez-Fernandez, 2022), for example, memory, emotional engagement, predictability, trust, rewards, and willingness to pay (Casado-Aranda & Sanchez-Fernandez, 2022).

There are three neuromarketing variables and metrics: cognitive, emotional and visual behaviour (Royo-Vela & Varga, 2022). Cognitive metrics measure degree of concentration, cognitive load and engagement. Emotion is measured by type and valence through emotional activation, impact and valence indicating changes in emotion, the intensity of each change and positive or negative emotions (Royo-Vela & Varga, 2022). Visual behaviour is measured through visual interest, visual behaviour and implicit association of visual interest. Visual interest allows marketers to identify which elements catch attention and which do not. Visual behaviour refers to the order in which elements are observed by participants (Royo-Vela & Varga, 2022). Through implicit association of visual interest, the degree of association between the consumer and the stimulus can identify which attributes provide greater brand association (Royo-Vela & Varga, 2022). The present research study has attempted to further understand visual behaviour, and attention in particular, with regard to consumer decision-making.

### **2.2.3. Advantages and disadvantages of consumer neuroscience**

Using neurophysiological techniques is advantageous for researchers as these techniques have the capacity to capture hidden unconscious mechanisms unlike traditional research methods. Furthermore, it is difficult for respondents to manipulate the experiment (Casado-Aranda & Sanchez-Fernandez, 2022). Moreover, neuroscience technology allows for continuous data collection (Casado-Aranda & Sanchez-Fernandez, 2022). Unlike traditional market research, which relies more on recall and imagination, neurophysiological tools provide moment-to-moment measurement of physiological responses during a task (Casado-Aranda & Sanchez-Fernandez, 2022). Thus, using neurophysiological tools alongside traditional research techniques can be used to corroborate or refute results (Casado-Aranda & Sanchez-Fernandez, 2022).

Although neuroscience is advantageous, there are disadvantages to using neuroscience tools such as cost, artificial context, an intensive analysis process, controversy, ethical concerns, and content validity (Casado-Aranda & Sanchez-Fernandez, 2022). Due to the cost of equipment as well as recruitment of respondents, neuroscience techniques are more costly than traditional market research and thus less accessible (Casado-Aranda & Sanchez-Fernandez, 2022). Furthermore, external validity of findings may be restricted due to the artificial context as the experimental environment may not mimic real life when using neuroscience technology (Casado-Aranda & Sanchez-Fernandez, 2022). High volumes of data are provided through neuroscience research methods thus intensive analysis is required (Casado-Aranda & Sanchez-Fernandez, 2022). According to Casado-Aranda & Sanchez-Fernandez (2021), there is opportunity for research that assesses visual attention toward product cues such as product names, brands, pictures of products and prices using eye-tracking measures (Casado-Aranda & Sanchez-Fernandez, 2022). The present research assessed visual attention toward product cues (price, product, and brand) in relation to consumer decision making.

### **2.3. EYE-TRACKING**

Foveated visual systems are subject to multiple eye-movements per second to bring the fovea to focus on objects or features that are wanted to be seen (Kümmerer et. al, 2016). This places emphasis on the importance of eye movements in understanding behaviour as humans have foveated visual systems (Kümmerer et. al, 2016). The eye-mind link refers to the positioning of the fovea towards a stimulus being processed or present in our thoughts (Carter & Luke, 2020). Therefore, eye-tracking can be used to measure visual attention (Carter & Luke, 2020). Eye-tracking metrics provide insight into cognitive processes (Carter & Luke, 2020). Despite the fact that eye movements may be consciously guided towards a specific location, eye movements are typically outside of conscious control (Carter & Luke, 2020). Eye motion is typically reflexive thus details of eye movements may not be recalled by an individual (Carter & Luke, 2020). Thus, tracking eye movements can provide further insight into unconscious processes garnering our attention (Carter & Luke, 2020).

Eye-tracking is a research technique used to study both behaviour and cognition (Bercea, 2013). This research method measures attention, which provides insight into consumer behaviour. Furthermore, eye-tracking can provide insights and an understanding of attention, arousal, cognitive load and perceptual fluency (Casado-Aranda, Sánchez-Fernández & Ibáñez-Zapata, 2023). Data from eye-tracking research indicates physiological metrics resulting in insight into what is looked at, the length of time an object is looked at as well as the scan path of the respondent (Casado-Aranda *et al.*, 2023). Eye-tracking metrics are measured and captured in particular defined areas called Areas of Interest

(AOIs), allowing researchers to understand what respondents looked at (Gourdon-Kanhukamwe, Riege & Vallée-Tourangeau, 2020).

Most eye-tracking research has been used to measure attention derived from the two visual attention processes or controls. Top-down visual attention has been found to influence purposeful selection of important or relevant information (Casado-Aranda & Sanchez-Fernandez, 2022), whereas bottom-up attention captures an individual's attention through features of a stimulus (Casado-Aranda & Sanchez-Fernandez, 2022).

Moreover, new age eye-tracking techniques have provided moment by moment insight into the attention processes of communication, allowing marketers to evaluate communication effectiveness and visual attention concerning advertising (Casado-Aranda, Sanchez-Fernandez & Ibanez-Zapata, 2023). A study by Casado-Aranda, Sanchez-Fernandez & Ibanez-Zapata published in 2023 provided a systematic review of past research on visual attention and advertisements as well as the relationships between eye-tracking measures and advertising effectiveness based on cognitive, behavioural and affective consumer responses.

Recently, advertising spend for digital advertising was estimated to have overtaken traditional advertising spending (Casado-Aranda *et al.*, 2023). This change has emphasized the shift from more traditional advertisements to new promotional strategies through online, mobile and virtual environments (Casado-Aranda *et al.*, 2023). Traditional research placed focus on advertising effectiveness of media and print effects on consumer attention, emotions, interest and likeability (Casado-Aranda *et al.*, 2023). However, social media networks and other technological advances have changed the way consumers interact with advertising due to easy accessibility as well as crowded advertising platforms (Casado-Aranda *et al.*, 2023). As a result of the vast quantities of information consumed daily by individuals, attention has become a scarce resource due to the brain's limited processing capacity (Casado-Aranda *et al.*, 2023). Improving the understanding of how consumers attend to advertising material and factors influencing visual attention as well as cognitive, affective and behavioural consumer responses may aid marketers in increasing advertising effectiveness (Casado-Aranda *et al.*, 2023). Eye-tracking is a popular research instrument used to assess visual attention and consumer responses (Casado-Aranda *et al.*, 2023). In the past eye-tracking research was complex and expensive; however, eye trackers are now more readily available for commercial use (Casado-Aranda *et al.*, 2023). This neuroscience technique has increased popularity for commercial use as eye-tracking is an advantageous tool in comparison to the self-report technique. This is a result of the ability to collect moment by moment physiological data (Casado-Aranda *et al.*, 2023). Furthermore, self-report data is subject to the influence of the familiarity bias as well as the memory of consumers (Casado-Aranda *et al.*, 2023). Thus, through the use of physiological data marketers can better understand and deduce insight into the subconscious mind of the consumer.

### **2.3.1. Eye-tracking Metrics**

Eye-tracking metrics provide researchers with evidence of how respondent attention is allocated to audiovisual information over time through observation (Casado-Aranda & Sanchez-Fernandez, 2022) as well as insights into cognitive processes (Carter & Luke, 2020). Even though eye movements may be consciously directed towards a specific location, eye movements are typically outside of conscious control (Carter & Luke, 2020). Eye motion is typically reflexive thus details of eye movements may not be recalled by an individual (Carter & Luke, 2020). Thus, tracking eye movements can provide further

insight into unconscious processes garnering our attention (Carter & Luke, 2020). This research method was used in the past to measure attention, visual fixation, search, and eye-movement patterns (Carter & Luke, 2020). Past research has used eye-tracking for advertising testing, evaluating user-experience, packaging design, product placement etc. (Carter & Luke, 2020).

Consumers typically scan product options before decision-making occurs thus eye movements can be used to retrieve value representations about available options (Vriens, Vidden & Schomaker, 2020) as well as, observe the sequence of fixations, return fixations and time consumers spend looking at a particular feature or stimuli (Casado-Aranda & Sanchez-Fernandez, 2022). Eye-tracking is a research tool used to record eye movements and gaze patterns and is commonly used as a measure of visual attention (Carter & Luke, 2020). The current research study used screen-based eye-tracking to assess attentional processes concerning advertisements of relevant brands. Although screen-based systems track the eyes only within certain limits, such as distance of respondent from the screen, participants are allowed to move their head within the range of the eye-tracker allowing them some freedom of movement (Farnsworth, 2017a.).

There are two main metrics described in eye-tracking research: fixations and saccades. Information processing occurs when a fixation on a particular area within a visual field is projected onto the fovea (Casado-Aranda & Sanchez-Fernandez, 2022; Casado-Aranda, Sánchez-Fernández & Ibáñez-Zapata, 2023). Elements within a visual field are perceived by the human eye with different resolutions (Kümmerer, Bethge & Wallis, 2022). Thus, human eye-movements direct the fovea toward relevant or useful information to gather information in high resolution (Kümmerer, Bethge & Wallis, 2022). The fovea is defined as a small central area of the retina in which the field of visual acuity is the highest (Kümmerer, Bethge & Wallis, 2022). A fixation is defined as the length of time in which the eyes are focused on a specific object (Royo-Vela & Varga, 2022). Fixations occur when the eye is still for about 200 to 300 milliseconds (Casado-Aranda *et al.*, 2023). Saccades indicate intervals between fixations showing the movement of the eyes between one fixation and the next (Bylinskii, Borkin, Kim, Pfister & Olivia, 2017). Attention is redirected during saccades, reducing visual perception and information processing until the eye becomes still (Casado-Aranda *et al.*, 2023). Eye-movements are thus able to discriminate between areas of interest within a visual field by selecting and processing relevant information or locations at the expense of others (Casado-Aranda *et al.*, 2023).

Focus was placed on fixations in the present study. Eye movements such as fixation locations and durations as well as saccades can be recorded and used to analyse visual perception, interest, and salience (Bylinskii *et al.*, 2017; Royo-Vela & Varga, 2022). Fixations are obtained from continuous eye movement data when looking at a visual display (Bylinskii *et al.*, 2017). Fixations can be analysed separately using specific Areas of Interest (AOIs) (Bylinskii *et al.*, 2017). Different eye-tracking metrics highlight various aspects of behaviour which are indicative of various underlying cognitive processes (Bylinskii *et al.*, 2017). Common eye-tracking metrics are the total number of fixations or Fixation Count (N), Total Fixation Duration (TFD) and Time to First Fixation (TTFF). For this research, heat maps, time to first fixation (TTFF), fixation count, First Fixation Duration (FFD) and total fixation duration (TFD) were assessed. These metrics are defined and outlined further in the methodology section.

#### 2.3.1.1. Area of Interest (AOI)

Eye tracking metrics are measured and captured in particular defined areas called Areas of Interest (AOIs) (Gourdon-Kanhukamwe, Riege & Vallée-Tourangeau, 2020). Areas of Interest are user-defined areas of a stimulus (Farnsworth, 2017a). This is useful when looking at advertisements, packaging or any stimuli with numerous features or objects. Each AOI is created for a single stimulus thus eye movements assigned to a particular AOI will determine how much attention is allocated to that specific AOI (Krajina, 2019).

#### 2.3.1.2. Time to first fixation (TTFF)

Time to first fixation refers to the time taken for a respondent to look at a particular AOI from stimulus onset (Casado-Aranda & Sanchez-Fernandez, 2022). TTFF can be used to measure for bottom-up and top-down visual attention (Casado-Aranda *et al.*, 2023). As a result of the brain's limited processing capacity, objects or AOIs within a field of vision are selected at the expense of other objects. The fact that a stimulus is selected first may result from visual salience or relevance with competitive stimuli (Casado-Aranda *et al.*, 2023). Thus, Time to First Fixation TTFF is used to identify attention-generating properties (Bylinskii *et al.*, 2017). Through the analysis of scan paths elements that are fixated on first and multiple times can be identified. Typically, textual elements such as titles, objects, paragraphs, and headers are fixated on first and for longer than pictorial elements (Bylinskii *et al.*, 2017). The textual elements typically identify what elements are the most important in the visualization (Bylinskii *et al.*, 2017). According to prior literature more time is spent reading text than looking at images (Bylinskii *et al.*, 2017).

Limitations of time to first fixation are that the initial effect may be because of visual design characteristics thus it is not guaranteed that a consumer's gaze will be held due to the viewers interest in the stimulus (Casado-Aranda *et al.*, 2023). Stimuli or elements of a stimulus may be attended to first due to physical properties that make the stimulus stand out from the environment or due to relevance of the stimulus in comparison to competitor stimuli and visual elements (Casado-Aranda *et al.*, 2023). Thus, visual stimuli that are relevant or stand out to the respondent will have a lower TTFF. Time To First Fixation is a common measure used in eye-tracking and is best used in combination with other eye-tracking metrics to understand visual attention as a whole (Casado-Aranda *et al.*, 2023). Other eye-tracking metrics that are used in this research alongside TTFF are discussed further below.

#### 2.3.1.3. Total fixation duration and Average fixation duration

Fixation duration is the amount of time spent fixating on a specific visual area (Bylinskii *et al.*, 2017). Fixation duration is linked to information content or complexity (Bylinskii *et al.*, 2017). Total fixation duration is defined as the sum of all fixation durations belonging to a particular area of interest (AOI). Average fixation duration can help interpret stimuli complexity or engagement (Bylinskii *et al.*, 2017). Past literature indicated that object of preference and choice are viewed for longer (Vriens *et al.*, 2020). Longer total fixation durations may indicate higher levels of processing like the intentional consideration of relevant information (Casado-Aranda *et al.*, 2023). However, high total fixation durations may also indicate respondent confusion (Casado-Aranda *et al.*, 2023). This is corroborated by the positive correlation between high cognitive load and fixation duration (Liu, Li, Yeh & Chien, 2022). According to Casado-Aranda *et al.*, 2023, average fixation duration can be used as a conversion metric for advertising. For example, the higher the fixation the more complex a stimulus may be. Shorter

fixation durations less than 200-250ms can be considered involuntary (Bylinskii *et al.*, 2017), whereas fixations longer than 300ms are thought to be encoded in memory. Average fixation duration is typically longer for stimuli containing visually engaging elements such as infographics or scientific diagrams (Bylinskii *et al.*, 2017). The duration of fixations is dependent on complexity and difficulty of stimulus content as well as the task (Bylinskii *et al.*, 2017). Thus, locations with higher fixation duration can be used to identify elements that are engaging cognitive resources of the observer (Bylinskii *et al.*, 2017).

#### 2.3.1.4. Fixation count

Fixation count is the number of times a consumer looks at a particular AOI and measures the interest or relevance of a particular AOI (Casado-Aranda *et al.*, 2023). The number of fixations identified using fixation counts is linked to a visual area's importance (Bylinskii *et al.*, 2017).

Measuring the fixation count and duration is advantageous as these measurements can be aggregated across multiple data points, are independent of image content and are computed easily by eye-tracking software. (Bylinskii *et al.*, 2017). These metrics are useful when respondents are completing an objective task (Bylinskii *et al.*, 2017). Bylinskii *et al.* (2017), conducted an analysis of 24 eye-tracking studies which identified possible interpretations for quantitative eye-tracking metrics (Bylinskii *et al.*, 2017). Total number of fixations may reveal information about efficiency of searching or engagement (Bylinskii *et al.*, 2017). Furthermore, fixations on AOIs can help interpret element importance or noticeability (Bylinskii *et al.*, 2017). Increased or more frequent fixations are made on relevant or interesting elements of a stimulus (Casado-Aranda *et al.*, 2023). Increased cognitive load results in decreased fixation frequency (Liu, Li, Yeh & Chien, 2022). Therefore, the more complex or busy a stimulus is, the higher amount of cognitive load needed to process relevant information, which may result in a lower level of attention. Thus, marketers can utilise fixation frequency to identify irrelevant or redundant information or elements and thus increase advertising effectiveness.

#### 2.3.1.5. Heat maps

Heat maps provide a visual representation of eye-tracking results highlighting important aspects of visual behaviour. Heat maps are used to indicate the distribution of looking across a stimulus and therefore the focus of visual attention. Heat maps are generated through various eye-tracking metrics such as absolute and relative fixation counts or fixation durations. This map provides a visual representation eye-tracking metrics and fixations using different colours (Royo-Vela & Varga, 2022). Namely, red, yellow and green (Royo-Vela & Varga, 2022). The colour red indicates a high number of fixations whereas yellow is an indication of an intermediate number of fixations and green exhibits a low number of fixations (Royo-Vela & Varga, 2022). An absence of colour on a heat map indicates that this area was not seen or was ignored (Royo-Vela & Varga, 2022). The heat maps indicate visual attention to various advertising stimuli as well as ximages such as Where is Wally, nature and a gestalt image.

#### 2.3.1.6. First Fixation Duration

First Fixation Duration refers to the amount of time a respondent spends fixating on an AOI for the first time (Farnsworth, n.d.a.). This eye tracking metric may indicate interest in a particular feature or object. Often, this eye tracking metric is used together with time to first fixation (Farnsworth, n.d.a.). Fast time to first fixations accompanied by longer first fixation durations indicate that an area may stand out and

is eye-catching (Farnsworth, n.d.a.). Furthermore, FFD can be used to determine usefulness or importance of information or features when searching for information by comparing FFD for AOIs.

### **2.3.2. Visual System and Eye-tracking**

The human visual system responds to features within an environment. Consumers navigate a visual environment that has been designed to attract and distract consumer attention. For example, consumers are presented with numerous visual stimuli through product packaging and advertisements (Orquin *et al.*, 2020). Humans are exposed to vast amounts of sensory information with limited processing capacity (Katsuki & Constantinidis, 2014). The brain relies on cognitive attentional processes to allocate neural resources to specific events (Katsuki & Constantinidis, 2014). The two visual attention processes are functions of attention (Katsuki & Constantinidis, 2014).

Bottom-up, or exogenous attention is the allocation of attention to a salient stimulus that is driven by external factors and inherent properties relevant to a background (Katsuki & Constantinidis, 2014). In other words, information is processed and automatically selected because features of stimuli stand out from the background and other elements (Katsuki & Constantinidis, 2014). Top-down visual attention is defined as the internal selection of a particular location or feature relevant to present behavioural goals (Katsuki & Constantinidis, 2014). Top-down visual attention is voluntary (Katsuki & Constantinidis, 2014).

The frontoparietal network is critical for both bottom-up and top-down attentional processes (Katsuki & Constantinidis, 2014). Allocating attention through the selection of relevant stimuli allows us to efficiently react to changes in an environment and achieve behavioural goals (Katsuki & Constantinidis, 2014). Past studies have indicated that searching for stimuli utilizing bottom-up factors allows for parallel processing of features without examining each visual element (Katsuki & Constantinidis, 2014). The most salient stimuli or features in an environment incur the greatest neural activation and thus are allocated attention (Katsuki & Constantinidis, 2014). However, without distinctive differences between target and background stimuli, processing of features through top-down factors requires intentional examination of all visual elements individually (Katsuki & Constantinidis, 2014).

Both attentional processes occur in visual cortical areas in the ventral and dorsal pathways (Katsuki & Constantinidis, 2014). In general, connections across cortical areas are shared indicating that feedback signals can move from higher to lower stages of the pathways. Thus, literature indicates that the two attentional processes are intricately intertwined (Katsuki & Constantinidis, 2014). According to Katsuki & Constantinidis, 2014, future research is necessary to determine and understand the roles of distinct cortical areas in the guiding attention and the contribution of various mechanisms to the attentional system (Katsuki & Constantinidis, 2014).

## **2.4. ADVERTISING AND CONTEXT**

Companies and organisations spend large sums of money to deliver advertising messages and persuade consumers to purchase products or services (Eram, 2020). Advertising is not restricted to one form; typical modes of advertising are print media, broadcast media, support media, internet media and social media (Eram, 2020). This research study focused on print media, in particular, copy advertisements for telecommunications brands that would be presented in a telecommunications brochure.

### **2.4.1. The Purpose of Advertising**

The purpose or objective of utilising an advertisement is to inform, persuade or remind consumers about products or services, marketing messages and other brand offerings as well as to meet company goals (Eram, 2020). Companies utilize advertising to reach specific goals such as increasing brand awareness, sales volume, and customer base, or to overcome negative publicity (Eram, 2020). Informative advertisements introduce new products or services, providing consumers with a basic understanding of the brand, product or service offerings and benefits. Informative advertisements typically include more copy focused on features and benefits for the customer (Eram, 2020). Due to market competition, marketers utilize advertisements to persuade consumers to purchase their products or utilize their services (Eram, 2020). Marketers place focus on quality, features, and prices. In addition to this, advertisements can also play on emotions to persuade a customer to purchase a product or service (Eram, 2020). For example, when targeting mothers, advertisements may appeal to the emotions of the mothers by including imagery of a happy baby or family. Finally, advertisements are used to remind consumers about product or service offerings and reinforce the brand message (Eram, 2020). This allows marketers to ensure and maintain customer awareness and deter customers from purchasing competitor products or services (Eram, 2020).

## **2.5. VISUAL ATTENTION**

Attention is defined as the cognitive ability to flexibly and selectively control limited computational resources and select relevant information against distractors (Lindsay, 2020; Onișor & Ioniță, 2021). Visual attention is a way in which consumers acquire information about products and optimise choices (Ladeira *et al.*, 2019). Thus, through understanding visual attention, marketers can better interpret consumer behaviour. For example, decision processes are affected by visual attention (Ladeira *et al.*, 2019). The visual attention process consists of bottom-up and top-down visual attention processes (Ladeira *et al.*, 2019). The two attentional controls can directly or indirectly affect consumer choices and thus decision-making via attention (Vriens *et al.*, 2020). Marketers can better understand visual attention through the two attentional processes, visual salience as well as the types of attention by utilising eye-tracking which will be discussed further below.

### **2.5.1. Bottom-Up and Top-Down Attention**

Two main processes govern attention: the top-down and bottom-up attention processes. Top-down attention is guided by higher-level cognition whereas bottom-up attention utilizes lower-level perceptual properties of a stimulus (Vanunu, Hotaling, Le Pelley & Newell, 2021). Bottom-up, or exogenous attention is the involuntary allocation of attention to a salient stimulus that is driven by external factors and inherent properties relevant to a background (Katsuki & Constantinidis, 2014). Bottom-up attention is described as attentional selection and can be guided by a stimulus and contextual features that allow an object to stand out in comparison to its surroundings (Alamia, Solopchuk & Zénon, 2018), whereas top-down or endogenous visual attention is an internal and voluntary process directing focus to a particular feature, object or area relevant to current behavioural goals (Katsuki & Constantinidis, 2014 & Schutt *et al.*, 2019). Top-down attention is selective attention which is driven to stimuli, features or special locations relevant to current tasks or goals (Alamia, Solopchuk & Zénon, 2018). The difference between attentional selection and selective attention pertains to the involuntary nature of bottom-up attention and voluntary nature top-down attention.

Bottom-up factors refer to stimuli features attracting fixations that are independent of the observer's internal state (Schutt *et al.*, 2018). Features of a stimulus can capture attention despite an individual's ability to direct attention, resulting in the application of bottom-up control over attention (Casado-Aranda & Sanchez-Fernandez, 2022). Factors influencing bottom-up attention identify the physical salience and ultimately distinctiveness of the stimulus in its environment (Suh, Wilson & On, 2021). This is attributed to factors such as shape, size and colour (Husić-Mehmedović, Omeragić, Batagelj & Kolar, 2017 & Suh *et al.*, 2021). Furthermore, factors influencing top-down attention include goals, intentions, and prior knowledge as well as task instructions, complexity, mood, cognitive load, customer involvement, familiarity, and expectations (Orquin, Bagger, Lahm, Grunert & Scholderer, 2020 & Suh *et al.*, 2021).

Both bottom-up and top-down attention influence where AOIs fixated on viewing natural scenes (Schutt *et al.*, 2019). There is an ongoing debate in literature with regard to the importance of bottom-up influence on natural viewing with emphasis on static stimuli (Schutt *et al.*, 2019). Research has shown that eye movements may be categorised by low-level and high-level factors (Schutt *et al.*, 2019). Bottom-up control is thought to be determined by low-level factors whereas top-down control is determined by high-level factors (Schutt *et al.*, 2019). Low-level features are simple factors such as colour, brightness and contrast (Schutt *et al.*, 2019). These features are brought to attention earlier in the visual hierarchy (Schutt *et al.*, 2019), whereas high-level features are more complex thus are extracted in higher cortical areas and encode information with an increased complexity (Schutt *et al.*, 2019). However, past research has indicated that both attentional controls may utilise both low-level and high-level factors. For example, bottom-up control may utilise high-level properties such as faces, object locations as well as unexpected locations in addition to low-level properties like colour brightness and contrast (Schutt *et al.*, 2019). This is important when understanding visual attention models and visual search (Schutt *et al.*, 2019).

Prior literature has suggested that there are top-down influences on the processing of low-level features which guide attention and eye movements (Schutt *et al.*, 2019). This emphasizes the importance of understanding how features or objects in marketing stimuli influence attention processes and decision making which will be discussed further below. Despite the bottom-up and top-down attentional processes being described separately, the two attentional processes influence one another (Katsuki & Constantinidis, 2014). Bottom-up salience has been seen to interfere with top-down processing at early and late periods of information search (Higgins, Leininger & Rayner, 2014). Marketers can use knowledge of consumer attention to increase advertisement salience and direct attention (Florack, *et al.*, 2020).

Furthermore, the role of the two attentional processes and salience is not well defined for consumer decision-making and blurred definitions are seen to lead to confusion and debate in literature. There has also been debate with regard to attention and consciousness and the two visual attention processes. Some definitions of attention state that attention requires consciousness. Attention is therefore defined as the mind clearly and vividly simultaneously taking possession of one of several possible objects or thoughts (Bordalo, Gennaioli & Shleifer, 2021). The requirement of consciousness provides a means for confusion and blurred definitions regarding visual attention and the visual attention processes as bottom-up visual attention is involuntary and thus may be interpreted as an unconscious allocation of attention to a specific object or feature (Bordalo *et al.*, 2021). This emphasizes the need for defining the roles and contributions of visual attention processes.

Pinto, van der Leij, Sligte, Lamme & Scholte (2013) conducted research to investigate whether attention is generated by two autonomous systems by showing a relationship between performance on top-down visual search tasks and bottom-up attention capture tasks (Pinto, van der Leij, Sligte, Lamme & Scholte, 2013). Results of the study concluded that the two attentional systems work separately (Pinto *et al.*, 2013); firstly, a system controlling deployment of top-down attention and a bottom-up system used to regulate attention to salient events (Pinto *et al.*, 2013). In other words, bottom-up and top-down visual attention are different. The findings of the study were supported by past literature (Pinto *et al.*, 2013). However, there is an ongoing debate regarding the plausibility of two independent attentional systems (Pinto *et al.*, 2013). Pinto *et al.* (2013) introduced the notion of bottom-up attentional capture as a primitive phenomenon during the early stages of visual processing and can be achieved by information from the initial response to incoming stimuli from the feedforward mechanism. Conversely, top-down attention was described as being controlled by cortical systems selecting information from multiple inputs based on goals and priorities as well as prior learning (Pinto *et al.*, 2013). Top-down attention has been found to be adaptable and can adapt to avoid distractors (Pinto *et al.*, 2013).

Contingent attentional capture theories argue that attention is not driven by the bottom-up process alone as top-down settings impact whether or not attention is captured (Pinto *et al.*, 2013). This was debunked by Pinto *et al.* (2013) and other prior literature indicating that stimuli may capture attention regardless of whether top-down factors and top-down effects occur after attentional capture (Pinto *et al.*, 2013). Furthermore, the study suggested that bottom-up attention is deployed in the first 100-150ms in the brain's feedforward mechanism of sensory information whereas top-down attention may only impact attention at later stages of information processing indicated by neural feedback loops (Pinto *et al.*, 2013). As far as is known, there is no specific time constraint on for how long deployment for each visual attention process occurs.

Pinto *et al.* (2013) addressed the ongoing debate regarding consciousness and attention. The two visual attention systems cause concern in this debate. Consciousness can be used to better understand timings of the visual attention processes. Blumenfeld et al. 2023 hypothesized a timeline of consciousness built on from prior work. This timeline is split by precursors for consciousness, consciousness (200-300ms) and consequences of consciousness (Blumenfeld et al. 2023). Consciousness has non-linear properties and involves a large scale of neural networks (Blumenfeld et al. 2023). Literature has stated that lower levels of consciousness such as signals in the primary visual cortex are more linear than higher order neural responses involving higher cortical areas (Blumenfeld et al. 2023). During the first stage of visual cortical processing bottom-up factors are used to direct attention from the visual cortex to the prefrontal cortex whereas top-down visual attention enhances neural activity focusing on a feature or location of interest with greater magnitude of neuronal firing across cortical hierarchy (Katsuki & Constantinidis, 2014). Precursors of consciousness are described as alertness, attention level, level of motivation, arousal and more (Blumenfeld et al. 2023). Consciousness is the transition between attention and memory (Blumenfeld et al. 2023). However, attentional engagement does not always result in conscious awareness (Blumenfeld et al. 2023). For example, it is possible to be consciously aware without being able to remember an interaction with a stimulus (Blumenfeld et al. 2023). Thus, attention and conscious awareness are not synonymous (Blumenfeld et al. 2023). Attentional engagement is thus needed from stimulus onset for conscious awareness of a visual event to occur, however, neural networks such as the frontoparietal network are necessary for a conscious event to be used in cognitive processes (Blumenfeld et al. 2023). A framework for consciousness was introduced by Blumenfeld et al. 2023 including four stages, detect, pulse, switch and wave. From stimulus onset, the primary visual cortex is activated detecting the stimulus in less than 100ms (Blumenfeld et al. 2023). A dynamic transient pulse then helps facilitate nonlinear signals necessary for consciousness within 200-300ms (Blumenfeld

et al. 2023). The aforementioned timings overlap bottom-up saliency networks for attention (Blumenfeld et al. 2023). This is followed by switch and sweep states where specific networks are not used to ensure processing of conscious stimuli and hierarchical cortical processing respectively before being processed into working memory (Blumenfeld et al. 2023). At approximately 350ms after stimulus presentation consciously perceived stimuli are said to result in a temporary decrease in the primary visual cortex and higher order processing networks potentially limiting distractions during conscious processing. Lastly, hierarchical processing occurs from lower to higher cortical areas resulting in post perceptual processing necessary for memory encoding and consequences of consciousness. This is where consciousness occurs (Blumenfeld et al. 2023).

Furthermore, unconscious processing can occur over short or long periods of time (Awh, Belopsky & Theeuwes, 2012). The area in the brain responsible for the orientation of attention is modulated by reward contingencies (Awh *et al.*, 2012). Thus, unconscious processing over a long period of time may occur as a result of reward based learning (Awh *et al.*, 2012). Factors such as past experiences and expected influence reward perceptions (Rushworth, Noonan, Boorman, Walton & Behrens, 2011). Reward based learning is based on the notion that predicting future outcomes is critical for survival (Schultz, Dayan & Montague, 1997). Prior research suggests that learning is driven by changing expectations regarding salient events such as rewards or punishments (Schultz *et al.*, 1997). When decisions yield more rewards than expected the value of the reward value is increases (Rushworth et al., 2011). The opposite is true for choices yielding lower rewards (Rushworth et al., 2011). Past literature has provided evidence for selection bias based on reward history (Awh *et al.*, 2012). Prior research assessed reward based selection through the presentation of target and distractor stimuli associated with the colour of a high monetary reward (Awh *et al.*, 2012). Participants were asked to focus on the target and ignore the colour distractor. However, when the distractor was presented with the same colour as the last target after a high reward, response time was slower (Awh *et al.*, 2012). This is an example of how reward based learning can influence decision making and result in bias towards previously rewarding features despite current goals or motivations. The present study does not utilise a reward based system.

Moreover, Bottom-up attention is automatic, involuntary, faster and is less flexible than top-down attention (Pinto *et al.*, 2013). The slow deployment and flexibility pertaining to top-down attention suggests that attention is conscious and is thus an effect of consciousness (Pinto *et al.*, 2013). However, bottom-up attention is thought to occur in the feedforward stage and thus can be considered a causal factor of consciousness (Pinto *et al.*, 2013). This notion is further justified by prior literature where objects are presented in isolation and near time thresholds indicating the effect of bottom-up attention on consciousness (Pinto *et al.*, 2013). Furthermore, bottom-up attention may result in an increase of conscious recollection for stimuli that have been viewed before and therefore may be more important for consciousness than top-down control (Pinto *et al.*, 2013). However, prior research has shown that bottom-up attention operates unconsciously and it is thus not probable that bottom-up attention can be referred to as a condition of consciousness (Pinto *et al.*, 2013). For example, stimuli can capture attention indicated through eye movements without the subject indicating awareness of the stimuli (Pinto *et al.*, 2013).

### **2.5.2. Visual Attention and Consumer Decision Making**

Consumer decision-making is an important aspect of marketing often used to segment and attract consumers as well as enhance promotion effectiveness (Khachatryan, Rihn, Behe, Hall, Campbell,

Dennis & Yue, 2018). Eye movements are used to further understand consumer choices (Suurmet, 2018). Neuroscience technology, such as eye-tracking, can assist marketers by analysing unconscious consumer processes such as decision-making and can fine-tune promotional material thereby improving attention, engagement and other factors that lead to decision-making (Hamelin & Harcar, 2020: 163-184).

Consumers are exposed to vast amounts of information on a daily basis resulting in competition for consumers' attention. The managerial assumption is that attention impacts consumers' decision-making (Bhatangar & Orquin, 2022) although exposure to products is an important tool used by marketers to increase sales. However, mere exposure to products and other marketing material does not equate to attention due to limited visual processing capacity (Bhatangar & Orquin, 2022). According to Florack, Eggera, & Hübnerb, 2020, research on selective attention has practical relevance for product placement and advertising as well as for products and brands competing for attention. Marketers can use knowledge of consumer attention to increase product or advertisement salience, by rebranding products and redirecting consumer attention (Florack, A. et. al, 2020).

Furthermore, marketers must understand consumers and their behaviour so as to produce effective advertisements and ensure sales (Aka, Okorie & Kehinde, 2022). Therefore, marketers need to focus on the buying process and not just on purchase decisions (Aka, Okorie & Kehinde, 2022). Generally, consumers follow the consumer decision-making process. This consists of five steps: recognition of need, information search, evaluation of alternatives, purchase decision, and post-purchase evaluation (Aka, Okorie & Kehinde, 2022).

There are four types of consumer buying behaviour, namely, dissonance-reducing buying behaviour, habitual buying behaviour, variety seeking buying behaviour, and complex buying behaviour (Kumar, Ahluwalia, Hazarika, Singh, & ChinmoyGoswami, 2022). This study will involve complex decision-making as participants will be viewing advertisements from various telecommunications brands. Complex buying decisions require extensive problem-solving and information search due to higher risk perception, expensive products, and alternatives (Kumar et. al, 2022).

Prior literature has focused on the relationship between visual attention and choice using eye-tracking (Zuschke, 2020) and assumes that visual attention occurs passively, serving the decision-making process, and actively through constructing decisions (Zuschke, 2020). Prior literature by Wedel & Pieters, 2000; Pieters & Wedel 2004; Pieters & Wedel, 2007 as well as Rayner, Miller, & Rotello 2008; and Rayner, Rotello, Stewart, Keir & Duffy, 2001 provided strong evidence for top-down control of visual attention (Zuschke, 2020). The research concluded that advertising elements such as brand, pictures and text generate consumer attention and translate brand memory differently (Zuschke, 2020). Through the manipulation of task instruction past research indicated that consumer attention to various advertising elements differed with task goals (Zuschke, 2020). In addition to this, personal characteristics of consumer decision-making such as involvement, motivation, familiarity, brands, time pressure and other factors can influence attention to advertising elements (Zuschke, 2020). In particular, time pressure was found to direct attention towards pictorial elements as opposed to text (Zuschke, 2020), whereas evidence from prior literature for bottom-up control of visual attention is based on visual saliency, size and location of visual stimuli (Zuschke, 2020). In particular, coloured advertisements, position and surface size positively influence visual attention and choice (Zuschke, 2020). The interplay of top-down control and bottom-up characteristics has not been well researched by either prior or current literature (Zuschke, 2020). However, bottom-up effects may play a role in goal-driven or top-down attention (Zuschke, 2020).

In contrast to passive visual attention, active visual attention is centred around visual attention as a predictor of choice (Zuschke, 2020). Visual attention may play a causal role in preference information due to the gradual shift of attention towards chosen options observed through gaze cascades. The attentional drift diffusion model by Krajbich, Armel, and Rangel, 2010, assumes that a greater number of fixations results in more preferences as well as random distribution of fixations (Zuschke, 2020). Other research studies indicated that fixation duration was a consistent predictor of choice (Zuschke, 2020).

Bottom-up factors such as saliency and positioning have been found to influence consumer choice (Zuschke, 2020). Past research studies manipulated saliency and time pressure to observe their influence on choice (Zuschke, 2020). Saliency was observed to influence choice more than preferences under increased time pressure, cognitive load and decision difficulty (Zuschke, 2020). Furthermore, centre bias i.e., positioning, results in an increased likelihood of visual attention and choice despite centre products not being evaluated more favourably (Zuschke, 2020). Furthermore, a study by Orquin and Mueller Loose in 2013 stated that the effect of visual attention on decisions may be a result of the mere exposure effect to items or elements fixated on and reduced risk of information non-attendance (Zuschke, 2020).

A study by Zuschke (2020) investigated the effect of process-tracing research on consumer decision-making. Findings of the study concluded that increased motivation results in focus on task relevant information and thorough product information processing. In addition, other top-down factors such as involvement, familiarity and expertise influenced information processing (Zuschke, 2020). Bottom-up factors such as size, position, saliency and reduced visual clutter are positively related to choice and visual attention (Zuschke, 2020). Bottom-up visual attention may affect choice under various conditions such as time pressure, high working memory demands, decision difficulty (rapid and non-rapid decision making) and increased cognitive load and task complexity in certain situations (Zuschke, 2020).

This research focused on information through visual search and choice tasks. Consumers typically conduct their information search through advertisements, opinions of friends or relatives, social media, the internet, and any other sources of information (Kumar et. al, 2022). To understand consumers' decisions and choices this study collected data related to price, pictorial elements, and relevant information (Ladeira et. al, 2019). Past studies have looked at these elements concerning the labelling of packaging, catalogues etc. (Ladeira et. al, 2019). Thus, the following hypothesis was developed.

***H1a: Total fixation duration on AOIs (price, product and brand) related to choice, have a positive relationship with consumer decision to purchase***

### **2.5.3. Types of Visual Attention**

Understanding attentional biases through feature-based decisions will allow marketers to better quantify and predict decisions involving multidimensional stimuli (Vo, 2020). Feature-based attention enhances the representation of features that are relevant or behaviourally salient and is governed by both bottom-up and top-down attentional processes (Vo, 2020).

Humans are exposed to vast amounts of sensory information but have limited processing capacity (Katsuki & Constantinidis, 2014). Thus, the brain relies on cognitive attentional processes to allocate

neural resources to specific events (Katsuki & Constantinidis, 2014). Past studies have indicated that searching for stimuli utilizing bottom-up factors allows for the parallel processing of features (Katsuki & Constantinidis, 2014). Attention is allocated to a salient stimulus, location or feature that results in the highest neural activation in a visual environment (Katsuki & Constantinidis, 2014). Some past literature has argued that feature-based attention is governed by top-down attentional control, creating a bias of attention towards relevant or behaviourally salient features (Vo, 2020). For example, when viewing an advertisement, a price-conscious consumer will focus their attention on features involving price. However, other literature has argued that feature-based attention results from bottom-up priming (Vo, 2020), for example, when viewing a visually rich advertisement, colour or location may attract attention and influence behavioural response. Competing features may thus distract attention (Vo, 2020). The present research study aims to improve the understanding of the role of visual attention in relation to consumer decision-making by considering features such as price, product, brand and pictures.

Marketing stimuli are complex with numerous features and objects in advertisements requiring context for consumers to receive the marketing message. Semantic features used in marketing such as people and faces are related to top-down attention (Suh, Wilson & On, 2021). Semantic features are embedded with additional meanings beyond physical features and thus require interpretation to guide visual attention (Suh *et al.*, 2021). High-level semantic features such as faces, text or symbols are not accounted for in saliency maps as the maps are constructed using physical features such as intensity, orientation and colour, providing an estimate for bottom-up attention (Takano *et al.*, 2021). Thus, visual attention to elements such as text in an advertisement cannot be estimated through the conventional saliency map models (Takano *et al.*, 2021).

High-level semantic features are not always represented by bottom-up saliency (Takano *et al.*, 2021). Takano *et al.* (2021) conducted an experiment using Japanese Hiragana, English letters, Thai characters and simple symbols. Recognition of high-level semantic characters may not involve attention due to familiarity, learning over time and culture, affecting visual saliency (Takano *et al.*, 2021). Thus, attention to characters is not always obtained from low-level features (Takano *et al.*, 2021). Faces are considered to be more salient followed by characters. Results of the study indicated that fixation ratios differed for characters and symbols thus a specific saliency for characters cannot be explained by physical features in a saliency map model (Takano *et al.*, 2021). Semantic features such as faces, objects symbols and text are used by marketers to provide consumers with context of an advertisement allowing the consumer to understand the product or service on offer and any other marketing messages. For the purpose of this research semantic features are referred to as contextual features.

Furthermore, fixations on faces are seen to occur in the early stages of visual search and preceding a short fixation at later stages of visual search (Schutt *et al.*, 2019). The transition from bottom-up to top-down control is likely to occur within the first fixation (Schutt *et al.*, 2019). Typically, the first three to five locations attended are associated with bottom-up factors. This is followed by attention based on top-down factors. Literature indicates that top-down factors are associated with final decisions and are more dominant of the two attention processes not including when non-target features are more salient (Suh *et al.*, 2021). The study by Schutt *et al.* (2021) assessed bottom-up and top-down control in a natural scene context (Schutt *et al.*, 2019). However, for this study features such as faces and specific objects (animals, symbols and text) will be included in the stimuli. Without distinctive differences between target and background stimuli, the processing of features through top-down factors requires an intentional examination of all visual elements individually (Katsuki & Constantinidis, 2014). To assess the impact of featural-based attention on the visual attention process the following hypotheses was

formulated to compare the difference in eye-tracking data between bottom-up features (contrast, brightness, and colour) and context (faces, text, and symbols).

*H1b: Contextual features subjectively rated as more important in informing decisions (product, price, and brand) will produce larger first fixation durations, total fixation durations and fixation counts compared to features rated as less important features.*

#### **2.5.4. Visual Attention and Consumer Preferences**

Consumer decision making is complex, involving stimuli, attention processing, working memory as well as consumer preferences. This research project will focus on the attentional processes which are discussed further below (Suurmets, 2018). Visual attention is an important factor in the consumer decision making process. Eye movements are used to further understand consumer choices (Suurmets, 2018). Tracking eye movement allows marketers to understand information processing and the consumer decision-making process (Suurmets, 2018). The visual system perceives information necessary for an immediate task, filtering out irrelevant information by fixating on stimuli to make, compare and formulate a set of considerations (Suurmets, 2018). A consideration set is a combination of accumulated evidence and a comparison of alternative products which a consumer may choose to purchase (Suurmets, 2018). According to Florack, Eggera, & Hübnerb, 2020, research on selective attention has practical relevance for product placement and advertising as well as products and brands competing for attention.

When searching for a product consumers utilise and switch between two acquisition strategies, product-based and attribute-based strategies, limiting attention to two or three attributes or products and alternatives (Suurmets, 2018). By utilising eye-tracking to analyse eye movements and visual processing there is potential to improve understanding of cognitive processes involved in consumer decision-making (Suurmets, 2018). Past research has not identified either economic or saliency models accounting for visual choice processes, thus further research through eye-tracking may contribute to understanding consumer decision-making processes and in turn benefit marketers (Suurmets, 2018). Marketers can use knowledge of consumer attention to increase product or advertisement salience, altering products and directing attention (Florack et. al, 2020).

#### **2.6. Bottom-up factors and consumer decision making**

Colour, contrast and brightness, and bottom-up factors, are visually salient properties that generate visual attention (Toh, Leng & Phua, 2021). Brands are constantly trying to differentiate themselves from competitors in order to achieve optimal positioning in the eye of the consumer (Hajdú, 2021). Senses such as sight, touch and smell are important to help us perceive the world around us (Hajdú, 2021). Sight helps us identify and differentiate brands as well as highlight key aspects of marketing stimuli (Hajdú, 2021). The role of colour is used across various marketing strategies. For example, brand logos that are bright are more likely to attract attention and in turn influence recall and purchase intention (Toh, Leng & Phua, 2021). However, without contrast from surroundings, colour and brightness alone may not attract consumers' attention or be recalled equally (Toh, Leng & Phua, 2021). These properties influence readability as well as legibility of advertisements thus resulting in increasing interest in the role of bottom-up factors such as colour (Toh, Leng & Phua, 2021).

Colour has been identified in past literature as a powerful marketing tool influencing consumer perception and buying behaviour. Marketing decisions taking colour into account are typically made using intuition as colour theory and colour marketing have broad theoretical foundations (Hadju, 2021). Despite this, it is important to understand the use of colour for aspects of marketing such as advertising, branding and packaging (Hajdú, 2021). Colour has an effect on the physical environment as well as a psychological effect due to the human biology and culture (Hajdú, 2021). This is dependent on hue, brightness and chroma (Hajdú, 2021). The human eye has the ability to distinguish a multitude of colours, each conveying an individual meaning and emotion as well as having a different psychological effect (Hadju, 2021). Industries often utilise certain colour combinations (Hadju, 2021).

Past research has indicated that colours can be grouped according to the effect on mood (Hajdú, 2021). Warm, cold and neutral colours all have a different effect on mood (Hajdú, 2021). Warm colours are considered as red and yellow as well as orange and brown (Hajdú, 2021), whereas cool colours are typically blues and greens. Neutral colours are more typically tones and shades such as grey, white and black (Hajdú, 2021). Furthermore, primary colours (red, yellow and blue) and secondary colours (mixtures of primary colours) can be split into pure and pastel groups. Pure colours are colours in which no black, white or other hues have been added (Hajdú, 2021). Pastel colours are colours that have been mixed with white (Hajdú, 2021). Prior literature has suggested that warm colours generate higher levels of attention than cooler colours; however, this is not supported by empirical evidence (Toh, Leng & Phua, 2021). Contrast between visual stimuli and the background regardless of colour are effective in attracting attention (Toh, Leng & Phua, 2021).

### **2.6.1. Top-down Factors and Consumer Decision Making**

Typically, consumers choose one of the most important attributes based on which they will make their final decision (Stankevich, 2017). Important attributes involved in decision-making are the product itself, price, brand and quality (Stankevich, 2017). For the purposes of this research task goals and motivation, or involvement in decision-making, were related to three key factors: product, price and brand.

#### **2.6.1.1. Product**

In order to remain successful, a product needs to meet the needs of the relevant target market better than its competitor(s) (Santos *et al.*, 2015). Eye-tracking can contribute to product success by understanding what attracts a consumer to a product, how the customer relates to a product and its packaging, as well as how consumers interact with, use and consumer the product (Santos *et al.*, 2015). Numerous studies have researched both the product and its packaging and how these elements influence attention and the consumer's decision to purchase. For example, an eye-tracking and word association study conducted by Fiszman, Velasco, Salgado-Montejo, and Spence in 2013 studied the effect of packaging elements on attention and marketing message (Santos *et al.*, 2015). The study concluded that certain packaging elements, such as pictures and the shape of the product, can be used to drive consumer attention (Santos *et al.*, 2015). Other prior literature used eye-tracking to understand visual attention behaviour concerning nutritional information on food labels. One study in particular placed focus on consumers who use analytical-rational thinking in comparison to intuitive-empirical thinking. The results of this study by Ares, Giménez, Bruzzone, Vidal, Antunez & Maiche (2013) indicated that analytical-rational thinking consumers conducted a more extensive search and analysis to inform their choices than intuitive-empirical thinkers (Santos *et al.*, 2015). The results of this study highlighted that attention was

determined using top-down factors as consumers tend to search for specific information provided on labels (Santos *et al.*, 2015). Furthermore, a study by Ares, Mawad, Giménez & Maiche (2013) assessed how consumers' information acquisition on food labels indicated that consumers attend to elements such as brand, information and pictures regardless of the product itself and the label design when considering a purchase decision (Santos *et al.*, 2015). Past research on eye-tracking provided evidence on the need for the application of eye-tracking technology to future empirical research regarding the visual behaviour of consumers (Santos *et al.*, 2015). Furthermore, past literature placed emphasis on the influence of top-down visual attention on consumer decision-making due to consumer attention towards specific information and elements of both the product and its packaging. This research study utilises product as a key element that has influence on consumer decision making.

#### 2.6.1.2. Price

The psychology of price is an important factor in consumer decision making. Price is a critical tool used by marketers to influence sales and increase market share (Santos *et al.*, 2015). The presentation of price influences information processing. For example, the positioning of a price display alongside a product may influence value perception and thus, consumer decision-making (Santos *et al.*, 2015). Marketers utilise bottom-up factors such as positioning, colour and contrast to present price to consumers in an attempt to influence the purchase decision. Past research by Grewal *et al.* in 2011 indicated that consumers respond to the colour of the prices (Santos *et al.*, 2015). For example, prices outlined in red are synonymous with a sale or 'special offer'. Furthermore, consumers typically view prices in a relative context. For example, consumers may make a decision to purchase in terms of the percentage saved on a cheaper item rather than the amount of money saved (Santos *et al.*, 2015). Santos *et al.*, 2015 identified opportunities for eye-tracking research concerning visual attention and price such as visual attention behaviour, behavioural patterns, presentation formats and others (Santos *et al.*, 2015). From a top-down perspective, a price-conscious consumer may have a goal or budget in mind, which will impact how they navigate marketing stimuli which influence decision making.

#### 2.6.1.3. Brand

Brand is an important element in consumer decision-making. Companies place focus on brand equity in order to generate brand loyalty and sales. Three drivers of brand equity are brand elements such as brand name, logos, slogans, music, packaging and endorsements; the product or service; and marketing communications as well as brand associations (Santos *et al.*, 2015). These elements are used to convey a brand's identity and associations (Santos *et al.*, 2015). Brand is an important factor to consider from a top-down perspective as top-down factors, goals and motivations as well as prior knowledge, may influence a respondent's decision making and visual attention. In addition to bottom-up and top-down factors and the influence on consumer decision-making as well as attention, visual salience is also a construct that generates visual attention and is synonymous with bottom-up visual attention processes. Visual salience in relation to the visual attention process and decision making is discussed in the following sections.

## 2.7. VISUAL SALIENCE

### 2.7.1. Visual Saliency

Saliency is a common term used in attention research (Schutt *et al.*, 2019). Visual saliency is defined as the noticeable subjective perceptual quality resulting in items or objects standing out from their neighbours and immediate attention capture (Berga and Otazu, 2022). In other words, visual saliency relates to the conspicuity of a visual feature or object in comparison to its surroundings (Orquin, Perkovic & Grunert, 2018). Visual saliency is referred to as the physical aspects of an object such as colour, shape and size. Numerous studies have indicated that visual saliency can influence decision-making through attention as a result of bias to more visually salient options both directly and indirectly (Vriens *et al.*, 2020; Zusccke, 2020). Saliency became synonymous with bottom-up control of eye movements according to early research models associated with predicting fixation locations (Schutt *et al.*, 2019). However, high-level features also influence fixation locations (Schutt *et al.*, 2019) and this has been noted in more recent literature with saliency models (Schutt *et al.*, 2019). Thus, saliency can refer to an image-based prediction in which locations are likely to be fixated on by human observers (Schutt *et al.*, 2019). Saliency models are computational models that predict a saliency map which highlights areas of an image that are likely to attract fixations (Kümmerer, Bethge & Wallis, 2022). In the past, saliency models utilised mainly low-level features based on the original feature integration theory (Kümmerer, Bethge & Wallis, 2022). However, over time high-level features and deep features were introduced into saliency models (Kümmerer, Bethge & Wallis, 2022).

Schutt *et al.* (2019) described the saliency model as any bottom-up model predicting fixation locations for an image regardless of feature complexity. Despite inconsistent terminology, eye-movement behaviour can be used to understand the interplay of bottom-up and top-down factors. Past research shows that the manipulation of low-level features is effective at the early stages of experiments; however, it can be overruled by task instructions as high-level features persist over time (Schutt *et al.*, 2019). Literature by Awh, Belopsky & Theeuwes (2012) supports this notion, stating that the top-down attentional process is more dominant. Low-level models are better predictors of early fixations. This is in line with the saliency model in which initial fixations are driven by bottom-up (low-level) factors (Schutt *et al.*, 2019). However, low-level feature performance declines over time (Schutt *et al.*, 2019).

Furthermore, past studies have argued for a distinction between attentional control and saliency (Parr & Friston, 2019). However, both attention and saliency represent beliefs about the capacity of sensory data with regards to current available data and data to be acquired (Parr & Friston, 2019). The fundamental link between attention and saliency can be explained by the cognitive bias of the “streetlight effect” (Parr & Friston, 2019). The streetlight effect is explained as an inebriated individual searching for keys under the spotlight provided by the streetlight as it is the only place the individual can see thus increasing the chance of finding the keys (Parr & Friston, 2019). In other words, attention is focused on information that is easily accessible and visible despite the level of relevance pertaining to the salient area. Thus, locations that are highly salient indicating information clearly should generate more attention within a visual field. In addition to this, motor control highlights an interaction between saliency and attentional gain (Parr & Friston, 2019). Research has suggested that commands are predictions which are defined as motor commands, or setpoints for oculomotor reflexes enacted by spinal or brain stem reflexes (Parr & Friston, 2019). A prediction that a location is foveated on entails high precision associated with the location which results in a saccade fulfilling the prediction. This

further emphasizes the link between attention and salience as covert attention to a location is biased in favour of an overt saccade to the salient location (Parr & Friston, 2019).

Parr and Friston (2019) concluded that attentional processes select sensory information to optimize current data and facilitate the acquisition of new sensory information. Attentional gain biologically reflects a modulation of synapses to focus on one type of sensory data implicating ascending neuromodulator systems and other mechanisms to process sensory information (Parr & Friston, 2019). However, attentional gain can be contextualized by signals from cortical and subcortical regions (Parr & Friston, 2019). Salience involves connections for areas representative of controllable states such as a fixations and their sensory consequences (Parr & Friston, 2019). Parr & Friston (2019) suggested that despite the mutual dependence of salience and attentional gain control, the two are best understood as separate perceptual operations. Gain control is used to balance influences on perception from competing sensory information and from prior beliefs (Parr & Friston, 2019). Thus, gain control is a top-down attentional control. The inability to balance the competing sensory information and prior beliefs may result in incorrect perceptions (Parr & Friston, 2019), whereas salience is defined by sensory input representing good perceptual experiences. A failure to compute salient information may result in a lack of understanding of sensory experiences (Parr & Friston, 2019).

### **2.7.2. Salience and Psychology**

Research by Bordalo *et al.* (2021) reviewed salience in the context of economic behaviour. Furthermore, this research highlighted applications of salience in advertising and other fields such as finance and politics (Bordalo *et al.*, 2021). Theory from this research corroborates and improves understanding of salience in a marketing or advertising context. Psychological research has identified that salient stimuli attract attention as a result of high contrast with the surrounding elements, an element of surprise relative to past experiences as well as prominence (Bordalo *et al.*, 2021). Bordalo *et al.* (2021) introduced models of salience that describe how bottom-up attention may alter economic choices due to the ability of salience to distract decision makers from current goals and or relevant choice attributes (Bordalo *et al.*, 2021) Stimuli are described as salient when attracting a decision maker's attention in a bottom-up manner. Bottom-up attention is automatic and involuntary. Despite the ability of salience to aid humans in identifying important elements for decision making, it may also distract us from current goals and distort decision making (Bordalo *et al.*, 2021). In economics attention is unlimited or driven by top-down attention due to current goals and expectations (Bordalo *et al.*, 2021). However, top-down factors such as goals may compete with factors of bottom-up attention (Bordalo *et al.*, 2021). Unlike standard economics, markets are overloaded with salient stimuli thus emphasizing the importance of bottom-up attention as salient stimuli may attract the consumer's attention even at the expense of original goals (Bordalo *et al.*, 2021). Bordalo *et al.* (2021) describes models of bottom-up attention in a psychological context to contrasting, salient and prominent stimuli and how they introduce ways to unify choice instabilities. The study proposed that bottom-up attention highlights the limitation of priming consumers with goals or supplying information to aid choice to relax attentional or informational constraints as often advertisement may provide information about some elements of choice that intentionally distract from other information or advertisement content (Bordalo *et al.*, 2021).

Bordalo *et al.* (2021) found evidence of changes in consumer preferences based on goal irrelevant changes in choice environments (Bordalo *et al.*, 2021). This instability can be attributed to bottom-up shifts in attention directed towards visually salient product attributes (Bordalo *et al.*, 2021). Salience theory describes choice instability created by the "decoy effect" as an event bottom-up attention due to

contrast (Bordalo *et al.*, 2021). For example, large price comparisons divert attention away from quality and towards price, resulting in consumers choosing the cheaper option (Bordalo *et al.*, 2021). However, if a third more expensive option was introduced, the difference between the prices would not be as marked (Bordalo *et al.*, 2021). Thus, the decoy effect can be used to benefit the lower priced good (Bordalo *et al.*, 2021). Surprise relevant to past experiences, in other words memory, results in salience effects in markets (Bordalo *et al.*, 2021). For example, an increased price in relation to a prior experience may result in a decision not to purchase (Bordalo *et al.*, 2021). Their research study states that there is an interplay between memory and bottom-up attention resulting in reference point effects (Bordalo *et al.*, 2021). Thus, as memory-based norms are associative of recall there may be a shift in behaviour due to goal irrelevant contextual cues as a result of an artificial surprise (Bordalo *et al.*, 2021). Moreover, prominence is another factor influencing consumer choice (Bordalo *et al.*, 2021). Often, not all attributes of products or services are visible when making a choice thus other factors influencing choice may be dismissed as they are not advertised, are strategically obscured, or will only materialise in the future (Bordalo *et al.*, 2021). An example of the effect of prominence is the infamous projection bias where current context plays a role in identifying goods prominence (Bordalo *et al.*, 2021). For example, catalogues for warm foods are more successful on colder days (Bordalo *et al.*, 2021). In a psychological context bottom-up attention offers ways to unify choice instability and yield predictions regarding bottom-up attention and memory (Bordalo *et al.*, 2021).

The psychology of salience, although not referring to visual attention, should be understood by marketers so as to provide greater insight into how consumers navigate consumer decision making, visual salience and decision making.

### **2.7.3. Visual Salience and Decision Making**

Past literature has indicated that distinctly displayed information has increased likelihood of being acquired and processed in comparison to less clearly displayed information (Milutinović, Ahonen-Jonnarth & Seipel, 2021). This is important to note in the context of consumer decision making as the increased use of salient information may result in other relevant information being ignored (Milutinović, *et al.*, 2021). Components of decision making that are clearly accessible have a high probability of being used in decision making (Milutinović, *et al.*, 2021). Salient features or information may result in a visual bias that results in attention arbitrary to decision goals (Milutinović, *et al.*, 2021). A study by Milutinović, Ahonen-Jonnarth & Seipel (2021) explored the effects of visual saliency on decision making quality. Results of this study suggested that for certain visualisation techniques (parallel coordinates and scatterplot matrices) and forms of saliency (colour and size) regarding multi-criteria decision making (MCDM), saliency can increase attention as well as quality of decision (Milutinović, *et al.*, 2021). However, the study measured attention regarding attachment to the preferred criterion indirectly and quantified the interaction with the visualisation near the attribute (Milutinović, *et al.*, 2021). Attention data was recorded using mouse data and click concentration by respondents (Milutinović, *et al.*, 2021). Attention to salient elements can be measured using gaze tracking (Milutinović, *et al.*, 2021). Findings of the study showed that saliency enhancement on preferred criteria did not have unfavourable effects on decision quality despite the use of factors such as colour and size as facilitating variables (Milutinović, *et al.*, 2021). However, under certain conditions visual saliency improved decision quality, for example, colour improved decision quality for parallel coordinates. Furthermore, this study found that visual saliency was seen to have greater influence when making fast decisions (Milutinović, *et al.*, 2021). This is corroborated by a previous study by Milosavljevic *et al.* (2012) that indicated that visual saliency has more influence on choice than preferences when making

fast decisions. The present research study utilised eye-tracking technology to gain further insight into decision making, attention and visually salient elements.

Visual attention is garnered by elements which differ from their surroundings, by, for example, standing out from the background and from other elements due to colour, contrast, intensity, orientation of movement or speed (Milutinović, *et al.*, 2021). Milutinović, *et al.* (2021). described this attraction as bottom-up visual selective attention. Thus, visual attention to items standing out from the background is unrelated to relevance of the salient object and purely sensory driven (Milutinović, *et al.*, 2021). Saliency models and maps have been researched in the past by Koch & Ullman (1985), Itti & Koch (2001), Kümmerer *et al.* (n.d.) and Kümmerer, Wallis & Bethge (2017) to mention a few. Itti and Koch (2001) suggested that more advanced attentional models need to include top-down attention. Top-down modulation is important to note as bottom-up selective attention describes the deployment of attention during the first few hundred milliseconds (Milutinović, *et al.*, 2021). This is agreed upon by a majority of researchers as indicated by the support for the notion that the two visual attention processes influence the allocation of attention (Milutinović, *et al.*, 2021). In keeping with this research, Milutinović, *et al.* (2021) found that there was no agreement on the extent of influence on attentional selection by the two visual attention processes. However, past literature reveals contrasting results indicating inconsistent findings. Research by Donk and van Zoest (2008) and Underwood *et al.* (2006) indicated that task demands can override saliency maps and top-down factors such as goals, and that expectations influence fixation patterns (Milutinović, *et al.*, 2021). Furthermore, findings showed that saliency is not always represented across the visual system and is most important for a few hundred milliseconds and is then overridden by top-down control (Milutinović, *et al.*, 2021). Thus top-down processes retain information concerning object presence instead of relative visual salience (Milutinović, *et al.*, 2021). In contrast, a study by Parkurst *et al.* (2002) presented findings where attention was most stimulus-driven just after presentation; however, it remained stimulus-driven to a lesser extent despite the activation of top down influences (Milutinović, *et al.*, 2021). This was corroborated by a study by Orquin *et al.* (2018) indicating that bottom-up and top-down processes are active simultaneously (Milutinović, *et al.*, 2021). This research study has looked at the role of visual attention processes in consumer decision making with the understanding that the context of the decision making as well as elements used in the advertisement to provide context are important.

Other literature by Orquin, Perkovic & Grunert (2018) reviewed eye-tracking research in decision making to show the subjectivity of decision makers to visual biases such as size, salience, position, emotional valence, predictability, and information elements, resulting in allocation of attention arbitrary to current goals. Presentation of information, regardless of format, will bias decision makers' attention or lack of attention and thus influence decision making (Orquin *et al.*, 2018).

Saliency models provide a map of areas that stand out the most from visual surroundings and predict attention for tasks such as decision making, visual search and scene viewing (Orquin *et al.*, 2018). Salient objects have been found to influence both fixation likelihood and order (Orquin *et al.*, 2018). Prior research states that salience can be used to direct attention of the decision maker to specific information by making elements stand out more in a visual environment (Orquin *et al.*, 2018). This can be done by increasing contrast and changing colour or orientation (Orquin *et al.*, 2018). However, using salience to promote relevant information has limitations as salience cannot be used to attract attention for all information (Orquin *et al.*, 2018). Salience is interpreted relative to all visual features within an environment thus increasing salience for a singular element may distract from and decrease overall saliency of other objects in the same visual environment (Orquin *et al.*, 2018). Research by Orquin *et al.* (2018) introduced an open question regarding whether visual salience interacts with top-down

control and to what extent. Past literature has suggested that saliency may interact with top-down control, however, other studies suggested that the interaction may not be relevant in a decision-making context (Orquin *et al.*, 2018). This research study addressed the interaction of the two visual attention processes with visual salience and consumer decision making by looking at the difference between visual saliency maps and short exposures in comparison to longer exposures of visual stimuli. For example, making unit prices more salient can help consumers identify the prices whilst shopping. This research paper did not aim to predict visual attention but rather intended to decipher the role of visual attention and salience on consumer decision making. Thus, this study compared eye-tracking research and saliency maps generated using the DeepGaze IIE saliency model which is discussed in the following section.

#### **2.7.4. DeepGaze II & IIE**

Saliency detection is used to summarise the allocation of attention to the most significant elements or subsets of data relative to neighbouring regions (Linardos, Kümmerer & Bethge, n.d.). Visual saliency is operationalised through the measurement of fixation locations (Linardos, Kümmerer & Bethge, n.d.). Past research has indicated that fixations are influenced by high-level features, for example, people, as well as low-level features that indicate spatial contrast (Linardos, Kümmerer & Bethge, n.d.). Saliency predication is referred to as fixation locations or the detection of salient objects (Linardos, Kümmerer & Bethge, n.d.). Following the introduction of the feature integration theory, the Itti-Koch model was created resulting in the first model to predict a saliency map from any picture without precomputing elementary features (Linardos, Kümmerer & Bethge, n.d.). The introduction of transfer and deep learning allowed for an improvement of saliency models (Linardos, Kümmerer & Bethge, n.d.).

DeepGaze II is a model that predicts where people look in images (Kümmerer, Wallis & Bethge, 2016). DeepGaze II uses features taken from the deep neural network, VCG-19, that is able to identify objects in images. VCG features are used to train readout layers indicating predicted saliency in comparison to other saliency models utilising deep features (Kümmerer *et al.*, 2016). Furthermore, Deep Gaze II provides improved fixation predictions by adding in high-level features, as earlier fixations are easily predicted by subsequent fixation densities (Schutt *et al.*, 2019). The findings of the study suggested that fixations during the first exploration are guided by the same high-level features as later fixations and low-level models are good predictors of first fixations (Schutt *et al.*, 2019). This corroborates past literature stating that low-level features influence primarily the first fixation (Schutt *et al.*, 2019). Furthermore, the study indicated that after the initial onset response, eye movements were not influenced by low-level features adding to prior literature's notion that objects and high-level features influence eye movements (Schutt *et al.*, 2019). Thus, low-level features could be explained by being of importance in a high-level sense (Schutt *et al.*, 2019). Little difference in fixation densities beyond the first fixation with changing contrast indicates that fixation distribution is more likely to be attributed to high-level factors (Schutt *et al.*, 2019). Moreover, fixation locations during visual search are not well predicted by saliency models (Schutt *et al.*, 2019). Thus, top-down control can override bottom-up control when viewing static visual scenes (Schutt *et al.*, 2019).

Following the development of DeepGaze II, researchers introduced an improved model DeepGaze IIE. DeepGaze IIE uses training on a readout network, centre bias weight and blur size (Linardos, Kümmerer & Bethge, n.d.) whereas feature extractor weights for this model are kept fixed during the training process (Linardos, Kümmerer & Bethge, n.d.). This model is pretrained using the SALICON dataset containing 10000 images where ground truth was established through mouse traces indicated by

observers as well as 1003 natural images from the MIT1003 dataset that were presented for 3 seconds (Linardos, Kümmerer & Bethge, n.d.). Images from the MIT1003 dataset were resized to either 1024 X 786 or 768 X 1024 as the dataset contained images of various dimensions (Linardos, Kümmerer & Bethge, n.d.). To ensure consistency stimuli/images used in the present study were resized to fit the aforementioned dimensions. Human fixations have been found to accumulate towards the centre of an image, thus the DeepGaze IIE model utilises a centre bias as a baseline model (Linardos, Kümmerer & Bethge, n.d.). Due to the ability of saliency models to predict probabilistic fixation distributions rather than deterministic classes, models predict both qualitatively and quantitatively (Linardos, Kümmerer & Bethge, n.d.). Models indicate qualitatively which areas have expected fixations and quantitatively how much more often a salient region is to be fixated on in comparison to any other region (Linardos, Kümmerer & Bethge, n.d.). This is indicated through a heatmap. Image pixels sorted into a predicted fixation density by probability are split into numerous groups of equal probability mass where prediction is split into three contour lines making four sections of decreasing size from yellow to green and then blue (Linardos, Kümmerer & Bethge, n.d.). Each section accounts for 25% of predicted fixation probability (Linardos, Kümmerer & Bethge, n.d.). After segregation of the predicted fixation density, empirically measured fixations in each area are counted (Linardos, Kümmerer & Bethge, n.d.). This method is used to test whether the model makes overconfident or underconfident predictions (Linardos, Kümmerer & Bethge, n.d.). Through the use of DeepGaze IIE this research was able to identify salient features on advertisements based on bottom-up factors such as colour, contrast and brightness which were compared and analysed alongside eye-tracking heatmaps and data. This allowed for more robust insight and understanding.

The following hypothesis is formulated to explore the effect of salience on goal-directed visual search, identify any differences between goal-directed and free-search fixation maps and assess the effect of salient objects on both bottom-up and top-down attentional processes within the consumer decision-making processes.

***H1c: On the visual search task, mobile eye-tracking will present a denser heat map with greater fixation densities on the item of importance compared to a purely bottom-up system (DeepGAZE IEI data)***

### **2.7.5. Visual salience and memory recall**

Memory is a consequence of attention and is referred to as the ability to recover past information in the mind (Onișor & Ioniță, 2021). Memory recall is defined as the ability to retrieve previous information whereas memory recognition is defined as the ability to identify information (Onișor & Ioniță, 2021). For this study focus was placed on memory recall.

Effective advertising techniques are important to understand as marketing practitioners need to promote a product or service and attract consumers (Onișor & Ioniță, 2021). An increase in online advertisements has emphasized the importance of product and corporate branding as well as the need for understanding advertising avoidance and thus attention to advertising (Onișor & Ioniță, 2021). Advertising avoidance is a phenomenon that has been seen online and on more traditional media types like magazines, newspapers, and television (Onișor & Ioniță, 2021). Bottom-up attention is attracted by salient stimuli (Onișor & Ioniță, 2021). Salient stimuli can stand out and be attended to regardless of the meaning or information provided by the specific element (Onișor & Ioniță, 2021). In comparison, the top-down attentional control process captures task or goal relevant information (Onișor & Ioniță, 2021). Onișor

& Lonita identified bottom-up and top-down factors that draw attention to online advertisements. Bottom-up factors, or salient features were considered to be the type of advertisement (text or text and pictures), shape, language of the advertisements, advertisement location, animation, taboo level of the message and facial expression of models in the advertisements (Onișor & Ioniță, 2021), whereas top-down factors were referred to as task goals, task type or complexity, motivation, and involvement (Onișor & Ioniță, 2021). This is in contrast to other literature stating bottom-up factors are referred to as physical properties. However, it is proposed that low-level and high-level properties can be used by both bottom-up and top-down visual attention processes.

### **2.7.6. Visual Saliency, Visual Attention and Visual Search**

Visual attention processes contribute to various tasks such as visual search, natural tasks and scene viewing (Bagger, 2016). Past literature does not decipher the relative contribution of top-down and bottom-up control on visual search in decision-making (Bagger, 2016). Deciphering the weight of each attentional control on decision-making is difficult. The results of a study by Bagger, Orquin, Lahm, Tsalis, & Grunert (2016) indicated that eye movements play a greater role in visual search (Bagger *et al.*, 2016). However, top-down manipulation had a larger impact on decisions due to the influence on the use of relevant and fixated information (Bagger *et al.*, 2016). This provided a research avenue to assess the strength of bottom-up and top-down processes on attention, as well as investigate situations in which bottom-up effects dominate visual search (Bagger, *et al.*, 2016).

#### **2.7.6.1. Free Search vs Visual Search**

Past literature by (Bylinskii, DeGennaro, Rajalingham, Ruda, Zhang & Tsotsos, 2015) identified operational definitions for eye-tracking tasks, namely, free-viewing and visual search with a free gaze. Free-viewing is operationalised as eye movements when given visual stimuli without task instructions and is measured using fixation locations as well as scan paths. Scan paths are defined as fixations linked by saccadic eye movements (Kümmerer, Bethge & Wallis, 2022). Free-viewing can be evaluated by comparing human fixations and scan paths with saliency maps (Bylinskii *et al.*, 2015). The operational definition of visual search with free gaze is the human response and eye movements towards features when presented with stimuli with both targets and distractors as well as instructions to respond to the target or distractor by fixating on it (Bylinskii *et al.*, 2015). Visual search with free gaze can be measured using response time and target prediction and evaluated by assessing the similarity between response time and target detection accuracy as well as evaluating fixation locations and scan paths against saliency maps (Bylinskii *et al.*, 2015). Saliency models are image computable thus by using software such as DeepGaze II & III, saliency maps can be formulated providing a visual representation of the likelihood of fixation at locations across stimuli (Linardos, Kümmerer & Bethge, n.d.). This can be compared to an eye-tracking heat map, gaze points and gaze paths. For this research study, both free search and visual search with task instruction will be reviewed and analysed. The hypotheses presented below were used to assess the contribution of bottom-up and top-down visual processes in consumer decision making.

***H2a: During a free search task, where participants are provided visual experiences with no specific goals, more salient objects (as determined by TFFF) will have a negative relationship with the accuracy of memory recall of those same objects during a free recall task.***

***H2b: More salient objects as determined by fixation durations and heat maps will have a directly proportional relationship with the accuracy of recall of those same items, as determined by the number of correct items recalled from memory, after the viewing experience.***

Furthermore, previewing a stimulus and information about the target may improve search performance (Schutt *et al.*, 2019). This was indicated by a change in saccade length and fixation duration (Schutt *et al.*, 2019). Schutt *et al.* (2019) argued for the top-down influence of eye movement in visual search. However, bottom-up features may have predictive value in contexts where bottom-up factors are informative of task locations (Schutt *et al.*, 2019). This implies that bottom-up factors can be overruled by top-down factors used in visual search except for the first fixation (Schutt *et al.*, 2019). This is in line with past literature stating early saccades and first fixations are often subject to a centre bias and are driven by bottom-up factors (Schutt *et al.*, 2019). For the purpose of this study, primed features refer to features participants are instructed to keep in mind when viewing a stimulus. Primed features are related to task goal and thus are used as a measure of top-down visual attention in this study. Prior literature suggests top-down visual attention is more dominant than bottom-up visual attention. However, bottom-up processes can be used to signal information highlighted by marketers through physical attributes. Therefore the following hypothesis was formulated to determine whether bottom-up eye tracking alone can explain consumer decision making.

***H3: Primed objects, which are specific features participants will be looking for, will produce greater fixation duration, fixation count and first fixation duration, compared to other salient features/objects seen during a visual search task.***

### 3. CHAPTER THREE: CONCEPTUAL FRAMEWORK

#### 3.1. INTRODUCTION

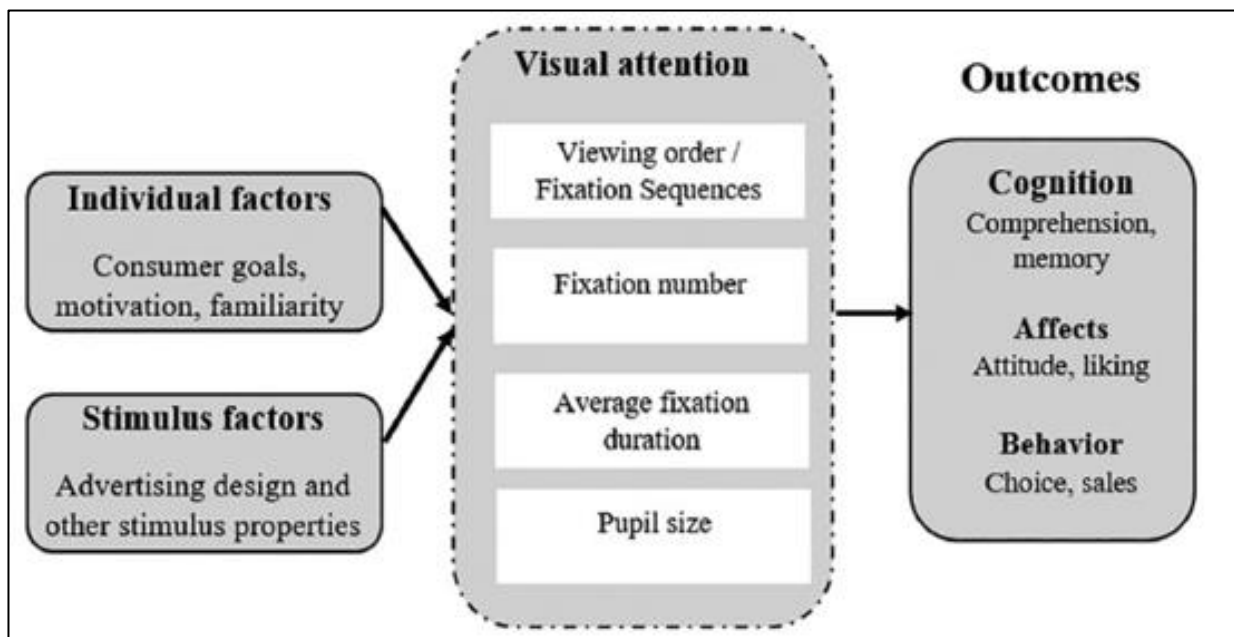
The conceptual framework for this study is discussed in this chapter. The conceptual framework was derived from a diagram depicting prospective research areas, a conceptual model as well as current and past literature.

#### 3.2. CONCEPTUAL FRAMEWORK

##### 3.2.1. Conceptual Framework

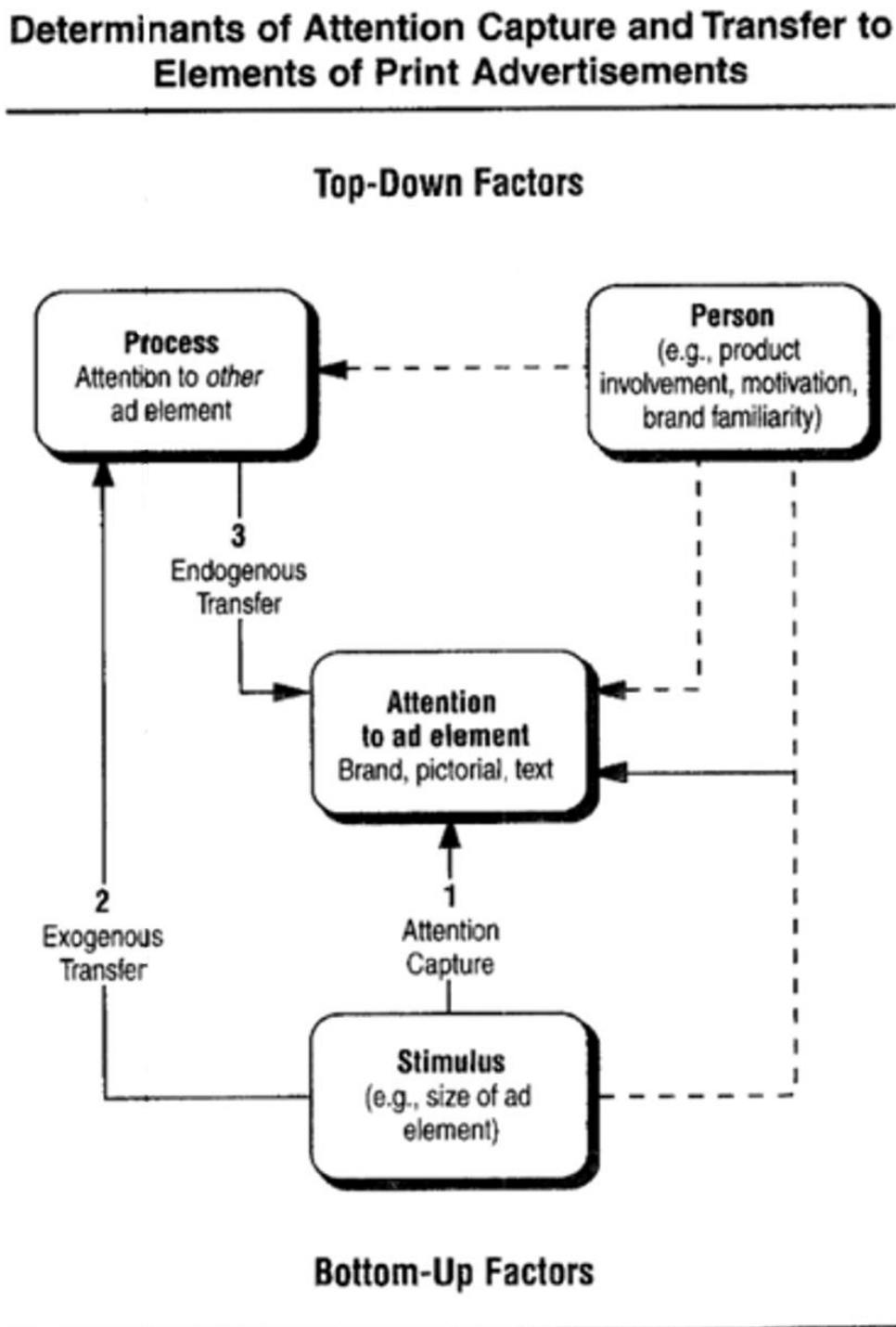
Casado-Aranda *et al.* (2023) created a diagram highlighting areas of future research, which can be seen in Figure 1 below. The research prospects were established by highlighting an application of the eye-tracking technique from the past decade of literature using SciMat software. SciMAT software is a tool that examines and classifies social, intellectual and conceptual frameworks of research fields (Casado-Aranda *et al.*, 2023). SciMAT software classifies and orders documents based on order of publication, journal publications and citations, creates co-word analyses to map the strength of association between information items including descriptions of the interactions between different fields and scientific research themes (Casado-Aranda *et al.*, 2023).

**Figure 1: Casado-Aranda et al. (2023) diagram highlighting prospective research area**



The figure above identifies key constructs utilised in the present research study, namely, top-down factors (Individual factors: Consumer goals, motivation and familiarity), bottom-up factors (Stimulus factors: Advertising design and other stimulus properties), visual attention and a behavioural outcome, consumer decision making (choice) (Figure 1) (Casado-Aranda *et al.*, 2023). Furthermore, the diagram presented by Casado-Aranda *et al.* (2023) has similarities to the AC-TEA model developed by Pieters & Wedel (2004) which can be seen in Figure 2 below.

Figure 2: Pieters & Wedel (2004) AC-TEA model: Determinants of Attention Capture and Transfer to Elements of Print Advertisements



The AC-TEA model was created on the basis that advertisements that capture attention attract consumers to select an advertisement from an environment with multiple advertisements and furthermore retain attention on that specific advertisement and its elements (Pieters & Wedel, 2004). Attention capture allows higher-order functions to focus on succinct and salient input (Pieters & Wedel,

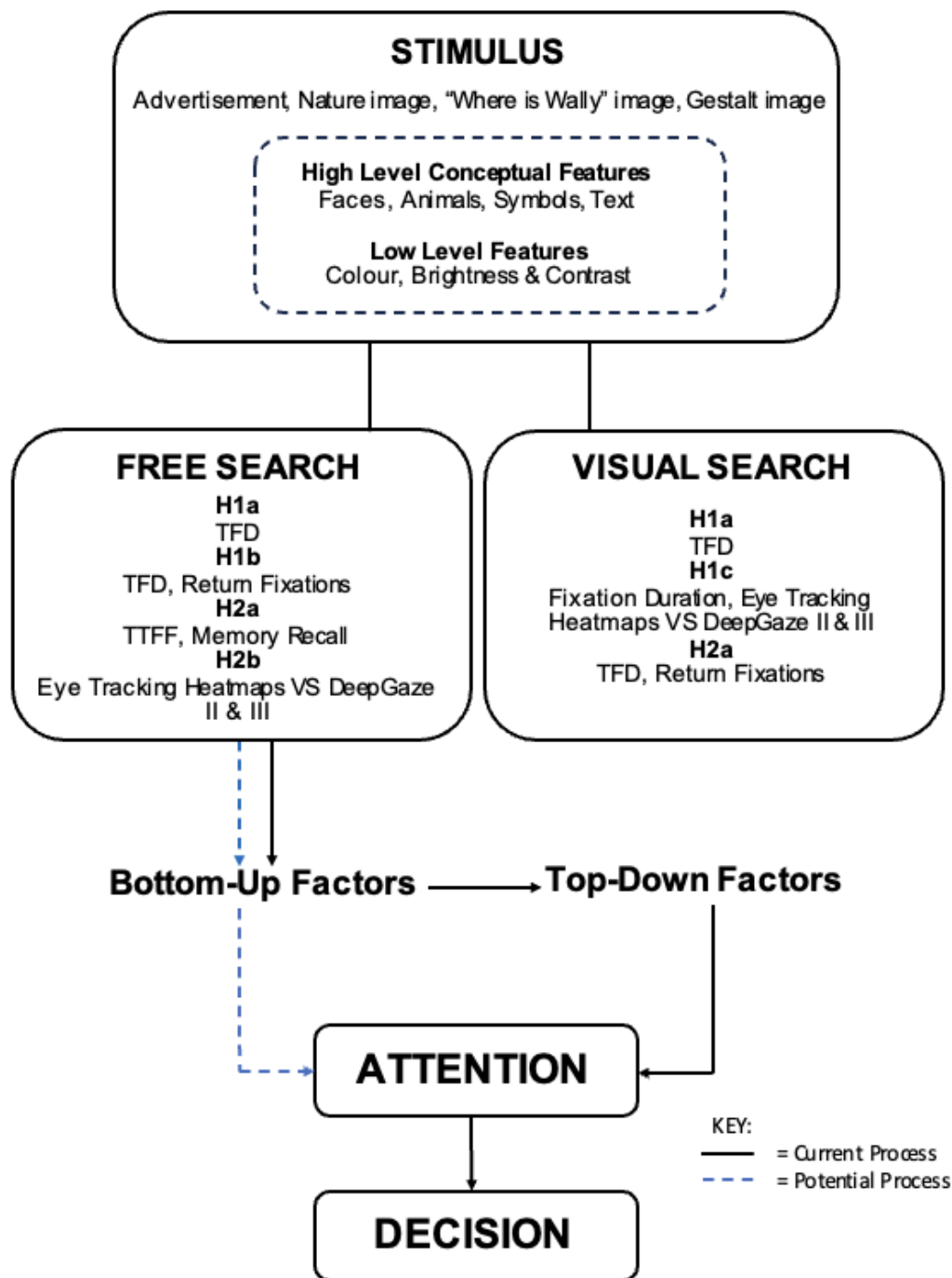
2004). The model is used to describe the visual attention process mechanisms (Exogenous and Endogenous visual attention to advertising (Pieters & Wedel, 2004). The model identifies two forms of attention capture, either independent or dependent of size (Pieters & Wedel, 2004). Furthermore, the model identifies two forms of attention transfer, independent (Endogenous/Top-down) and dependent (Exogenous/Bottom-up) (Pieters & Wedel, 2004). In the model top-down factors are referred to as the person (e.g.: familiarity and motivation) and the process (attention to other elements). Attention transfer occurs when attention to a particular advertising element is dependent on other advertising elements.

For example, exogenous attention transfer occurs as a result of stimulus features such as size, shape, colour etc. whereas endogenous transfer occurs as a result of attention to an advertising element independent of incremental properties such as size, shape etc. In other words, endogenous transfer is a cue for redirection of an attention independent stimulus or person properties. Top-down factors relating to a person, namely, product involvement and brand familiarity and other factors such as overall advertisement size and magazine type were used as covariates used in this study as control variables (Pieters & Wedel, 2004). Thus, according to Pieters & Wedel (2004), the endogenous attention transfer mechanism transfers attention to other elements independent of the factors that guided attention to the initial element in the first place. However, Pieters & Wedel 2004 stated that there was little research on endogenous attention transfer in complex scenes like advertisements.

Recent literature states that top-down and bottom-up visual attention is synonymous with endogenous and exogenous attention respectively. Upon review of current and past literature, it is evident that attention is guided by two mechanisms. Namely, top-down and bottom-up attention. As previously stated, top-down attention refers to endogenous or goal orientated attention whereas bottom-up attention is exogenous or stimulus driven (Yu, Droulers & Lacoste-Badie, 2022). Top-down attention involves higher level processing and task instruction or goals (Yu et. al, 2022). In comparison, bottom-up attention involves low-level properties or saliency cues (colour, brightness and contrast) resulting in attention to different salient, novel or unexpected stimuli (Yu et. al, 2022). However, prior literature states that high-level and low-level properties may be utilised interchangeably by bottom-up and top-down attention. High-level semantic features such as faces, text or symbols, are not accounted for in saliency maps as the maps are constructed using physical features such as intensity, orientation and colour, providing an estimate for bottom-up attention (Takano *et al.*, 2021). Thus, visual attention to elements such as text in an advertisement cannot be estimated through the conventional saliency map models (Takano *et al.*, 2021). Due to the complex nature of marketing stimuli, advertisements include high-level semantic features such as faces, symbols and text etc. as well as low-level features that are indicative of spatial contrast. The present study uses stimuli including both high and low-level features.

This research design has been formulated to assess the difference between saliency models and eye-tracking heatmaps in an attempt to better understand the role of visual salience on visual attention on consumer decision making. The present study aimed to evaluate the role of visual attention processes in consumer decision making through eye-tracking. The conceptual framework provides an outline for the proposed potential role of the visual attention processes in consumer decision making. Based on the previously described models by Casado-Aranda *et al.* (2023) and Pieters & Wedel (2004) as well as other past and current literature, a conceptual model is presented below (Figure 3) to provide a visualization of the current study.

**Figure 3: Conceptual Framework adapted from Pieters & Wedel (2004) AC-TEA model & Casado-Aranda et al. (2023) diagram**



The above conceptual framework (Figure 3) utilises key elements of the current research study. This includes consumer decision making, attention, bottom-up and top-down factors, free and visual search as well as high-level and low-level features. Each construct has been discussed in the literature review. Based on prior and current literature this model has been developed to provide the framework for this study and summarises the current visual attention process according to literature alongside a proposed process of visual attention.

## **4. CHAPTER FOUR: RESEARCH METHODOLOGY**

### **4.1. INTRODUCTION**

In the following section the research methodology is outlined and discussed with particular focus on the research philosophy and design, sampling, data collection, procedures, data analysis and ethical considerations.

### **4.2. THE RESEARCH PHILOSOPHY**

Researchers adopt a quantitative, qualitative or a mixed-methods approach when carrying out respective research. A mixed-method research approach utilises a combination of quantitative and qualitative research. This research is driven by the research question. Research studies are typically guided by a research paradigm. A research paradigm refers to the philosophical position concerning the truth and reality of a particular research problem and how it is understood (Dawadi, Shrestha & Giri, 2021).

A paradigm is defined as a set of assumptions, norms or standards consisting of agreed-upon knowledge, criteria of judgement, problem fields and how assumptions can be considered by research (Nunan, Birks & Malhotra, 2020). Popular research paradigms are positivist, interpretivism, constructivism, pragmatism and dialectical positions (Dawadi, *et al.*, 2021; Shan, 2022). There are various research approaches that can be used to uncover truth and knowledge (Dawadi *et al.*, 2021). Mixed-methods research is defined as a research methodology incorporating numerous methods to address a research question(s) in an appropriate manner through collection, analysis and interpretation of both qualitative and quantitative data (Dawadi *et al.*, 2021).

There are multiple research paradigms (Dawadi *et al.*, 2021). Positivism, interpretivism, constructivism and pragmatism are popular research paradigms. Positivism is defined by knowledge confirmation and consequent affirmation based on the senses (Dawadi *et al.*, 2021). Positivism or quantitative research was the main research method used in the past (Dawadi *et al.*, 2021). This research paradigm undergoes an objective approach as knowledge is gained through objectively verifiable facts using quantitative measures (Dawadi *et al.*, 2021). Quantitative researchers are typically positivists, utilising scientific statements that can be verified through quantitative tools resulting in objective findings (Dawadi *et al.*, 2021). Although historically positivism was used as the main research method, post-positivism researchers increased interaction with research participants (Dawadi *et al.*, 2021). Post-positivism research includes both quantitative and qualitative research methods utilising both objective and subjective approaches to research designs (Dawadi *et al.*, 2021). For example, a combination of quantitative and qualitative methods using surveys as well as interviews or respondent observation (Dawadi *et al.*, 2021).

Consequently, interpretivism and constructivism research paradigms and the use of qualitative research were used as a result of the inability of quantitative research to address relevant research questions (Dawadi *et al.*, 2021). The interpretivism research paradigm utilises qualitative research methods such as interviews, focus groups etc. to understand subjective meanings (Dawadi *et al.*, 2021). For example, social scientists utilise an interpretivist research paradigm in order to understand and interpret social phenomena (Dawadi *et al.*, 2021). In comparison, constructivism is an alternative research paradigm based on the notion that active construction of knowledge occurs where there is human interaction in the real world (Dawadi *et al.*, 2021). Constructivism does not follow a singular research methodology.

Instead, this paradigm is based on the generation of knowledge through multiple research approaches and perspectives (Dawadi *et al.*, 2021). An additional research paradigm, pragmatism, does not force researchers to choose between positivism and post-positivism, or interpretivism and constructivism (Shan, 2022).

Lastly, pragmatism uses multiple methods guided by a specific research problem (Dawadi *et al.*, 2021). This research paradigm uses both subjective and objective knowledge to achieve research objectives (Dawadi *et al.*, 2021). Pragmatism does not distinguish between the use of qualitative or quantitative research methods and instead places focus on using appropriate methods to understand the research question (Dawadi, *et al.* 2021; Shan, 2022). This research paradigm thus utilises a mixed-methods research design following one or multiple combinations of the aforementioned paradigms (Dawadi *et al.*, 2021). Qualitative research is utilised in a mixed methods research design to improve understanding of the research context with tools such as interviews and observations (Dawadi *et al.*, 2021). In comparison, quantitative research helps derive objective findings (Dawadi *et al.*, 2021). Similarly, with regard to the pragmatic research paradigm, researchers may follow a dialectical position (Shan, 2022). A dialectical position is defined as the active welcoming of more than one philosophical position, methodology or type of method which directs decisions in order to provide improved understanding of research phenomena (Shan, 2022). This research study follows a pragmatic research paradigm utilising mixed methods which is further discussed below.

### **4.3. RESEARCH STRATEGY AND DESIGN**

A research design is defined as a framework for conducting research in which specific details of procedures are outlined and identified to solve research problems and objectives (Nunan, Birks & Malhotra, 2020). Qualitative research is unstructured research utilising smaller samples to provide depth, insight and understanding (Nunan, Birks & Malhotra, 2020). This type of research is utilised to develop interpretive meanings explaining phenomena (Crick, 2021). In comparison, quantitative research is referred to as a research technique seeking to quantify results with the application of either some form of measurement or statistical analysis (Nunan, Birks & Malhotra, 2020). Quantitative research provides descriptive meanings behind psychological constructs, identifying and examining relationships between variables (Crick, 2021).

As seen in publications in journals, marketing on an academic level is dominated by quantitative research (Crick, 2021). Qualitative research is seen to be valued less than quantitative studies by reviewers and in journals (Crick, 2021). Despite this, qualitative research has been seen to have a profound effect on marketing research and strategic thinking (Tenny, Brannan & Brannan, 2022). Qualitative research can be used to describe phenomena such as behaviours, attitudes and experiences that may be hard to capture quantitatively (Tenny, Brannan & Brannan, 2022). For example, consumer decision making is complex and an in-depth understanding of how or why a consumer may have come to a decision cannot be deciphered by the choice itself. Qualitative and quantitative data are not opposites or mutually exclusive thus can be integrated to identify relevant correlations (Tenny, Brannan & Brannan, 2022). Consumer decision making and visual attention are complex constructs, thus the present study followed the research design outlined below.

The present study utilised a conclusive research design using descriptive research through experimentation. This research design was chosen in order to provide insight into managerial decision making for visual attention processes and advertising through eye-tracking. The objective of conclusive

research is to test hypotheses and examine relationships (Malhotra, 2010). This type of research design follows a formal structured approach using a large representative sample and quantitative analysis (Nunan, Birks and Malhotra, 2020). This study aimed to improve the understanding of the role of bottom-up and top-down attentional processes in decision-making, in other words, the influence of the two visual attention processes on decision making as determined by eye tracking metrics. Descriptive research is a type of conclusive research designed with the objective of describing something (Nunan, Birks & Malhotra, 2020), typically, market characteristics or functions (Nunan, Birks & Malhotra, 2020). Descriptive research is characterised, pre-planned and structured research with specific research questions and hypotheses (Nunan, Birks & Malhotra, 2020). The present research study is hypothesis-driven and experimental in nature.

The current study made use of a mixed-methods approach. The focus of this study was placed on quantitative analysis of eye-tracking results and hypothesis testing. As well as a qualitative analysis providing a comparison between eye-tracking heatmaps and DeepGaze IIE outputs as well as survey responses and key press data.

A mixed-methods research design is advantageous due to the integration of post-positivism and interpretivism (Dawadi *et al.*, 2021). Furthermore, this research design allows for methodological flexibility and in-depth analysis and insight into research findings and objectives (Dawadi *et al.*, 2021). Utilising both qualitative and quantitative measures, researchers can be more advantageous in a context where research phenomena cannot be understood by qualitative or quantitative methods alone (Dawadi *et al.*, 2021). By integrating a mixed-methods approach researchers can delve deeper into complex research problems from multiple perspectives (Dawadi *et al.*, 2021). Dawadi *et al.* (2021) described six justifications for a mixed-methods research design. Firstly, closed-ended quantitative data and open-ended qualitative data can allow researchers to generalise findings and gain deeper insight into the research problem (Dawadi *et al.*, 2021). Secondly, both quantitative and qualitative research provide value. Through the combination of the research methods researchers can produce more robust findings and research implications (Dawadi *et al.*, 2021). Mixed-methods allow for a holistic view of research findings which may provide additional insights that can be used to substantiate theories and identify future research avenues (Dawadi *et al.*, 2021). Furthermore, epistemological differences between qualitative and quantitative methods are mitigated through a mixed-methods research design. The combination of research methods allows for a comprehensive understanding of research phenomena (Dawadi *et al.*, 2021). The fourth justification lies in the ability of the mixed methods approach to obtain accurate conclusions by capitalising on and compensating for the strengths and weaknesses of either qualitative or quantitative methods (Dawadi *et al.*, 2021). This can be attributed to the fifth justification, data triangulation. Data triangulation is referred to as the direct comparison between quantitative and qualitative findings allowing for diverse data, strong inferences and improved insights (Dawadi *et al.*, 2021). Data triangulation promotes validation and credibility of findings and conclusions obtained from each approach (Dawadi *et al.*, 2021 & Nunan *et al.*, 2020). Lastly, this research design allows for refined conclusions resulting from the findings from one method informing the use of another method (Dawadi *et al.*, 2021).

#### **4.4. SAMPLING**

The sampling procedure of this study is outlined in the following sections. The target population, sampling technique and sampling frame will be discussed.

#### **4.4.1. Target Population**

The target population is referred to as the collection of a group of individuals that possess information sought by the researcher from which inferences will be made (Nunan, Birks and Malhotra, 2020). For this study, the target population was restricted to individuals aged 18 to 60 who reside in the Cape Town metropolitan area. Participation was restricted to the Cape Town metropolitan area since data collection was done at the Neural Sense offices located there. The age range for this study was selected due to the effect of age on eye-tracking quality; however no age specifications for eye-tracking studies were found in literature. Furthermore, the age range was chosen to ensure respondents were familiar with content and marketing material of South African telecommunications brands. School-goers and adults achieve better eye-tracking results due to the oculomotor system which develops from childhood into adulthood, thus the age range starts at 18 (Holmqvist *et al.*, 2022). However, with the onset of old age eyes may become hooded, and droop, and older individuals may have developed eye problems (Holmqvist *et al.*, 2022). As developmental effects and eye problems will affect the data collected by the eye-tracker, participants between the ages of 18 and 60 years old were selected. In 2019 a global mobile consumer survey was conducted with 1000 South African participants. The majority of the participants (96%) who were between the ages of 16-34 owned a smartphone while 98% of the participants aged 35-45 owned a mobile phone (Schaefer and Chivandire, 2020). In addition to details about telecommunications brands, smartphone brands and usage across SA, this study noted the smartphone brands preferred by Generation Z and Millennials so as to be familiar with the target population. Moshfegh (2020) conducted research on global market share of smartphone brands and smartphone use across four generations, namely, Generation Z, Millennials, Generation X and Baby Boomers in SA and found that Android is the leading mobile operating system globally, followed by Apple iOS (Moshfegh, 2020). According to this research, millennials and Generation X span across the ages of 25 to 55 years of age (Moshfegh, 2020). Although the aforementioned research study was open to participants between the ages of 18 and 60, the present research study only recruited participants identifying as Generation Z and millennials (18-35) due to research schedule constraints and participant availability (Moshfegh, 2020). The majority (53%) of Generation Z and millennials under the age of 35 globally use Apple mobile products with 28% using Samsung mobile devices and related products (Moshfegh, 2020). In view of this global as well as South African market share, the products advertising stimuli used in the present study were relevant for the target population.

#### **4.4.2. Sampling Method**

The total sample was  $N = 70$ . The sample was acquired from students who attend the University of Cape Town and the general public. Participation in this study was voluntary. Participants were invited to participate in this research study through the UCT DSA research invitations mailing list subject to DSA approval. Simple random sampling, convenience sampling and snowball sampling were used in this research study. Simple random sampling allows for an equal probability of selection for willing participants (Nunan, Birks and Malhotra, 2020). Convenience sampling methodology was used to acquire the sample. This a non-probability sampling technique (Nunan, Birks and Malhotra, 2020). Convenience sampling is a sampling technique used by obtaining a sample based on convenient elements such as the use of students (Nunan, Birks and Malhotra, 2020). A list of willing participants was compiled based on response to the research invitation and participants were randomly selected to partake in this study. Furthermore, this study utilised a snowball sampling method. Snowballing is a non-probability sampling technique in which the initial group of participants is selected randomly and

subsequent parties are selected based on referrals of the initial participants (Nunan, Birks and Malhotra, 2020).

Data was collected at the Neural Sense offices in Claremont, Cape Town as well as at the University of Cape Town upper campus. Data collection was restricted over a month-long period from 9am and 4pm due to the use of available office space and a reserved room in the Menzies Building at UCT from Monday the 15th of May 2023 to Monday the 12th of June 2023. The sample size of participants was restricted since data collection could only be done during working hours when some participants were not available. The data collection allowed for multiple findings; however, time restrictions, the location of the venue and the nature of this research resulted in a smaller sample size. Due to the complex nature of consumer neuroscience studies participants are subjected to a rather time-consuming experimental process. Furthermore, the respondents needed to travel to the research venue which meant that the time available for data collection was further restricted. As this research was not incentivised it was difficult to recruit participants. Participants were asked to reveal their age; however, due to the time constraints for data collection the majority of participants fell within the age range of 18 to 35. Participants were also asked to indicate their education level. However, 3 participants indicated that they had a secondary level of education and the remaining 67 participants had a tertiary level of education.

#### **4.4.3. Sample Size**

Sample size refers to the number of elements to be included in the study (Nunan, Birks and Malhotra, 2020). Due to the complex nature of this study as well as the length of time needed for data collection a smaller sample of 70 participants was used. According to Sapir, Hershman, & Henik; 2021; Ansorge, Laeng, Plfüger, Valuch, & Wallner, 2015; “We’re Gonna Need a Bigger Sample”, n.d.; and Payne, Rigby, Stewart, Tate & Vass, 2018, a sample size of 30 is sufficient for robust eye-tracking studies of a similar nature. However, there is no specified sample size for eye-tracking studies. Sample sizes vary across the neuromarketing industry and are dependent research design, neuroscience tools as well as research question (Nagel, n.d.). For example, sample sizes for eye-tracking studies by neuromarketing companies such as BrainGroup Global and Neurons Inc have indicated a sample size of at least 65 and 40-50 people for in person studies respectively (Nagel, n.d.). Furthermore the sample size was assessed through a post-hoc power analysis with G\*Power (Faul, Erdfelder, Lang, & Buchner, 2007; and Faul, Erdfelder, Buchner & Lang, 2009). The post-hoc power analysis indicated a probability of error (1-B error) of 0.99 for a sample size of 70, which is robust when making multiple comparisons or testing multiple hypotheses.

#### **4.4.4. The Sampling Frame**

The sampling frame is defined as a representation of the elements of the target population which provides a means to identify the target population (Nunan, Birks and Malhotra, 2020). The present study required participants to fall within the age range of 18 to 60 years of age and are residents in the Cape Town metropolitan area. All the respondents met the required criteria. All the respondents were presented with the same stimulus; however, the order of stimuli was randomized. Randomisation is a tool used for the control of extraneous variables. Extraneous variables are other variables than the independent and dependent variables that may influence the results of an experiment (Nunan, Birks and Malhotra, 2020).

#### **4.4.5. Relevant Brands**

Brand awareness and familiarity are important factors in determining consumer decision-making and buying decisions (Moisescu, 2009). In particular, brand awareness is often considered the main factor resulting in the inclusion of the brand in a consumer's consideration set (Moisescu, 2009). The present study utilised participants between the ages of 18 and 60, thus advertisements used in the study needed to be recognizable across a wide age range. Telecommunications brands are well known across South Africa (SA) thus participants would likely be able to relate to and evaluate advertising material. Telecommunications companies/brands have been highly ranked in South Africa with top brands in the country being MTN, Vodacom, Cell-C and Telkom ("South Africa 100...", 2022). The telecommunications sector had a turnover of R388 billion in 2022 ("South African (JSE)...", n.d.) with the SA mobile services sector accounting for around 7.29 billion U.S. dollars of revenue in 2021 ("South Africa telecom services...", 2022). In addition to this, the telecommunications industry has a high media ad spend in SA ("Telecommunication Industry AdSpend...", n.d.). Vodacom, MTN and Cell-C accounted for approximately 90% of the overall market in 2020 (O'dea, 2020). As of December 2021, Vodacom had a leading market share of 42%, followed by MTN with 31% and Cell C with a share of 17% (Msomi, 2022 & Taylor, 2023).

Research conducted in 2023 showed that Android mobile operating systems dominate the market in South Africa occupying over 80% of the market share. Apple is the next leader in the mobile operating systems market with a market share of around 19%. (Statista Research Department, 2023). Furthermore, approximately 20-22 million people use a smartphone in SA and this is expected to grow despite popular use of feature phones (Taylor, 2023). Samsung is the leading brand for mobile phones in SA, followed by Huawei and Apple (Taylor, 2023). Vodacom is currently the leading mobile network operator in South Africa. Vodacom, MTN and Cell C account for 90% of the market share for mobile network operators.

Mobile access penetration, in other words, the percentage of people having regular access to a mobile phone, was 95% in 2018 (O'dea, 2020). Banking and telecommunications are the top sectors concerning brand value in South Africa ("South Africa 50...", 2021; "South Africa 100...", 2022). However, despite high brand rankings, telecommunications companies have a poor reputation in terms of trust ("South Africa 50...", 2021). Moreover, South Africa has high-data costs, connectivity issues are common, and there is the very real high risk of theft of mobile phones. Accordingly, many subscribers may take out multiple mobile subscriptions across brands in an attempt to save money and account for connectivity issues (McCrocklin, 2021). Marketing stimuli from the four brands, MTN, Vodacom, Cell-C and Telkom were used in this research study and willing participants were screened to ensure familiarity with these relevant brands.

### **4.5. DATA COLLECTION**

Data collection for this study included self-report data as well as consumer neuroscience data collected through eye-tracking. Further data output was generated using a saliency model, DeepGaze IIE.

#### **4.5.1. Self-report data collection methods**

Self-report data for this study was generated through survey responses and key press data. The questionnaire was created using Qualtrics, an online survey generator. The questionnaire is provided in

Appendix A. Further self-report data was generated during the eye-tracking experiment by using key presses. There are advantages and disadvantages to using self-report data. Self-report data may be subject to bias as respondents may feel pressured by researcher presence or other factors. Neuroscience technology was used alongside the self-report data to get unbiased, subconscious data from respondents which is discussed further below.

#### **4.5.2. Eye-tracking data collection method**

Eye-tracking technology allows marketers to record and analyse the movement of respondents' eyes during behavioural processes (Casado-Aranda *et al.*, 2023). This provides market researchers with insight into the underlying cognitive processes of consumer behaviour (Casado-Aranda *et al.*, 2023). Eye-tracking research can improve aspects of advertising such as consumer decision making due to the ability to understand factors or advertising elements influencing consumer attention and advertising effectiveness (Casado-Aranda *et al.*, 2023).

In the past head-mounted eye-trackers were used to allow participants to move their head freely and naturally (Casado-Aranda *et al.*, 2023). However, some table-mounted eye-trackers required a chest rest to prevent respondents' head movements (Casado-Aranda *et al.*, 2023). Nowadays, eye-trackers utilise multiple reflections resulting in dissociating eye rotations from head movements and more precise tracking processes allowing participants to move their head with more freedom (Casado-Aranda *et al.*, 2023).

Tobii Tech is currently the world leader in eye-tracking solutions and services used to study human behaviour (Casado-Aranda *et al.*, 2023). Common Tobii Tech eye-tracking systems are Tobii Pro Glasses, Tobii Pro Spectrum, Tobii Pro Fusion, Tobii Pro Spark, Tobii Pro Nano and Tobii X2-30 as well as Tobii Pro Labs software ("Eye tracking products for...", n.d.; and "How to set up and...", 2023). Tobii Tech provides solutions to decode head and eye movements using artificial intelligence (AI), machine learning and computer vision expertise gathering insight into an individual's physical and cognitive status as well as attention ("What is eye tracking? How does eye tracking work", n.d.).

Eye-tracking uses sensor technology to decode, detect and follow what a person is looking at in real time ("What is eye tracking?", n.d.; Santhoshikka, Laranya, Harshavarthini, Preetha & Saran Kumar, 2021). Data streams provided by eye-tracking systems include information such as pupil position, gaze vector for each eye and gaze point ("What is eye tracking?", n.d.; Kumar, Mathur, & Jauhari, 2016). Eye-tracking systems are comprised of cameras, light sources and computing capabilities using algorithms, machine learning and advanced image processing to translate the camera feed into data points ("What is eye tracking?", n.d.; Santhoshikka *et. al.*, 2021). Tobii Tech have developed eye-tracking systems that can be used on large populations across various environments, machines and devices including laptops, virtual reality headsets, vehicles and more ("What is eye tracking?", n.d.; Santhoshikka *et. al.*, 2021). Tobii Tech has a mission to ensure an eye-tracking system for everyone, everywhere and for every device. The company has created eye-tracking systems supporting the widest variation of eye shapes, colour and retinal reflectivity as well as head movements and that can be used irrespective of ambient light and target device ("What is eye tracking?", n.d.). Furthermore, Tobii Tech adheres to standards and supports lean principles for data transfer, consumption and computational load, ensuring user privacy and integrity ("What is eye tracking?", n.d.). Tobii Tech technology has over 700 patents within the eye-tracking field allowing accessibility to the products by all ("What is eye tracking?", n.d.).

### **4.5.3. DeepGaze IIE and III**

DeepGaze IIE, a highly-ranked saliency model developed by Matthias Kummerer, was used to generate predicted fixations in an image. DeepGaze II and IIE output provided a purely bottom-up or stimulus-driven prediction of attentional capture as well as a control for experiments as outputs are computer generated (Schutt *et al.*, 2019). Furthermore, DeepGaze III was used to provide an additional saliency map including fixation history randomly selected from the eye-tracking data.

## **4.6. Data Collection Procedures**

The eye tracking experiment instructions, fixation crosses, questions and stimuli can be found in Appendix C from figures 5.1-5.38. The experiment was run on a laptop with the screen set up approximately 57-60 cm away from the eyes of the participants. The Tobii X2-30 Eye-tracker was placed at the base of the laptop screen in order to record eye-tracking data. A visualisation of the eye-tracker and set-up used in the experiments is provided in Appendix B in Figures 1, 2.1, 2.2, 3 and 4. A standardised nine-point calibration and validation procedure was performed at the start of the experiment for each participant. An example of the calibration output is presented in Appendix B in Figure 4. Calibration was conducted on Tobii Pro Labs by presenting a set of calibration targets. A nine-point calibration was chosen due to the larger number of targets generating more information for the system to optimize the 3D eye model. The calibration included an optimisation and validation phase. Once complete the software presented validation errors and results which were either approved or denied by the researcher and/ or research assistants ("Eye tracker calibration and validation", 2023). Calibration was repeated until the average accuracies of gaze samples were lower than 1° (Liu *et al.*, 2022). Furthermore, a fixation cross, a cross which participants needed to look at for 500ms to advance to the next stimulus, was used to avoid centre bias prior to viewing each stimulus. For Experiment 1 a fixation cross was provided placed in the middle of the screen whereas for Experiments 2 and 3 a fixation cross was placed randomly in six locations on the outer edges of the screen. An example of how the fixation cross was used in the experiment can be seen in the outline of the study design found in Appendix C in Figures 5.2, 5.3, 5.6-5.8, 5.12-5.13, 5.16-5.17, 5.23-5.24, 5.34 and 5.35.

Unprimed visual stimuli were shown for 500 milliseconds whereas visual stimuli for primed tasks were shown for 6 seconds. The timing was chosen due to bottom-up attention occurring at the early stages and top-down attention occurring at later stages of visual search (Pinto *et al.*, 2013). Research suggests bottom-up attention can deploy from 100-150ms whereas top-down attention takes 300ms to deploy when looking beyond special locations and 300-500ms for featural-based attention (Pinto *et al.*, 2013). As previously stated in the literature review, fixations occur when the eye is still for about 200 to 300 milliseconds (Casado-Aranda *et al.*, 2023). Therefore, too short an exposure may not result in the recording of any eye-tracking metrics on visual stimuli. To the best of knowledge, there is little research relating to or identifying specific time-denoting deployment of both bottom-up and top-down attention. Furthermore, the majority of research used to assess the two visual attention processes involved the use of simple stimuli such as shapes and did not utilise complex features such as text, images and logos. Advertisements include numerous features and images not tested for in this context by prior literature. Thus, in order to account for complexity, the upper end of the threshold for deployment of top-down attention was used. Prior literature has noted that increases in exposure time can lead to increased perceptual processing (Von Hippel & Hawkins, 1994). Furthermore, exposure time is identified in literature as a limiting factor regarding perceptual processing (Von Hippel & Hawkins, 1994). Task demands and other factors such as motivation and attention determine the need for exposure time to

facilitate perceptual processing (Von Hippel & Hawkins, 1994). Furthermore, according to prior literature and Guo *et al.* (2023), it is understood that cognitive psychology and neuroscience researchers believe that the human vision system processes only parts of the possible stimuli in detail and the rest of the stimuli is unprocessed (Guo *et al.*, 2023). Furthermore, participants completed both free search and visual search tasks. This was validated by past literature that used the aforementioned tasks to evaluate the influence of attentional processes (Schutt *et al.*, 2019). Task instructions and stimuli were presented on screen and respondents answered memorisation and choice tasks using the keyboard.

Experiment 1 consisted of a context-embedded visual search task. The stimulus included a difficult visual such as a natural environment, Gestalt image or a "Where is Wally?" poster. This type of visual was selected due to the lack of differentiation between features and the background as well as image complexity. Stimuli were randomized. This experiment utilized both purposeful/directed and non-directed tasks. The sample were exposed to four stimuli for 500 milliseconds each and one stimulus for 6 seconds. Four of the five stimuli were shown without instruction or purpose. The "Where is Wally" image was shown to participants instructing them to find Wally.

Experiment 2 consisted of a non-primed and primed visual search task. Experiment 2A was the non-primed task and experiment 2B was the primed task. During experiment 2A participants were shown an advertisement without being prompted. This was their first time viewing the advertisement. Participants then completed a memorization task related to the advertisement which included a multiple-choice question. Stimuli for experiment 2A were shown for 500ms each. The order of stimuli presented to respondents was randomized. Following the memorization task participants completed experiment 2B. Experiment 2B consisted of a primed visual search task in which the participant was provided with preceding and proceeding questions. Stimuli were shown to the respondents for 6 seconds. Participants were instructed to view an advertisement and make a choice after viewing each stimulus. After viewing the final stimulus for experiment 2B participants were asked questions regarding their decision-making. Respondents were asked to indicate how much product, price and brand informed their decision-making using a Likert scale of 1 to 5 with 1 referring to least likelihood and 5 being the highest likelihood. Comparisons between experiments 2A and 2B were made using eye-tracking and DeepGaze IIE heatmaps, time to first fixation TTFF, total fixation duration TFD, fixation count, and memory recall.

Experiment 3 consisted of a primed search task. The respondents were given preceding task instructions and then shown an advertisement for 6 seconds. After viewing each advertisement, respondents were asked to make a choice. The advertisements shown were different from experiments 2A and 2B to avoid any memory or learning. Heatmaps provided through DeepGaze IIE were compared with heatmaps generated through eye-tracking data. Comparisons were made between consumer decision-making preferences in terms of brand, price and product generated through preceding questions and eye-tracking data for each element, eye-tracking heatmaps, DeepGaze II and III output as well as fixation count and total fixation duration.

## **4.7. Measurement Instruments**

### **4.7.1. Questionnaire**

A questionnaire was provided to all 70 participants. The questionnaire was generated using Qualtrics. Qualtrics is an online platform used to generate, distribute and record questionnaire data. This questionnaire included questions regarding education level, age, familiarity with the four South African

brands and types of cell phones (e.g., Android and iPhone) as well as which service provider and cell phone device participants were currently using. Questions regarding why respondents choose to take out cell-phone contracts based on advertisement features (for example, phone type, phone brand, visual clutter, price etc.) were limited as this may have led to bias when viewing advertisements. In addition to the questionnaire, Tobii Pro labs and the Tobii X2-30 eye-tracker were used in this experiment.

#### **4.7.2. Consumer Neuroscience Instruments**

This research utilised Tobii Pro Labs software and the Tobii X2-30 screen-based eye-tracker. The Tobii X2-30 has been discontinued and replaced by the Tobii Pro Nano. However, due to availability of equipment and the capabilities of the Tobii X2-30, this eye-tracker was used in the current research. Tobii Pro labs software was chosen due to its ability to process and prepare large amounts of eye-tracking data, and has various analysis and visualisation tools as well as precise and consistent timing accuracy resulting in reliable data (“Eye-tracking software...”, n.d.). A Tobii Pro X2-30 eye-tracking device was used to record all eye-tracking data. The study examined heat maps, first fixation duration (FFD), total fixation duration (TFD) and time to first fixation (TTFF). The Tobii X2-30 is a screen-based eye-tracker used for fixation-based research (“Easy to use...”, 2018; “User’s Manual Tobii X2-30”, n.d.). Furthermore, the eye tracker is portable, non-invasive and includes robust capabilities such as tolerance for corrective lenses, head movements and lighting (“Easy to use ...”n.d.). Due to the nature of this research design and the location of data collection it was necessary for the eye-tracker to be portable.

#### **4.7.3. DeepGaze IIE**

DeepGaze IIE output was generated through a code provided on GitHub. GitHub is a platform used for software development as well as version control and collaboration, allowing software developers to store, manage and share their code (“Hello world”, n.d.). The DeepGaze IIE code was run using JupyterLab and python coding language. JupyterLab is a web-based interactive development environment for notebooks, code and data (“JupyterLab: A Next-Generation...” n.d.). The dataset contained images of various dimensions which were resized to either 1024×786 or 768×1024 in order to remain consistent with the DeepGaze saliency models.

### **4.8. Scaling**

Scaling is defined as the creation of a scale where measured objects are located on a continuum (Nunan, Birks and Malhotra, 2020). Reliability is defined as the extent to which a scale produces consistent results if repeated measurements are made on the characteristic. Likert scale questions required the participants to indicate the level of importance for each factor in informing their decisions. Respondents were asked to indicate their choice on a 5-point Likert scale (1=little to no importance in informing decision, 5=the most important factor informing decision making). Tests for reliability of scales were not run as the scale was used as a grouping instrument and not to measure internal consistency of the construct.

### **4.9. Data Analysis**

Data collected in this study was analysed with Tobii Pro Labs, JASP, GitHub Jupyter and Microsoft Excel. Tobii Pro Labs software provided an advanced analysis of the eye-tracking data. Heatmaps,

Areas of Interest (AOIs), Key press data and eye-tracking metrics resulting from the data collection were exported from the software. Contextual stimuli and advertisement stimuli used in this study are presented in Appendix D in Figures 6.1-6.5 and Figures 7.1-7.2 respectively. Advertising stimuli are numbered and labelled from A-D to differentiate between telecommunications brands advertisement variations. Telecommunications brands Cell-c, Telkom, Vodacom and MTN are labelled A,B,C and D respectively. The AOIs for each stimulus are displayed in Appendix D in Figures 8.1-8.12. AOIs identifying important elements in each image were created for data analysis. AOIs for the advertisements were sectioned into 4 factors for analysis, namely, product, price, brand and pictures (Appendix D: Figure 8.1-8.7). Furthermore, the AOIs were created on Wally, the dog in the gestalt image, the owl, the lion and the snake (Appendix D: Figure 8.8-8.12). Product AOIs included an image of the product, price of AOIs included all textual elements indicating price, brand of AOIs included the brand logo and pictures were any other pictures or elements not included in product, price and brand AOIs. For example, pictures included headlines and surrounding images, images of people and 5G symbols.

Heatmaps indicate relative intensity values captured by the eye-tracker using colour representation (Farnsworth, n.d.b. b.). Areas with higher intensity of values are associated with hot colours like red, whereas areas with lower values captured are represented by cooler colours like green (Farnsworth, n.d.b. ). On a heat scale, red indicates relatively more attention and green indicates relatively less attention (Farnsworth, n.d.b. ). Pure green is the lowest value, pure red is the highest value and pure yellow is the middle value (Farnsworth, n.d.b. ). Parts of the stimulus that did not record eye-tracking metrics have a value of 0 and thus remain transparent (Farnsworth, n.d.b. ). When comparing heatmaps marketers can understand what attracts the most attention or which feature is the most salient (Farnsworth, n.d.b. ).

Furthermore, eye-tracking metrics such as Time to First Fixation (TFF), Total Fixation Duration (TFD), First Fixation Duration (FFD) and Fixation Count (N) were exported as a Microsoft Excel document. Key press data was also exported as a part of the Microsoft Excel document. Key press data was sorted and recoded to zeros and ones indicating preference and choice.

Eye-tracking data was analysed using descriptive and inferential statistics as well as through identifying similarities and differences between eye-tracking heatmaps amongst stimuli as well as DeepGaze IIE output. All stimuli were run through the code for DeepGaze IIE. The code for the saliency models was acquired through GitHub and run using Jupyter and python language coding. This provided a heatmap based on saliency features such as colour, contrast and brightness. Heatmaps obtained through Tobii Pro Labs and DeepGaze saliency model output are presented in Appendix G in Figures 13.1.1-13.5.2, 13.1.2-13.5.2, 14.2-14.4, 15.2-15.4, 16.2-16.3, 17.2-17.3, 18.2-18.3, 19.2-19.3 and 20.2-20.3.

Jeffrey's Amazing Statistics Program (JASP) is a software program used for statistical analysis. JASP was used to analyse descriptive statistics and inferential statistics for hypothesis testing. Descriptive statistics provide researchers with a summary of data relating to the sample without drawing inferences based on probability theory (Kaliyadan, Kulkarni, 2019). Common descriptive tools are frequency distribution tables, percentages such as measures of central tendency (Mean, median and mode), measures of variability (Range statistics, variability, standard deviation and coefficient of variation) and measures of shape (Skewness and Kurtosis) (Nunan *et al.*, 2022 & Kaliyadan, Kulkarni, 2019).

Inferential statistics were used to draw conclusions on hypotheses. This study utilised hypothesis testing in order to test the hypotheses outlined in the literature review and generate results and findings.

Hypothesis testing has predefined procedures used to accept or reject the hypotheses (Goss-Sampson, 2022). Hypothesis tests used in this research paper are independent sample t-tests, Mann-Whitney U tests, ANOVA, Kruskal-Wallis tests and binomial tests. The aforementioned statistical tests are discussed and defined below.

Independent Sample t-tests were conducted to assess the differences between groups. Independent sample t-tests were utilised due to a singular construct and two levels of grouping variables. An independent sample t-test, more specifically a Student's test, is a parametric tests used to assess whether there is a difference between the means of two independent groups (Goss-Sampson, 2022). This type of statistical test requires a continuous dependent variable and an independent variable comprising of two groups (Goss-Sampson, 2022). A student t-test was used to conduct statistical analysis for normally distributed data.

A Mann-Whitney U test is a non-parametric equivalent for the independent sample t-test that is not held to the assumption of normality (Goss-Sampson, 2022). Normality of the independent variable should be measured on a continuous scale and be approximately normally distributed with no significant outliers (Goss-Sampson, 2022). A Shapiro-Wilk test is used to test for normality (Goss-Sampson, 2022). Small deviations from normality are usually acceptable as the t-test is robust (Goss-Sampson, 2022). However, this does not apply when group sizes are too different (Goss-Sampson, 2022). The ratio between group sizes should be less than 1.5. Furthermore, data can be transformed if normality is violated (Goss-Sampson, 2022). If group sizes are very different and data is not normally distributed, a Mann-Whitney U test is used (Goss-Sampson, 2022). Mann-Whitney U tests were conducted on data that was not normally distributed.

For this research the dependent variables used are TFD, FFD, TTFF and Fixation Count. Mann Whitney tests were used to test for model significance at the 5% significance level. The null and alternative hypothesis for Mann Whitney U tests are as follows.  $H_0$ : There is no difference in central tendency between the two groups,  $H_1$ : There is a difference in central tendency between the two group (Goss-Sampson, 2022). Grouping variables are 'yes' or 'no' answers for consumer decision-making and preferences are coded by 1's and 0s respectively. Assumptions of the parametric independent sample are group independents and normality of the dependent variable. Group independence requires that a participant can only be in either the 'yes' or 'no' category and not both.

Analysis of variance (ANOVA) is a statistical technique for examining the differences between means for two or more populations (Nunan, Birks and Malhotra, 2020). This statistical analysis was chosen due to a singular construct and more than two grouping variables. A one-way Analysis of variance (ANOVA) is used to compare the means of three or more grouping variables or conditions. This can be done using both independent and repeated measures. ANOVA is an omnibus test providing an F-statistic that determines whether the datasets explained variance is greater than the unexplained variance (Goss-Sampson, 2022).  $H_0$ = There is no significant difference between all group means and  $H_1$ = There is a significant difference between all group means (Goss-Sampson, 2022). However, due to ANOVA being an omnibus test there is no indication of where significant differences occur (Goss-Sampson, 2022). Thus, post hoc tests are used to determine the location of group differences (Goss-Sampson, 2022). Post hoc tests are used instead of multiple pairwise comparisons in order to combat the familywise error or cumulative Type I error due to stricter acceptance criteria (Goss-Sampson, 2022). Assumptions of ANOVA are that the independent variable must be categorical, the dependent variable is continuous, groups are independent, dependent variables are normally distributed, there are no significant outliers, and that there is homogeneity of variance between the groups to ensure a reliable

p-value for the F-stat (Goss-Sampson, 2022). If the last three assumptions are not met, a non-parametric equivalent called the Kruskal-Wallis test is considered. Assumptions are tested for an ANOVA by using a Levene's test, a Q-Q plot and descriptive statistics. A Levene's test indicates that homogeneity of variance is not significant and a Q-Q plot shows that data appears to be normally distributed and linear (Goss-Sampson, 2022). If assumptions are not met or data is nominal, a Kruskal-Wallis non-parametric ANOVA is used. This is a rank-based test equivalent to the ANOVA used to compare two or more independent samples of equivalent or different sample sizes (Goss-Sampson, 2022). Furthermore, post hoc tests are used to identify which specific groups are statistically different from each other (Goss-Sampson, 2022). More specifically, Dunn's post hoc test is used. Dunn's post hoc test was calculated to determine group differences (Goss-Sampson, 2022). Bonferroni and Holm's tests were used for correction (Goss-Sampson, 2022). Bonferroni gives, albeit conservative, control for Type I errors despite the risk of a reduction in statistical power. The Holm-Bonferroni test is a sequential Bonferroni test that is less conservative (Goss-Sampson, 2022).

A binomial test is a non-parametric test for dichotomous categorical datasets (Goss-Sampson, 2022). For example, yes and no datasets (Goss-Sampson, 2022). The binomial test assesses whether or not the population sample frequency is statistically different from a known or hypothesized population frequency (Goss-Sampson, 2022). In other words, a binomial test is a statistical test assessing the goodness-of-fit for dichotomous variables. Binomial tests assess the goodness of fit for the observed number of observations in each category to the number expected under a specified binomial distribution (Nunan, Birks and Malhotra, 2020). Dichotomous variables were used in this study to indicate preference of factors used to inform consumer decisions as well as the respondent decision itself. For example, respondent preference for a factor identified in task 3 was coded to 1 and factors not preferred were given the code 0. Furthermore, dummy variables were used to code for consumer decisions recorded as 1 for yes and 0 for no. The null hypothesis ( $H_0$ ) tests whether the sample frequency is equal to the expected population frequency (Goss-Sampson, 2022). In order to use a binomial test, one-sample t-test assumptions need to be met (Goss-Sampson, 2022). Assumptions are that the test variable must be a dichotomous scale (e.g., yes or no), sample responses are independent and the sample size is less but represents the population (Goss-Sampson, 2022).

#### **4.10. ETHICAL CONSIDERATIONS**

This study was approved by the University of Cape Town's Higher Degrees Committee, the Ethics in Research Committee as well as the Marketing Academic Committee to ensure the present study would not compromise any participants of the study throughout the research process. Participants were randomly selected. Participation in this research was voluntary and participants had the option to withdraw consent to participate without penalty, regardless of the stage of the research process. A cover letter was provided as a research invitation indicating requirements for participation such as familiarity with relevant brands and the nature of the study. Furthermore, an informed consent form and a verbal explanation was provided at the beginning of the study to all willing participants stating information pertaining to the study and their participation, the nature of the research, ethical considerations and exclusion criteria. This study ensured that participants remained anonymous and responses recorded through eye-tracking technology were confidential, stored on a secure, password-protected device and used only for this research study. This research was non-invasive and participants' eye movements were recorded from a distance. Furthermore, due to the anonymisation of data, data reported does not contain any identifiable participant information. Storage and management of all data and information obtained in this study complied with the current POPIA act. DSA approval was acquired due to the likelihood of

participation by UCT students. COVID-19 provided a need for further ethical considerations. A COVID compliance form was completed by all participants before entering the research premises. This form was distributed electronically to minimise contact with participants and included a temperature screen as well as a brief risk questionnaire. In addition, participants could choose to wear a mask based on previous COVID – 19 restrictions. Finally, the incentive for participation in this study was used to offset travel costs and the participants' time.

#### **4.11. CONCLUSION**

This chapter has outlined the research methodology used to conduct this research and provided justification for the research methods used to meet the objectives of the study.

## **5. CHAPTER FIVE: PRESENTATION AND INTERPRETATION OF FINDINGS**

### **5.1. INTRODUCTION**

The following sections present and interpret the study findings. Results were obtained from both qualitative and quantitative analysis. Descriptive statistics, reliability tests and tests for normality are described followed by an analysis of each hypothesis using inferential statistics and the qualitative analysis. Results were generated through Tobii Pro Labs, DeepGaze IIE& III code (GitHub & Jupyter), Microsoft excel and JASP.

### **5.2. DESCRIPTIVE STATISTICS**

This section outlined descriptive statistics for the sample population and self-report data.

#### **5.2.1. Sample composition**

Respondents completed a questionnaire prior to the collection of eye-tracking data to identify demographic data as well as brand and product familiarity and use. By continuing with the questionnaire participants confirmed that they met and understood the criteria for an eye-tracking study. Respondents were required to have normal or corrected vision to participate in the present study. All of the participants consented to participate in the study and understood the study criteria provided in the consent form and cover letter.

67 respondents fell between the ages of 18 and 34 and three (3) respondents were between the ages of 35 and 60. A table indicating respondents' ages can be found in Appendix E in Table 1. Three participants indicated having a secondary level of education, with the remaining 67 participants indicated having a tertiary level of education. A summary of the ratio of respondents' education level can be seen in Appendix E in Table 2. Due to the nature of the study including a longer data collection process as well as travel time and the exclusion criteria, the population demographics were not large enough to make inferences on different generations or levels of education. Other demographic factors such as gender and race were not recorded in this study.

Furthermore, respondents indicated familiarity with and use of telecommunications brands (MTN, Vodacom, Telkom and Cell-C) and product mobile operating systems (Android and Apple). At least 60 participants were familiar with all of the telecommunications brands with all of the telecommunications brands. In particular, approximately 25% of the respondents were familiar with each brand. More specifically, 25.28% of respondents were familiar with MTN, 25.66% with Vodacom, and 24.53% indicated familiarity with both Telkom and Cell-C (Appendix E: Figure 9.1).

Moreover, participants were required to indicate which mobile operation system they used. The majority of respondents were Vodacom users indicated by 63.16% of the target population, followed by MTN users making up 22.37%, Telkom with 9.21% and Cell-C with 5.26% (Appendix E: Table 3 and Figure 9.2). Respondents were also asked to indicate their familiarity with mobile operating systems and their use of either the apple or android mobile operating system. Forty-five point sixty-one percent (45.61%; 52 respondents) and Fifty-four point three-nine percent (54.39%; 62 respondents) of the target population were familiar with the Android and Apple mobile operating systems respectively (Appendix E: Table 4). Therefore, the majority of the target population were familiar with both mobile operating

systems presented in the stimuli. Furthermore, 84.51% (60 respondents) indicated that they were users of Apple products with the remaining 15.49% (11 respondents) being Android users (Appendix E: Table 5). A bar graph is presented in Figure 9.3 to provide a visualisation of the respondents' distribution of mobile operating system users.

### **5.2.2.Interval Data Descriptive Statistics**

Scaled data was used to indicate preference, factor importance, decision making as well as attention measured using eye-tracking metrics is discussed. Self-report data from respondents was recorded using key presses during the eye-tracking experiment. Self-report data included memory recall, importance of choice factors using a Likert scale, consumer decision, as well as preference for which factor was used to inform respondent decisions. Task 2 presented respondents with a 500ms flash exposure of three advertisements. Respondents were asked to indicate which factors (product, price, brand, pictures, all of the aforementioned or none) they were able to recall after the flash exposure. A pie chart is presented in Appendix E in Figure 9.4 to provide a visualisation of the distribution of factors recalled by the respondents.

Sixteen percent (16%) of the 70 respondents indicated that they could recall all the elements of the advertisements (Appendix E: Table 6). Seven percent (7%) of the sample indicated that they did not recall any of the elements during the flash exposures (Appendix E: Table 6). Seven percent (7%) of the sample indicated that they could recall the product only (Appendix E: Table 6). Pictures and brand were recalled by the majority of respondents as indicated by 19% of the population recalling both the pictures and brand (Appendix E: Table 6). This does not include the number of respondents who indicated that they could recall more than one of the factors but not all of them. Data from respondents who could recall more than one item were recorded manually. Thirteen percent (13%) of the population were able to recall product, brand and pictures (Appendix E: Table 6). Only 1% of the sample indicated that they could recall product, brand and price (Appendix E: Table 6). Additionally, 10% of the sample recalled brand and pictures only and 8% recalled brand and product only (Appendix E: Table 6). Brand was recalled by all the respondents who recalled multiple elements. This indicated that the majority of the respondents were able to recall brand from the flash exposures.

Furthermore, in Task 2 respondents were asked to indicate how important each factor (product, price and brand) was in informing their decision to purchase or not on a scale of 1-5 with 1 being of little/no importance to 5 being the most important factor informing decision making. Results of the Likert-Scale questions were used to provide insight into the contextual importance of each factor. Participants were shown three advertisements twice, first for 500ms, followed by a 6 second exposure to the stimulus. Descriptive statistics for total fixation duration per factor and each level of importance is presented in Appendix E in Table 7 and Figure 9.5. Fifty-one point forty-three percent (51,43%) of participants indicated that brand was an important factor in informing their decision (Level 4 and 5) whereas 38,57% of participants identified price as an important factor informing their decision (Level 4 and 5). The majority of participants indicated that product was a highly important factor informing their decision with 42,86% and 28,57% of the sample rating product 5 out of 5 and 4 out of 5 respectively.

Finally, respondents were asked to identify which of the three factors (product, price and brand) were most important to them when making a decision to enter into a cell phone contract. Results for respondents' preference for each factor is presented in Table 8 in Appendix E. Respondents were told to keep this choice in mind whilst viewing the advertisements. A pie chart is presented in Figure 9.6 of

Appendix E to provide a visualisation of the distribution of the preferred factors used when viewing the advertisements. The majority of the participants, 57,14%, identified product as the most important factor (Appendix E: Table 8) while 22,86% indicated price was the preferred factor informing their decision. The remaining 20% of participants chose brand as the preferred factor to consider when choosing a cell-phone contract (Appendix E: Table 8).

Furthermore, descriptive statistics were calculated to show the number of respondents who were either users or non-users of each brand and the reasons for their decision. A summary of the distribution of preference by telecommunications brand users is provided in Table 9 and Figure 9.7 in Appendix E. Each brand had seven adverts which were presented to all 70 participants. The majority of the respondents were Vodacom users followed by MTN, Telkom and Cell-C. Figure 9.7 provides a bar graph depicting the relationship between users' and non-users' decisions on brand stimuli. The graph shows that users chose not to purchase more than purchase on all advertisements including the brand which they used. Furthermore, non-users chose to purchase and not to purchase more than users for all brands excluding Vodacom. An independent sample t-test was conducted and group descriptive statistics were analysed to assess the relationship between users and decision making. Descriptive plots (Appendix E: Figure 9.8) and statistics (Appendix E: Table 10) indicated that the mean decision by brand users was greater for brand users who chose to purchase (mean=0.278) than for users who chose not to purchase (mean=0.242)

In addition to brand users, descriptive statistics for mobile operating system users and non-users were also assessed relative to their decision (Appendix E: Table 11). Figure 9.9 presented in Appendix E provided a visual representation of the distribution between choice based on users and non-users based on the mobile operating system shown in the stimuli. Descriptive statistics (Appendix E: Table 11) showed that android users did not choose to purchase more than they chose not to purchase android products. However, non-android users chose not to purchase more than to purchase for android products. Users of apple products chose to purchase more than not to purchase when shown advertisements with apple products whereas non-users of the apple mobile operating system chose not to purchase more than to purchase when looking at stimuli for apple products. An independent sample t-test was conducted resulting in group descriptive plots. Descriptive plots (Appendix E: Figure 9.10) and statistics (Appendix E: Table 12) indicate that the mean decision by product or mobile operating system users is greater for product users who chose to purchase (mean=0.621) than users who chose not to purchase (mean=0.322).

In addition to self-report data generated through survey responses, descriptive statistics were calculated for the number of fixations on AOIs during short and long exposures. Stacked bar graphs in Appendix E in Figures 9.11.1 to 9.11.6 are presented to provide a visual representation of the differences between the percentage of AOIs fixated on and not fixated on for short and long exposures. Results were drawn from Task 2A and 2B for three advertisements. Advertisements shown for a short period of time are labelled with the advertisement number followed by two letters indicating the telecommunications brand featured in the advertisement. In contrast, long exposures are labelled by advertisement number followed by three letters deciphering the advertisement's brand. For example, the short exposure for Advertisement 1 is labelled 1aa whereas the long exposure is labelled 1aaa. Advertisements 1-3 had varying levels of complexity. Advertisement 1 was simple and the price was easy to see. Advertisement 2 was simple with no distractors and included multiple prices which would influence consumer decision-making due to numerous alternatives. Advertisement 3 was complex, with multiple distractor features such as faces and the price was small in comparison to Advertisements 1 and 2. A graph is

presented for each type of AOI, price (Figure 9.11.1), product (Figure 9.11.2), brand (Figure 9.11.3) and pictures (Figure 9.11.4-9.11.6).

Across all AOI types, price, product, brand and pictures, the majority of respondents did not fixate on these AOIs during the short exposures. Fixation results across price AOI for short exposures indicated that approximately 90% of respondents did not fixate on the price. In comparison, during the long exposure above 60% of respondents fixated on the price (Appendix E: Figure 9.11.1). Therefore, we can conclude that as respondents did not fixate on price during the short exposure, bottom-up visual attention could not have been involved in the consumer decision-making process as they did not attend to the feature and therefore could not fully comprehend the information presented to make an informed decision.

Similarly, fixation results on short exposures indicated that when advertisements included a single product image, approximately 80% of respondents did not fixate on the product image (Appendix E: Figure 9.11.2). However, when there were two product images, approximately 80% of respondents did not fixate on the one product image and around 50% did not fixate on the other product image. In contrast, approximately 70% of participants fixated on product images during the long exposure.

During the short exposure around 80% of respondents did not look at brand across all variations of the advertisement (Appendix E: Figure 9.11.3). Similarly, brand was also not fixated on during the long exposure to the stimuli. Advertisements 1B and 3B indicated fixations by between 60% and 70% of participants during the 6-second exposure. However, the majority of the advertisements resulted in fixations on brand ranging from 10%-60% of respondents. This result indicates that overall, brand was fixated on less than other features such as product and price. A lower number of fixations on brand may be attributed to familiarity and memory regarding each brand such as colours and headlines or slogans.

All other elements of the stimuli other than product, price and brand were considered to be pictures. Some advertisements included more pictorial features to add distractor elements to the advertisement and increase complexity. Advertisements 1 and 3 included pictorial elements used to distract attention. Advertisement 1 pictures include a boy, a 5G symbol, a headline and random branding (Advertisements 1C and 1D). Advertisement 3 included pictures of two boys, a girl, a headline, emoticons surrounding the headline and other random pictures. Advertisement 2 included only images and information relating to product, price and brand; however, pictorial elements were the 5G symbol and a contract deals banner. Advertisement 1 was less complex than advertisement 3. Advertisements 1-3 are presented in Appendix D in figure 7.1. Overall, fixation on pictures increased over time. Similar to product, price and brand, the majority of respondents did not fixate on pictorial elements during the short exposure (Appendix E: Figures 9.11.4-9.11.6). For Advertisement 1, participants fixated mostly on the headline. All other pictorial features for Advertisement 1 were fixated on by fewer than 10% of respondents and T&C's were not fixated on (Appendix E: Figures 9.11.4). Focus on the headline was not unlikely as it was placed just above the centre of the page and occupied a large portion of the advertisement. For Advertisement 2, less than 10% of respondents fixated on all pictorial elements (Appendix E: Figures 9.11.5). Finally, for Advertisement 3, fixations were mainly on headlines and headline emoticons (Appendix E: Figures 9.11.6).

Group descriptive statistics and descriptive plots were conducted through an independent sample t-test to assess the percentage of respondent fixations on AOIs during short and long exposures. Descriptive plots (Appendix E: Figure 9.12) and statistics (Appendix E: Table 13) show that the mean percentage of respondents who fixated on AOIs was greater for longer exposures (mean=0.582) than short

exposures (mean 0,076). Therefore, there was a greater number of fixations with increased exposure time.

Furthermore, differences in the fixation percentages across advertisements could be as a result of product image, picture and price sizing and positioning. Brand features were not changed across all three advertisements. In Advertisement 1 (Appendix D: Figure 7.1. 1A-1D) the product image takes up a large portion of the advertisement and has few distractors. In Advertisement 2 (Appendix D: Figure 7.1. 2A-2D) two product images were presented whereas, in Advertisement 3 the product image was smaller, just off centre and contained numerous distractor features (Appendix D: 7.1. 3A-3D). Despite advertisement simplicity or complexity, the majority of the respondents did not fixate on product, price or brand during the short exposure.

### **5.3. THE RELIABILITY OF THE SCALES**

Reliability is defined as the extent to which a scale produces consistent results if repeated measures are made on the same characteristic (Nunan, Birks and Malhotra, 2020). This section outlined the reliability of scales in order to determine whether scales used in the present study were reliable measures of key constructs in this research.

#### **5.3.1. Item Reliability**

Likert scale questions were used in this study and required the participants to indicate the level of importance for each factor in informing their decisions in order to group participants and contextualise the importance of factors influencing decision making. Tests for reliability of scales were not run as the scale was used as a grouping instrument and not as a direct measure and comparison of scale. The Likert scale was used to categorize respondent data into groups to be compared and analysed against eye-tracking metrics. Cronbach's alpha is used to test reliability of scales. For the purpose of this research reliability of scales was not assessed as Likert scales were used as a grouping tool and not to measure a specific marketing construct. Cronbach alpha is assessed to test item reliability when scales are used to measure a particular construct. For example, Cronbach alpha may be used to measure internal consistency of respondent answers to questions relating to how relaxed or stressed someone may feel as these variables may have the same outcome. As consumer decision making is complex and no consumer is the same, factors used to aid consumer decision making such as price and product may vary in scale answers that are indicative of how important each factor is in informing decisions.

### **5.4. VALIDITY**

Validity is referred to as the extent to which a measure collects what it is supposed to collect (Farnsworth, 2017b) or the extent to which a measurement represents characteristics that exist in the phenomenon under investigation. Eye-tracking calibrations were conducted for each respondent and internal validity was measured and assessed by the researcher prior to the start of the experiment.

### **5.5. TESTS FOR NORMALITY**

Popular tests for normality are the Shapiro-Wilk test for normality and Levene's tests for equality of variances. A summary of the tests for normality for each hypothesis is presented below. The results of Shapiro-Wilk and Levene's tests used to test for normality are summarised in Table 1 below. The

following hypothesis was used to test normality:  $H_0$ : The data was normally distributed,  $H_1$ : The data was not normally distributed. Assumption checks and Q-Q Plots for each hypothesis can be found in Appendix F in Tables 14.1-14.21 and Figures 10.1-10.7 respectively.

**Table 1:** Summary of Tests for Normality

<b>H1A</b>		<b>Shapiro-Wilk</b>	<b>p-value</b>		<b>Conclusion</b>
Task 2&3 including pictures	TFD	Not chosen: W=0.809 Chosen: W=0.837	< .001 < .001		Data is not normally distributed
TASK 2 including pictures	TFD	Not chosen: W=0.810 Chosen: W=0.859	< .001 < .001		Data is not normally distributed
TASK 3 including pictures	TFD	Not chosen: W=0.808 Chosen: W=0.816	< .001 < .001		Data is not normally distributed
Task 3 excluding pictures	TFD	Not chosen: W=0.784 Chosen: W=0.797	< .001 < .001		Data is not normally distributed
Task 3 Preferred AOI and purchased	TFD	Not chosen: W=0.772 Chosen: W=0.901	< .001 < .001		Data is not normally distributed
<b>H1A</b>		<b>Levenes's test</b>	<b>p-value</b>	<b>Q-Q Plot</b>	<b>Conclusion</b>
Task 3 excluding pictures	TFD	F=175.321	< .001	Positively Skewed	Data is not normally distributed
<b>H1B</b>		<b>Levene's test</b>	<b>p-value</b>	<b>Q-Q Plot</b>	<b>Conclusion</b>
H1Bi	TFD	F=56.491	< .001	Positively Skewed	Data is not normally distributed
H1Bii	N	F=2.532	0.001	Positively Skewed	Data is not normally distributed
H1Biii	FFD	F=20.060	< .001	Positively Skewed	Data is not normally distributed
<b>H2A</b>		<b>Shapiro-Wilk</b>	<b>p-value</b>		<b>Conclusion</b>
	TTF	Not Recalled: W=0.960 Not Recalled: W=0.955	< .001		Data is not normally distributed
		<b>Levenes's test</b>	<b>p-value</b>	<b>Q-Q Plot</b>	
		F=1.030	0.409	Normal	Data is normally distributed
<b>H2B</b>		<b>Shapiro-Wilk</b>	<b>p-value</b>		<b>Conclusion</b>
	TFD	Not Recalled: W=0.245 Recalled: W=0.333	< .001		Data is not normally distributed
		<b>Levenes's test</b>	<b>p-value</b>	<b>Q-Q Plot</b>	<b>Conclusion</b>

Continued on the following page...

		F=106.698	< .001	Positively Skewed	Data is not normally distributed
<b>H3</b>		<b>Shapiro-Wilk</b>	<b>p-value</b>		<b>Conclusion</b>
	N	Not Preferred: W=0.835 Preferred: W=0.918	< .001 < .001		Data is not normally distributed
		<b>Levenes's test</b>	<b>p-value</b>	<b>Q-Q Plot</b>	<b>Conclusion</b>
		F=31.934	< .001	Positively Skewed	Data is not normally distributed
		<b>Shapiro-Wilk</b>	<b>p-value</b>		<b>Conclusion</b>
	FFD	Not Preferred: W=0.477 Preferred: W=0.538	< .001 < .001		Data is not normally distributed
		<b>Levenes's test</b>	<b>p-value</b>	<b>Q-Q Plot</b>	<b>Conclusion</b>
		F=6.522	< .001	Positively Skewed	Data is not normally distributed
		<b>Shapiro-Wilk</b>	<b>p-value</b>		<b>Conclusion</b>
	TFD	Not Preferred: W=0.752 Preferred: W=0.850	< .001 < .001		Data is not normally distributed
		<b>Levenes's test</b>	<b>p-value</b>	<b>Q-Q Plot</b>	<b>Conclusion</b>
		F=38.526	< .001	Positively Skewed	Data is not normally distributed
<b>User and Decision</b>		<b>Shapiro-Wilk</b>	<b>p-value</b>		<b>Conclusion</b>
	Product User	Not purchased: W=0.589 Purchased: W=0.615	< .001 < .001		Data is not normally distributed
	Brand User	Not purchased: W=0.531 Purchased: W=0.560	< .001 < .001		Data is not normally distributed
<b>Exposure Time</b>		<b>Shapiro-Wilk</b>	<b>p-value</b>		
	% Fixated on AOI	Short Exposure: 0.643 Long Exposure: 0.917	< .001 < .001		Data is not normally distributed

All tests for normality rejected the null hypothesis at the 5% significance level for all constructs where  $p\text{-value} < 0.05$ . A common trend across the Shapiro-Wilk's and Levene's tests was that the majority of the results indicated that data was not normally distributed as the majority of the p-values were less than or equal to 0.001. However, results of a Levene's test for H2A indicated that TTF and memory recall data was normally distributed ( $p=0.409$ ). Thus, in the case of non-normal data, alternative tests were used for both the independent sample t-tests and Analysis of Variance (ANOVA). Specifically, Mann-Whitney U tests, Kruskal-Wallis tests and Dunn's Post Hoc Analysis were conducted.

## 5.6. INFERENCE STATISTICS: QUANTITATIVE DATA ANALYSIS

This section provides an outline of findings as a result of hypothesis testing for each hypothesis discussed in the literature review. In addition to self-report data, fixation data was used to measure attention. Specific eye-tracking metrics used to measure attention were Time To First Fixation (TTFF), Total Fixation Duration (TFD), First Fixation Duration (FFD) and Fixation Count (N). Fixation data was recorded in milliseconds (ms). Furthermore, eye-tracking data was collected for the entire image and advertisement as well as specific Areas of Interest (AOIs). Respondents were shown four images as well as seven advertisements. Each image and advertisement was mapped out with individual AOIs for specific features. AOIs used for each stimulus can be seen in figures 8.1-8.12 in Appendix D. Inferential statistics were used to assess and analyse the present study's hypotheses and draw inferences from the data collected in this research. Parametric and non-parametric independent sample t-tests and Analysis of Variance (ANOVA), post hoc comparisons as well as binomial tests were used in this study to test the hypotheses. More specifically, non-parametric tests such as Mann-Whitney U tests, Kruskal Wallis H tests and Dunn's post hoc analysis tests were conducted when data was not normally distributed.

### 5.6.1.H1a

Past literature provided strong evidence for top-down control of visual attention in consumer decision making. Furthermore, prior literature described fixation duration as a consistent predictor of choice (Zuschke, 2020). Contextual features such as price, product and brand play an important role in consumer decision making. The following hypothesis was used to assess the role of top-down processes in decision making by understanding the relationship between total fixation duration on Areas of Interest (features) related to choice and other salient features as well as explore the effect of salience on goal directed visual search. Statistical tests were run to assess total fixation duration and decision results for both task 2B and 3 alone and together.

**H1a: Total fixation duration on AOIs (price, product and brand) related to choice, correlates positively with consumer decision to purchase.**

**Table 2:** H1a Mann-Whitney U-test for TFD and Feature type (AOIs) for Task 2B and 3

	Test	Statistic	df	p
TFD	Mann-Whitney	$3.416 \times 10^{+6}$	5507	< .001

Results of the Mann Whitney U-test for both task 2B and 3 (Table 2) indicated that respondents who decided to purchase experienced significantly greater TFD on AOIs relevant to choice than respondents who decided not to purchase,  $U(5507) = 3.416 \times 10^{+6}$ ,  $p < .001$ . Thus, overall total fixation duration for AOIs was positively related to decision for long exposures in Task 2B and 3.

**Table 3:** H1a Mann-Whitney U-test for TFD and Feature type (AOIs) for Task 2B

	Test	Statistic	df	p
TFD	Mann-Whitney	618413.000	2391	< .001

A Mann-Whitney test was used was conducted to assess total fixation duration against decision making in task 2B. Results are presented in Table 3 above. Results indicated a significant positive effect on TFD for AOIs related to choice during long exposures to stimuli in Task 2B,  $U(2391) = 618413$ ,  $p <$

.001. Therefore, the present study concluded total fixation duration for AOIs was positively related to decision for long exposures in Task 2B.

Furthermore, for hypothesis 1A, the relationship between TFD and decision was assessed for long exposures for both Task 2B and Task 3. Task 3 required respondents to select a factor to inform their viewing and decision therefore statistics were calculated to assess the relationship between consumer decision making and TFD on preferred AOIs product, price, and brand. AOIs included pictures, price, product, and brand features. Participants had the option of using price, product, and brand to inform their decision making. Preferential factors did not include pictorial features as a factor used to inform decision making. Therefore, inferential statistics for task 3 were thus run to assess TFD and decision-making including pictures (Table 2.3) and including only price, product, and brand (Table 4).

**Table 4:** H1a Mann-Whitney U-test for TFD and Feature type (AOIs) for Task 3 including pictorial features.

	<b>Test</b>	<b>Statistic</b>	<b>df</b>	<b>p</b>
TFD	Mann-Whitney	$1.127 \times 10^{+6}$	3114	0.120

Results of the Mann Whitney U-test for H1A and Task 3 including pictorial features indicated that there was no significant relationship between TFD and decision,  $U(3114) = 1.127 \times 10^{+6}$ ,  $p = .120$  (Table 4).

**Table 5:** H1a Mann-Whitney U-test for TFD and Feature type (AOIs) for Task 3 excluding pictorial features.

	<b>Test</b>	<b>Statistic</b>	<b>df</b>	<b>p</b>
TFD	Mann-Whitney	991524.000	2938	0.034

However, the present study placed focus on features influencing consumer decision making such as product, price, and brand. Consequently, statistical analyses were conducted using results from task 3 relating to the three features and excluding pictorial elements unrelated to decision making. Results of a Mann-Whitney U-test presented in Table 5 indicated a significant effect on the relationship between total fixation duration and decision when looking at product, price, and brand,  $U(2938) = 991524$ ,  $p = .034$ .

**Table 6:** H1a Mann-Whitney U-test for TFD and Preference for feature type (AOIs)

	<b>Test</b>	<b>Statistic</b>	<b>df</b>	<b>p</b>
TFD	Mann-Whitney	599847.500	2938	< .001

Further testing presented in Table 6 presented above, showed a statistically significant association between total fixation duration and preferred features deemed as most important by respondents when viewing the advertisements. Results of a Mann-Whitney test assessing the relationship between preferred AOIs, and total fixation duration resulted in a statistically significant relationship between preferred factors for decision making (product, price, or brand) and total fixation duration (TFD),  $U(2938) = 599847.500$ ,  $p < .001$  (Table 2.5).

As a result of the significant relationship between TFD and preferred factors used in decision making, a Mann-Whitney U test was conducted to understand the relationship between total fixation duration and preferred AOI features when respondents decided to purchase. Data from task 3 was used for this

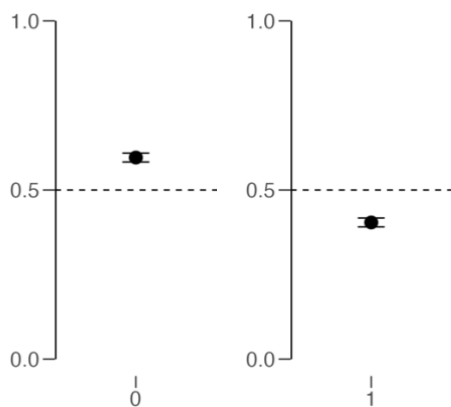
statistical test and results are presented in Table 2.6 below. Respondents experienced significantly greater TFD on preferred items when consumers decided to purchase than on items not preferred and not purchased,  $U(2938) = 312381.500$ ,  $p < .001$  (Table 2.6).

**Table 7:** H1a Mann-Whitney U-test for TFD and Preference for feature type (AOIs) and decision to purchase.

	Test	Statistic	df	p
TFD	Mann-Whitney	312381.500	2938	< .001

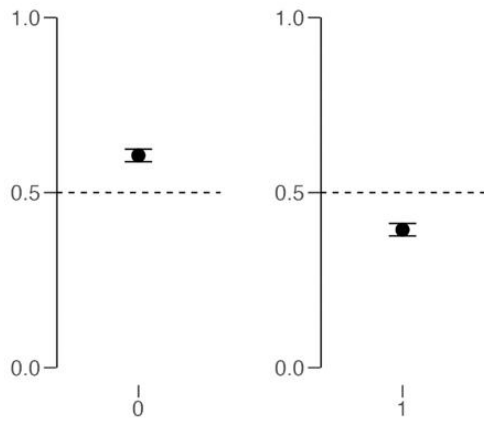
A binomial test was conducted for H1A (Appendix F: Table 15.1). The results of this test indicated a  $p < .001$  for both levels of decision and preference (Appendix F: Table 15.2). The proportion of participants across task 2 and 3 who reported that they would not choose to purchase the contract and would choose to purchase the contract was 59.60% and 40.40 % respectively when using a test value equal to 0.5 (Appendix F: Table 15. 1). The binomial test revealed that the proportion of respondents who did not choose to purchase was significantly higher (59.60%,  $p < .001$ ) than was expected and those who chose to purchase (40.4%,  $p < .001$ ) was significantly lower than the number expected. Descriptive plots of the binomial distribution presented in Figure 4 below provide a visualization of the distribution between variables of decision in task 2B and 3.

**Figure 4:** Descriptive Plot for Binomial Distribution of Decision Results in Task 2B and 3

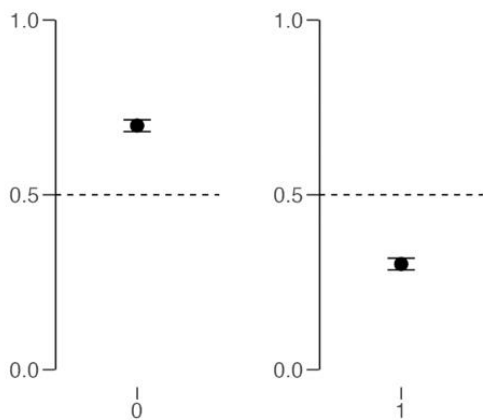


Furthermore, results of the binomial test for task 3 (Appendix F: Table 15.2) indicated a proportion of 60.6% and 39.4% for those who chose not to purchase and chose to purchase respectively as well as a 69.8% and 30.2% proportion for factors not preferred and factors preferred respectively. Binomial tests for both decision and preference resulted in  $p < .001$  (Appendix F: Table 15.2). Descriptive plots of the binomial distribution presented in Figures 5 and 6 below provide a visualization of the distribution between variables of decision and variables of preference. It is evident that the proportion of respondents who did not choose to purchase is higher than expected and the proportion of respondents who chose to purchase is lower than expected. Similarly, the proportion of respondents who preferred the factor is significantly lower than expected and the proportion of respondents for factors not preferred was higher than expected.

**Figure 5: Descriptive Plot for Binomial Distribution of Decision Results in Task 3**



**Figure 6: Descriptive Plot for Binomial Distribution of Preference Results in Task 3**



**Table 8:** H1a Kruskal-Wallis test for TFD, Feature type (AOIs) and preference when decided to purchase for Task 3

Factor	Statistic	df	p	p
Preferred and said yes	105.207	1	< .001	< .001
Type	1252.437	2	< .001	< .001

Both a Kruskal-Wallis test and Dunn’s non-parametric Post Hoc tests were conducted on results generated from task 3 to assess TFD against AOIs price, product and brand chosen to inform decisions. Results of the Kruskal-Wallis H-test for task 3 presented above in Table 8 indicated a significant relationship between TFD and chosen preferred factors as well as TFD and type. This was indicated by an  $H(1)=105.207, p < .001$  for decision and  $H(2)=1252.437, p < .001$  for type (Table 15.10).

Marginal means and descriptive plots were assessed to compare TFD for preference and decision by type. Marginal means are presented in Table 15.3 in Appendix F. Marginal means were lower for brand, price and product for respondents who did not choose to purchase despite preference than respondents who preferred an AOI or feature and decided to purchase.

Furthermore, Dunn’s post hoc comparisons were conducted for responses indicative of preference and decision as well as type. Dunn’s post hoc test for preferred factor and decision presented in Appendix

F, Table 15.4, resulted in  $z=-10.257$ ,  $p < .001$  between TFD for respondents who did not choose to purchase and TFD for respondents on preferred AOIs when decided to purchase. Therefore, we could conclude that there were statistically significant differences between TFD for respondents who preferred a feature and decided to purchase and TFD for respondents who decided not to purchase regardless of preference. Dunn's post hoc test for type (Appendix F: Table 15.5) indicated that the TFD for brand was significantly different to price and product. Results indicated  $z = -24.792$ ,  $p < .001$  and for brand vs price and,  $z = -33.676$ ,  $p < .001$  for brand vs product, whereas results showed a  $z = -9.627$ ,  $p < .001$  between price and product. Large z-scores indicated that the expected mean difference between the two groups differed by multiple standard deviations indicating significant differences between the groups. Furthermore, Dunn's p-value and adjusted p-values (Bonferroni and Holms) were all  $< .001$  for both preference and decision and type. Thus, results showed statistically significant difference between brand and price, brand, and product, as well as price and product. Furthermore, product and price generated greater total fixation durations than brand. Finally, results indicated that product produced greater total fixation durations than price.

### 5.6.2.H1b

Hypothesis 1b proposed that differences in fixation duration as well as fixation counts, and first fixation durations will indicate the amount of attention given to contextual features in comparison to bottom-up factors (contrast, colour, brightness) within a visual experience. Contextual features were identified through Likert scale questions indicating feature importance. Hypothesis 1B was used to explore the effect of salience on goal-directed visual search and compare the difference in eye-tracking data between contextual features and other salient features presented in a stimulus.

***H1b: Contextual features subjectively rated as more important in informing decisions (product, price, and brand) will produce larger first fixation durations, total fixation durations and fixation counts compared to features rated as less important features.***

**Table 9:** H1b Kruskal-Wallis Test for Factor importance and Type (Total Fixation Duration)

Factor	Statistic	df	p
Factor importance	37.075	4	< .001
Type	896.113	2	< .001

Results of the Kruskal-Wallis test presented above in Table 9 showed a significant difference between factor importance and total fixation duration ( $H=37.075$ ,  $p < .001$ ) as well as TFD and type ( $H=896.114$ ,  $p < .001$ ). Therefore, we rejected the null hypothesis and conclude that there was a significant difference between total fixation duration and contextual features indicated by factor importance as well as feature type.

In addition to this, Dunn's post hoc comparisons indicate a significant difference for between importance level 1 and 2 ( $z=-2.698$ ,  $p = .007$ ), 1 and 3 ( $z=-2.766$ ,  $p = .006$ ), 1 and 4 ( $z=-4.323$ ,  $p < .001$ ), 1 and 5 ( $z=-5.617$ ,  $p < .001$ ), 2 and 5 ( $z=-3.153$ ,  $p = 0.002$ ) as well as 3 and 5 ( $z=-3.515$ ,  $p < .001$ ) (Appendix F: Table 16.1). Descriptive statistics for levels of importance informing decision making are presented in Appendix E in Table 7. Results of Dunn's post hoc comparison showed that there was a difference between features ranked 1 and features ranked 2-5. However, a large z-score indicated that there was greater difference between features ranked 1 and features ranked 5 and 4, followed by features ranked 2 and 5 and 3 and 5. Therefore, there was a greater difference between total fixation duration

for factors perceived as more important in informing decision making than factors that were less important in informing decision making.

Similarly, Dunn’s post hoc comparisons by type showed a significant difference in TFD between brand and price ( $z=-25.636, p < .001$ ), brand and product ( $z=-25.914, p < .001$ ) as well as price and product ( $z=-2.056, p=0.04$ ) (Appendix F: Table 16.2). Dunn’s post hoc test provides a p-value as well as additional p-values for Bonferroni and Holm’s Bonferroni correction (Goss-Sampson, 2022). Adjusted p-values to account for family-wise error resulted in statistically significant p-values for Dunn’s post hoc comparisons for factor importance and type (Appendix F: Table 16.2). Results showed greater difference between brand and product in comparison to price and product based on greater z-scores calculated.

**Table 10:** H1b Kruskal-Wallis Test for Factor importance and Type (Fixation Count)

<b>Factor</b>	<b>Statistic</b>	<b>df</b>	<b>p</b>
Factor importance	5.383	4	0.250
Type	7.040	2	0.030

Results of the Kruskal-Wallis test presented above in Table 10 indicated that there was no significant difference between factor importance and fixation count ( $H=5.383, p=0.250$ ). However, the results indicated a statically significant difference between fixation count and type ( $H=7.040, p=0.030$ ).

Finally, Dunn’s post hoc test was run to test for any significant relationship between variables of factor importance as well as type, the results of which are presented in Appendix F in Table 16.3 and 16.4 respectively. Dunn’s post hoc test indicated a significant difference between fixation count between respondents who chose a factor importance of 1 and 2 ( $z=-2.150, p=0.032$ ) (Appendix F: Table 16.3). Furthermore, Dunn’s post hoc test indicated significant differences between fixation count for price and product ( $z=-2.510, p=0.012, p_{\text{Bonferroni}}=0.036, p_{\text{Holm}}=0.036$ ) (Appendix F: Table 16.4). Therefore, the overall fixation count did not indicate a difference between levels of factor importance or contextual importance as well as feature types.

**Table 11:** H1b Kruskal-Wallis Test for Factor importance and Type (First Fixation Duration)

<b>Factor</b>	<b>Statistic</b>	<b>df</b>	<b>p</b>
Factor importance	4.302	4	0.367
Type	117.907	2	< .001

Results of the Kruskal-Wallis test presented in Table 11 showed that there was no significant difference between factor importance and first fixation duration ( $H=4.302, p=0.367$ ) and a significant difference between FFD and type ( $H=117.907, p < .001$ ). Dunn’s post hoc test indicated a significant difference in first fixation duration for respondents who chose a scale variable of 1 and a scale variable of 5 ( $z=2.030, p=0.042$ ) (Appendix F: Table 16.5). However, adjusted p-values accounting for family-wise error did not indicate a significant difference between FFD for rankings 1 and 5 ( $p_{\text{Bonferroni}}=0.423, p_{\text{Holm}}=0.423$ ) (Appendix F: Table 16.5). All other comparisons were insignificant. Furthermore, Dunn’s post hoc comparisons indicated significant differences in FFD between brand and price ( $z=-8.529, p < .001$ ) and price and product ( $z=9.537, p < .001$ ) (Appendix F: Table 16.6). However, there was no significant difference between brand and product ( $z=-1.202, p=0.229, p_{\text{Bonferoni}}=0.688, p_{\text{Holm}}=0.229$ ) (Appendix F: Table 16.6). Therefore, FFD for brand was significantly lower than for price and FFD for price was significantly greater than for product.

### 5.6.3.H1c

Hypothesis 1c was formulated to determine whether bottom-up eye-tracking alone can explain consumer decision-making, to understand the effect of salience on goal-directed visual search as well as identify any differences between goal-directed and free-search fixation maps. As DeepGaze IIE heatmaps provide a purely bottom-up representation of visual attention, theoretically, on a visual search task, eye-tracking will produce a denser heatmap with greater fixation densities. H1c was not tested using inferential statistics and will be discussed in the following section: Qualitative Data Analysis: DeepGaze IIE and Heatmaps.

***H1c: On the visual search task, eye-tracking will present a denser heat map with greater fixation densities on the item of importance compared with a purely bottom-up system (DeepGAZE II data)***

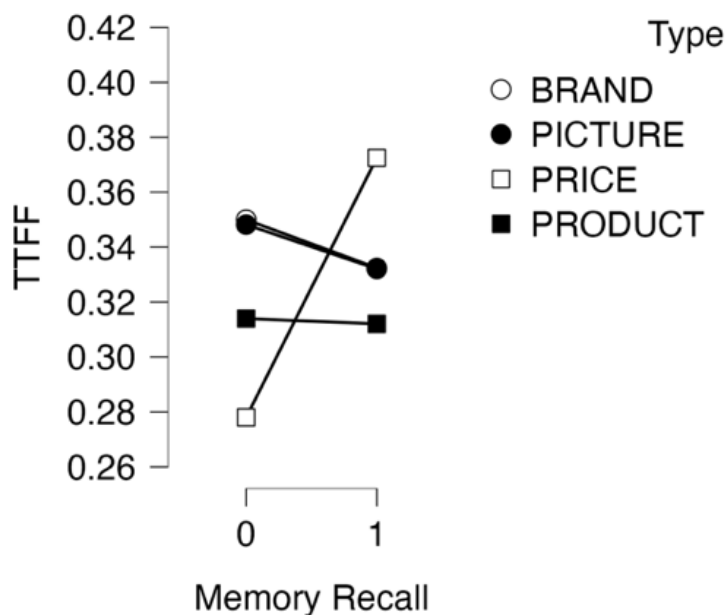
### 5.6.4.H2a

Hypothesis 2a and 2b were used to assess the contribution of bottom-up and top-down visual processes in consumer decision making through the statistical analysis of TTFF and TFD as well as heatmaps. Results pertaining to heatmaps are discussed in the following section.

***H2a: During a free search task, where participants are provided visual experiences with no specific goals, more salient objects (as determined by TTFF) will have a negative relationship with the accuracy of memory recall of those same objects during a free recall task.***

The hypothesis was tested in experiment 2A. This hypothesis was formed based on the notion that objects seen earlier will be recalled more readily by memory. It was proposed that during a free search, where participants are given no instructions, the amount of attention given to salient items (as determined by TTFF) would affect the accuracy of memory recall on the same items. A descriptive plot is presented in Figure 7 below providing a visual representation of the average time to first fixation across features presented that were recalled by respondents.

**Figure 7:** Descriptive plot of TTFF for features and memory recall

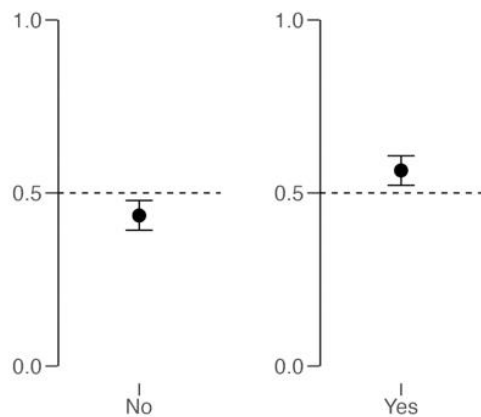


**Table 12:** H2a Mann-Whitney U-test for Memory Recall (Time to First Fixation)

	Test	Statistic	df	p	Effect Size	SE Effect Size
TTF	Mann-Whitney	35307.500	536	0.558	-0.007	0.050

The results showed that there was no statistically significant relationship between time to first fixation and accuracy of memory recall of those same items,  $U(536)=35307.5$ ,  $p\text{-value}=0.558$  (Table 12).

The results of the binomial test indicated a  $p = 0.003$  for both levels of memory recall and feature type  $p < .001$  (brand, price, and product) as well as a  $p = 0.635$  for pictures and feature type. An outline of the binomial test can be seen in table 17.1 of Appendix F. The proportion of participants who reported that they could not recall and could recall features was 43.5% for not recalled and 56.5% for recalled with a test value of 0.5 (Appendix F: Table 17.1). The binomial test revealed that the proportion of respondents who did not recall features was significantly less (46.5%,  $p=0.003$ ) than was expected and those who could recall features (42.9%,  $p=0.003$ ) was significantly more than the number expected. Descriptive plots are presented in Figure 6 below to provide a visual representation of the binomial distribution of memory recall.

**Figure 8:** Descriptive Plots for the Binomial Test for Recall (Time to First Fixation)

Moreover, an ANOVA was conducted to further understand the relationship between TTF with memory recall and type. Homogeneity assumptions of ANOVA were met. Results of the ANOVA presented in Table 13 below indicated that there was no significant difference between TTF and memory recall ( $F=0.454$ ,  $p=0.501$ ). However, the results showed a significant difference between TTF and type ( $F=2.806$ ,  $p=0.039$ ).

**Table 13:** H2a ANOVA Results for Memory Recall and Type (Time to First Fixation)

Cases	Sum of Squares	df	Mean Square	F	p	$\eta^2$
Memory Recall	0.005	1	0.005	0.454	0.501	$8.372 \times 10^{-4}$
Type	0.089	3	0.030	2.806	0.039	0.016
Memory Recall * Type	0.039	3	0.013	1.230	0.298	0.007
Residuals	5.573	530	0.011			

The results of post hoc comparisons are presented in Appendix F, Table 17.2 for memory recall and Table 17.3 for type. The results of post hoc comparisons indicated no significant difference between

TTF and memory recall with a  $p=0.501$  and mean difference of  $-0.015$  (Appendix F: Table 17.2). Post hoc comparisons indicated a significant difference between TTF for picture and product with  $p$ -tukey= $0.022$  and mean difference of  $0.027$  (Appendix F: Table 17.3). However, there were no other significant differences for TTF and feature type (Appendix F: Table 17.3).

### 5.6.5.H2b

**H2b: More salient objects as determined by fixation durations and heatmaps will have a positive relationship with the accuracy of recall of those same items, as determined by the number of correct items recalled from memory after the viewing experience.**

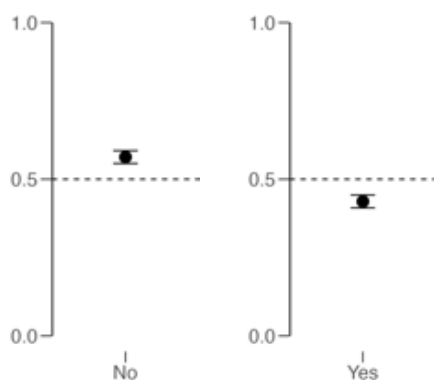
This hypothesis was tested in experiment 2A. It was proposed that during a free search task, where participants are given no instructions, the amount of attention given to salient items as determined by fixation durations and heatmaps (fixation density) will affect the accuracy of memory recall on the same items. A Mann-Whitney Independent sample t-test was used to test for model significance. Results are presented in Table 14 below. The null hypothesis was rejected as  $U(2287)=612923$ ,  $p < 0.01$ , and it was concluded that there was a significant relationship between total fixation duration and accuracy of memory recall of those same items.

**Table 14:** H2b Mann-Whitney U-test for Total Fixation Duration and Memory Recall

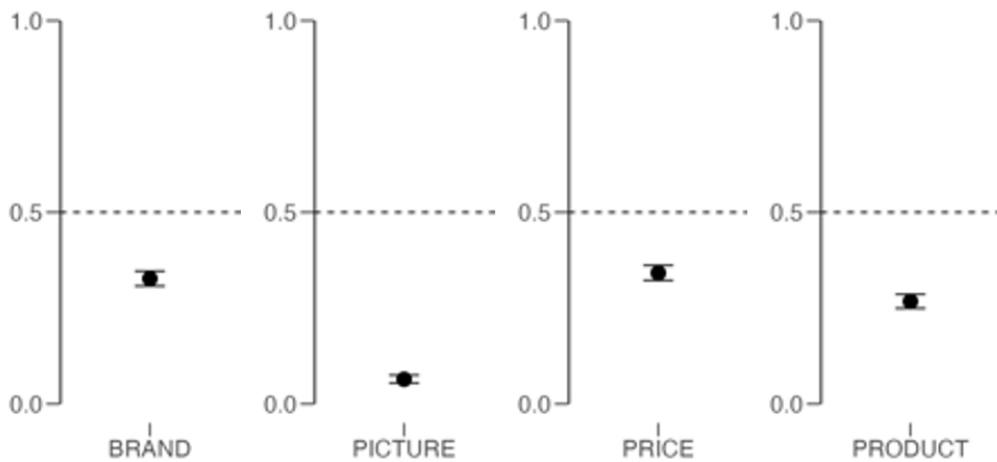
	Test	Statistic	df	p	Effect Size	SE Effect Size
TFD	Mann-Whitney	612933.000		<.001	-0.045	0.024

A binomial test was conducted in addition to the independent sample t-test and descriptive statistics. The binomial test is presented in Appendix F, Table 18.1 with descriptive plots showing the binomial distribution for memory recall in Figure 9 and Figure 10. The results of this test indicated  $p$ -values  $< .001$  for both levels of memory recall and feature type. The proportion of participants who reported that they could not recall and could recall features was 57.1% for not recalled and 42.9% for recalled with a test value of 0.5 (Appendix F: Table 18.1). The binomial test revealed that the proportion of respondents who did not recall features was significantly more (57.1%,  $p < .001$ ) than was expected and those who could recall features (42.9%,  $p < .001$ ) was significantly less than the amount expected.

**Figure 9:** Descriptive Plots for the Binomial Test for Memory Recall (Total Fixation Duration)



**Figure 10:** Descriptive Plots for the Binomial Test for Feature Type (Total Fixation Duration)



Results of the Kruskal-Wallis test presented below in Table 15 indicated a significant relationship between TFD and type,  $U(3)=197.063$ ,  $p < .001$ , as well as TFD and memory recall  $U(1)=14.941$ ,  $p < .001$ .

**Table 15:** H2b Kruskal-Wallis Test for Memory Recall (Total Fixation Duration)

Factor	Statistic	df	p
Type	197.063	3	< .001
Memory Recall	14.941	1	< .001

The results of Dunn’s post hoc test for TFD and type provided in Appendix F Table 18.2 indicated a statistically significant difference at 5% significance level between brand and picture ( $z=-8.774$ ,  $p < .001$ ), brand and price ( $z=2.228$ ,  $p=0.026$ ), brand and product ( $z=-8.754$ ,  $p < .001$ ), picture and price ( $z=10.073$ ,  $p < .001$ ), picture and product ( $z=3.424$ ,  $p < .001$ ) and price and product ( $z=-10.952$ ,  $p < .001$ ). Similarly, the results of Dunn’s post hoc test for TFD and memory recall provided in Appendix F Table 18.3 indicated a statistically significant difference between features recalled and not recalled ( $z=-3.865$ ,  $p < .001$ ). Adjusted p-values remained statistically significant. Therefore, the mean total fixation duration for AOIs recalled by respondents was higher than the mean TFD for AOIs not recalled by respondents, mean TFD was lower for brand than for pictures and product but higher than for price, mean TFD was higher for picture than for product and mean TFD for price was lower than for product.

### 5.6.6.H3

**H3: Primed objects, which are specific features participants will be looking for, will produce greater fixation duration, fixation count and first fixation duration, compared to other salient features/objects seen during a visual search task.**

Hypothesis 3 utilized results from experiment 3 to identify any differences between eye-tracking metrics recorded on primed areas of interest against other features in the advertisement. Participants identified which factor out of product, price and brand was preferred to aid decision-making and were instructed to keep this factor in mind when viewing the advertisement. Hypothesis 3 was used to compare the difference in eye-tracking data between bottom-up and contextual (top-down) features.

**Table 16:** H3 Mann-Whitney U-test for Fixation Count split by Preference

	<b>Test</b>	<b>Statistic</b>	<b>df</b>	<b>p</b>
Fixation Count	Mann-Whitney	807965.000	3449	< .001

The results indicated that the Mann-Whitney U-statistic was significant ( $U(3449)=807965$ ,  $p < .001$ ). It was therefore concluded that there was a significant difference between fixation count for primed features and non-primed features (Table 16). More specifically, fixation count is greater on primed features.

**Table 17:** H3 Mann-Whitney U-test for Total Fixation Duration split by Preference

	<b>Test</b>	<b>Statistic</b>	<b>df</b>	<b>p</b>
TFD	Mann-Whitney	798478.500	3449	< .001

Furthermore, results of the Mann-Whitney statistical test present above in Table 17 were significant,  $U(3449) = 798478.500$ ,  $p < .001$ . Therefore, TFD for preferred or primed features was greater than non-primed features seen during a visual search task.

**Table 18:** H3 Mann-Whitney U-test for First Fixation Duration split by Preference

	<b>Test</b>	<b>Statistic</b>	<b>df</b>	<b>p</b>
FFD	Mann-Whitney	$1.152 \times 10^{+6}$	3449	0.130

Results of the Mann-Whitney test shown above in Table 18 indicated there was no significant difference between first fixation duration for preferred primed factors and salient features seen during a free search task,  $U(3449)=1.152 \times 10^{+6}$ ,  $p=0.130$ .

**Table 19:** H3 Kruskal-Wallis Test for Preference (Total Fixation Duration)

<b>Factor</b>	<b>Statistic</b>	<b>df</b>	<b>p</b>
Preferences	3.454	2	0.178
Type	405.304	3	< .001

The Kruskal-Wallis test (Table 19) was conducted to assess hypothesis 3 and identify relationships between eye-tracking metrics and preferred or primed factors used in decision making. Results showed that there was no significant difference between factor importance and total fixation duration ( $H=3.454$ ,  $p=0.178$ ) as well as a significant difference between TFD for feature type ( $H=405.304$ ,  $p < .001$ ). Therefore, we concluded that there was no significant difference between total fixation duration and preferred or primed features. Furthermore, it was concluded that there was a significant relationship between total fixation duration and feature type.

Dunn's Post Hoc comparisons were conducted to identify any differences between TFD and feature type (Appendix F: Table 19.1). Results indicated that there was a statistically significant difference between brand with picture, price, and product as well as between picture with price and product and price with product. All p-values resulting from Dunn's Post Hoc comparisons for feature type were less than .001. In particular, results of Dunn's post hoc analysis were showed z-values of  $z=-10.365$  for brand and picture,  $z=-14.640$  for brand and price,  $z=-18.990$  for brand and product,  $z=-6.144$  for picture

and price,  $z=-12.013$  for picture and product and  $z=-5.426$  for price and product. Furthermore, Dunn's post hoc comparisons for feature type by preference (Appendix F: Table 19.2) resulted in statistically no statistically significant differences between TFD for preferred features between brand and price ( $z=0.710$ ,  $p=0.478$ ), brand and product ( $z=-0.891$ ,  $p=0.373$ ) and price and product ( $z=-1.816$ ,  $p=0.069$ )

**Table 20:** H3 Kruskal-Wallis Test for Preference (Fixation Count)

Factor	Statistic	df	p
Preferences	6.842	2	0.033
Type	504.675	3	< .001

Furthermore, a Kruskal-Wallis test was used to identify relationships between fixation count, preferences and type. The Kruskal-Wallis test resulted in statistically significant differences between fixation count ( $H=504.675$ ,  $p< .001$ ) and type as well as preferences ( $H=6.842$ ,  $p=0.033$ ) (Table 20). Therefore, we rejected the null hypothesis for both type and preferences and concluded that there was a statistically significant difference between fixation count for feature type and preferred factors used in decision making. Dunn's post hoc tests indicated statistically significant differences between fixation count between brand and all other AOIs as well as between pictures, price and product and between price and product (Appendix F: Table 19.3). Results showed significant comparisons between brand and picture ( $z=-11.151$ ,  $p< .001$ ), brand and price ( $z=-14.511$ ,  $p< .001$ ), and brand and product ( $z=-21.343$ ,  $p< .001$ ). Similarly, a significant comparison was indicated between picture and price ( $z=-4.921$ ,  $p< .001$ ) and picture and product ( $z=-14.187$ ,  $p< .001$ ). Price and product ( $z=-8.722$ ,  $p< .001$ ) also had statistically significant differences in fixation count. Finally, Dunn's post hoc comparisons for preference resulted in statistically significant differences in fixation count for brand and product ( $z=-2.554$ ,  $p=0.011$ ,  $p_{Bonferroni}=0.032$ ,  $p_{Holm}=0.032$ ) (Appendix F: Table 19.4).

**Table 21:** H3 Kruskal-Wallis Test for Preference (First Fixation Duration)

Factor	Statistic	df	p
Preferences	1.744	2	0.418
Type	33.447	3	< .001

Lastly, a Kruskal-Wallis test was conducted to analyse first fixation duration on preferred AOIs and feature types. Results of the Kruskal-Wallis test are shown in Table 21 above. Significant results were shown for both FFD on type indicated by  $H= 33.447$ ,  $p< .001$  for type. However, results showed no significant difference between FFD on preferred AOIs,  $H= 1.744$ ,  $p=0.418$ . Dunn's post hoc comparisons (Appendix F: Table 19.5) showed significant differences between brand and picture ( $z=-3.256$ ,  $p= .001$ ), brand and price ( $z=-3.807$ ,  $p< .001$ ) as well as picture and product ( $z=4.049$ ,  $p< .001$ ) and price and product ( $z=4.723$ ,  $p< .001$ ) (Appendix F: Table 19.5). All adjusted p-values remained statistically significant. Furthermore, results of Dunn's post hoc comparisons showed no statistically significant comparison for FFD between preference factors as all p-values were greater than 0.05 (Appendix F: Table 19.6).

### **5.6.7. Users and Exposure Time**

In addition to the hypotheses, inferential statistics were run to assess relationships between telecommunications brand users and mobile operating system users as well as the difference between percentage of AOIs fixated on for short and long exposures. Independent sample tests were used to test

these relationships. An independent sample t-test was conducted to assess the relationship between decision making and whether respondents were users of the product in the advertisement. Results of the Independent Sample T-test are presented in Appendix F in Table 20.1. A Mann-Whitney U-test showed a positive relationship between decision making and whether respondents were users or non-users of the mobile operating system for the product  $U(1959)=328164$ ,  $p < .001$  (Appendix F: Table 20.1). This indicated that respondents were more likely to decide to purchase when they were users of the mobile operating system for the product presented in the stimulus.

Similar to the finding on mobile operating systems, i.e., being either apple or android users, being a brand user was also seen to have an impact on decision. Results of a Mann-Whitney U-test indicated a statistically significant relationship amongst being a brand user and decision  $U(1959)=451557.500$  and  $p=0.036$  (Appendix F: Table 20.2).

Finally, results of the independent sample t-test were used to assess the relationship between percentage of respondents who fixated on AOIs for short exposures (A) and long exposures (B) are presented in Appendix F, in Table 20.3. Results of the non-parametric Mann-Whitney U-test resulted in  $U(367)=2206.500$ ,  $p\text{-value} < .001$  (Appendix F: Table 20.3). The mean percentage fixated on for AOIs was 7.6% for short exposures and 58.2% for long exposures. Therefore, it was clear that the percentage of respondents who fixated on areas of interest in the stimuli was dependent on exposure time.

## **5.7. QUALITATIVE DATA ANALYSIS**

Qualitative data was generated through self-report data, heatmaps and DeepGaze IIE saliency model output. The qualitative data analysis assisted in comparing visual salience indicated by eye-tracking heatmaps and DeepGaze IIE output as well as giving a deeper understanding on what factors were deemed most important and preferred by the respondents. The heatmaps and DeepGaze IIE output for all stimuli are presented in Appendix G: Hypothesis 1c. These results were compared and analysed to investigate the differences and similarities between eye-tracking data and the saliency model. Heatmaps provide a visualisation of where the most attention is garnered through a colour scale of red, yellow and green. Red indicates higher levels of attention, followed by yellow and then green. Areas without colour were not fixated on. Furthermore, saliency is indicated in DeepGaze IIE heatmaps by the darkness and concentration of colour in specific areas. Yellow areas indicated by DeepGaze IIE results indicate high areas of visual salience. Green areas indicate less salience and blue areas indicate no salience.

### **5.7.1. Self-Report Data**

Self-report data was collected through a questionnaire prior to the eye-tracking experiment as well as during the eye-tracking experiment. Self-report data during the eye-tracking experiment was used to identify items recalled by memory (Task 2A), how important contextually driven features were in informing decisions (Task 2B), preferred factors used in decision making (Task 2B) as well as respondent choices (Task 2B and 3).

The majority of the participants in this study were between the ages of 18 and 35 and had a tertiary level of education. Questionnaire and eye-tracking data were collected and findings indicating both descriptive and inferential statistics for qualitative and quantitative data are discussed below. Respondent familiarity across all four telecommunications brands and mobile operating systems were

equally distributed. Furthermore, the majority of the respondents were Vodacom users, followed by MTN, Telkom and Cell-C. In addition to this the majority of the target population were apple users.

The results of Task 2A indicated that the majority of respondents (97%) were able to recall most elements despite not fixating on or attending to all elements or features presented in the advertisements. Only 7% of respondents were unable to recall any features presented in the advertisements. Respondents were required to indicate importance of product, price and brand in informing their decision in Task 2B in order to identify elements that were contextually important for consumer decision-making. Product was identified as contextually important for the majority of respondents. Price was considered a neutral factor informing decisions. However, more consumers indicated that both price and brand were more important than not important when making a decision.

Task 2A focused on bottom-up visual attention as participants were not given any instructions and participants were exposed to stimuli for a short period of time. Task 2B was used to assess visual attention through a free search where respondents were not provided with any task instructions or goals. Task 3 focused on the top-down visual attention process and visual search. Despite the difference in respect of issuing or not issuing task instructions for tasks 2B and 3, visual attention had a similar distribution as seen by eye-tracking heatmaps produced for the long exposure.

Participants were asked to identify a preferential factor which they would consider when viewing the advertisement and making a decision in task 3. The majority of the respondents indicated that product was the preferred factor to consider when looking to buy a cell-phone contract. The remaining respondents' preferred factor was evenly distributed between brand and price for respondents who identified product as their preferred decision factor, as 10 respondents were users of more than one telecommunications brand, whereas, participants who preferred price and brand were all users of one telecommunications brand. Therefore, the product-conscious consumer may not always be concerned with price or brand. Furthermore, distribution of preference for apple users indicated that product was important for the majority followed by price and then brand. Similarly for Android users, product was the most important factor informing viewing and choice, followed by brand and price. Overall, product was identified as the most important factor when looking to purchase a cell-phone contract. Findings across all four brands indicated that more respondents who were non-users chose not to purchase a contract. However, users of Telkom and Cell-C responses resulted in a more even choice distribution. Participants were only provided with a short amount of time to make a decision. Purchasing a cell-phone is considered a complex buying decision thus consumers usually take time to search for product information and evaluate alternatives.

### **5.7.2. Heatmaps and DeepGaze IIE results**

A denser heatmap will provide deeper insight into what is generating visual attention for consumers. Overall, eye-tracking heatmaps produce a denser heatmap than DeepGaze IIE by highlighting specific features that are visually attended to, allowing marketers to identify visually salient elements based on the bottom-up visual attention process. One may argue that DeepGaze IIE provides a denser heatmap as it provides a distribution of visual saliency across an entire image. However, bottom-up attention can only be deployed to one item at a time thus identifying the most salient feature on the advertisement.

During experiments 1, 2 and 3 participants were asked to view various images and advertisements. Heatmaps were generated through Tobii Pro Labs. Task 1 included images such as a dog, snake, lion,

owl (shown for 500ms) and ‘Where is Wally? (Shown for 6 seconds with an instruction)’ image. A side-by-side comparison of eye-tracking heatmaps and DeepGaze IIE output for task 1 can be found in Appendix G in figures 13.1.1-13.5.1 & 13.1.2-13.5.2 respectively. The images shown to participants were camouflaged animals, a Gestalt image of a dog and a Where is Wally? image. These images were chosen as it was hypothesized that respondents might not pay visual attention based on bottom-up factors to elements important in providing image context even if the AOIs were deemed the most salient by DeepGaze IIE software. Comparisons of the eye-tracking heatmaps and DeepGaze IIE results are discussed below for each stimulus.

#### 5.7.2.1. Gestalt Dog image (Figure 13.1.1 and 13.1.2)

The eye-tracking heatmap presented in Figure 13.1.1 showed that respondent fixations were concentrated on the centre of the image, more specifically, the front leg of the dog. The DeepGaze IIE output presented in Appendix F in Figures 13.1.2 indicated the entire dog as the most salient feature of the image followed by the patterns on the ground. The centre of the image, the centre of the bottom section of the image, as well as the top left corners were identified as the other salient areas by the concentration of yellow colour in those areas. Despite the use of a fixation cross to account for fixation bias, participants’ attention remained in the centre of the image during the short exposure.

#### 5.7.2.2. Owl image (Figure 13.2.1 and 13.2.2)

The eye-tracking heatmap indicated a distribution of fixations across the centre of the owl’s wing and face (Appendix G: Figure 13.2.1). The red colour on the heatmap indicated that attention was more concentrated on the owl’s wing. Other areas such as the owl’s face were also fixated on but to a lesser extent. This can be seen through the yellow and green colours on the image. The DeepGaze IIE heatmap (Appendix G: Figure 13.2.2) outlined the owl as the most salient element placing emphasis on the owl’s face.

#### 5.7.2.3. Lion image (Figure 13.3.1 and 13.3.2)

DeepGaze IIE identified the lion’s face as the most salient element in the image. In particular the right eye, nose and mouth. This can be seen in Appendix G in Figure 13.3.2. In comparison the eye-tracking heatmap presented in Figure 13.3.1 of the Appendix indicated higher fixation densities on the centre of the image. However, the green of the heatmap indicated that some visual attention was generated by the lion, in particular, the left eye of the lion was fixated on.

#### 5.7.2.4. Snake image (Figure 13.4.1 and 13.4.2)

The DeepGaze heatmap for the snake is provided in Appendix G in Figure 13.4.2. Salient areas are marked by a bright yellow colour just left of the centre at the top of the image which decreases in concentration in a diagonal line towards the right-hand corner. The area highlighted by DeepGaze focuses on a lighter leaf. The eye-tracking heatmap for the snake image (Appendix G: Figure 13.4.1.) depicted visual attention on the centre of the image through concentration of red, yellow and green colours on the centre of the image.

#### 5.7.2.5. Where is Wally? image (Figure 13.5.1 and 13.5.2)

Participants were instructed to find Wally, a cartoon figure wearing a red and white striped shirt and a hat. The eye-tracking heatmap for this image can be found in Appendix G in Figure 13.5.1. When viewing the Where is Wally image participants focused their attention just above the centre of the image. This was indicated by the red colour. Furthermore, some attention was distributed across the lower and middle section of the image as indicated by the green colour. The Where is Wally image is complex with numerous colours, figures and objects making it hard to identify salient objects and find Wally. The DeepGaze IIE output is presented in Appendix G in Figure 13.5.2. The DeepGaze IIE saliency map indicated high levels of saliency in the centre of the top of the image and just below the right corner. Overall, the saliency map indicated the most visual salience at the top of the image in the centre as well as on the right-hand side of the image starting from the top and getting gradually less salient lower down. Areas on the top half of the image were more salient than the bottom half; however, some areas near the bottom of the image were indicated as salient.

When compared, the eye-tracking and DeepGaze IIE heatmaps showed different fixations and predicted fixations for salient areas of the stimulus respectively. The eye-tracking heatmap with a longer exposure (Figure 13.5.1) is more similar to the DeepGaze IIE output (Figure 13.5.2). DeepGaze IIE is thus more likely to be accurate in predicting fixations on salient elements for longer exposures. Furthermore, DeepGaze IIE depicts fixation predictions based on visual salience across an entire stimulus based on physical properties. Thus, based on the results depicted by the eye-tracking heatmaps it was evident that during an extremely short exposure respondents did not distribute attention across an image, instead visual attention was focused on one area. Overall, heatmaps for the short exposures showed visual attention was depicted in the centre of the stimuli with some attention placed on important elements when placed near the centre of the image.

Fixations on all stimuli in task 1 were distributed mostly around the centre of the image despite the difference between the exposure times. However, an increased exposure time resulted in more fixations across the whole image as indicated by the green colour distribution throughout the “Where is Wally?” stimulus. The central visual attention during the short exposure may be as a result of central fixation bias despite the use of a fixation cross as an avoidant of this bias as well as short exposure time. Due to the short exposure time participants were unable to scan the image as a whole and did not look at the element that was most contextually important. Furthermore, some respondents indicated confusion and said that they did not know what they had seen as the stimulus presentation was fast. According to prior literature, the bottom-up visual attention process is deployed at 100ms. To the best of knowledge there is no other specified time for deployment and no threshold for this attentional process. The exposure time used to measure bottom-up attention was set at 500ms due to the complexity of visuals used. This allowed ample time for deployment of the bottom-up visual attention process and did not exceed the threshold for deployment of top-down visual attention processes. Therefore, bottom-up visual attention may not result in attention to visuals or information that may be the most important in conveying a contextual message despite its salience and thus may not impact consumer decision making. There is little to no research regarding the timing of the attentional processes. Thus, future research could address the timing of both visual attention processes when looking at complex visual stimuli that require context to understand.

In addition to the images shown in experiment 1, participants were shown eight advertisements with four telecommunications brands variations of each. Three advertisements were shown first for 500ms and then a second time for 6 seconds in Experiments 2a and 2b. The remaining four advertisements

were only shown for 6 seconds in Experiment 3. The first three advertisements had two heatmaps which were compared and analysed against each other as well as the saliency heatmap generated through DeepGaze IIE. Furthermore, eye-tracking data was collected and heatmaps were provided for the last four advertisements. The final four advertisements were also compared to the DeepGaze output. The heatmaps and DeepGaze IIE output can be found in Appendix G: Hypothesis 1c from figures 14.1-14.4, 15.1- 15.4 and 16.1-16.4 for Experiment 2a and 2b and Figures 17.1-17.3, 18.2-18.3, 19.1-19.3 and 20.1-20.3 for Experiment 3. Advertisement variations for each brand are labelled using the letters A, B, C and D for Cell-C, Telkom, Vodacom and MTN respectively. The 500ms exposure was used to identify visual attention to visually salient features based on bottom-up factors, whereas the 6-second exposures were used to identify visual attention based on top-down factors in the decision-making process.

#### 5.7.2.6. Advertisement 1

Red areas indicated high levels of attention for the short exposure of 500ms were placed on the headline, brand and 5G symbol across all four advertisement variations (Appendix G: Figure 14.2). Lower attention levels were generated on brand and the product itself, shown by the green colour (Appendix G: Figure 14.2). Respondents did not look at price in advertisements 1a, 1c and 1d (Appendix G: Figure 14.2). The headline generated the most attention in the short exposure. This is in line with the DeepGaze IIE saliency model. Therefore, bottom-up visual salience can be associated with fixation predictions of the DeepGaze IIE saliency model.

Furthermore, the heatmaps for advertisement 1, when shown for 6 seconds found in Appendix G: Figure 14.3, indicated that the most amount of visual attention was placed on advertising elements communicating information about the price which can be seen by the red colour of the heatmap. DeepGaze predicted fixations for all advertising elements. The DeepGaze output indicated various levels of visual salience which were indicated through colour intensity based on predicted fixations similar to eye-tracking heatmaps. Eye-tracking data indicated that attention was placed on salient areas where deep gaze predicted fixations. However, eye-tracking data provided a denser heatmap on elements such as price and product description (as seen in advertisements in Appendix G: Figure 14.3:1A,1B,1C and 1D). These elements are important in the context of consumer decision-making. Visual salience indicated by DeepGaze IIE results were different for advertising elements across advertisement variations (Appendix G: Figure 14.4). For example, in Advertisement 1A (Appendix G: Figure 14.4: 1A) the headline, boy, brand and price were the most prominent features depicted by the saliency model; however, in Advertisement 2B the boy and brand were the most salient features despite the only differences in the two advertisements relating to the colour of the background and phone as well as branding elements such as slogans. Despite deep gaze not depicting factors such as product, price and brand as the most salient across all variations of the advertisement, respondents' visual attention was focused on product and price as well as the 5G element. These factors all provide consumers with the information they need and context that may help inform decisions. In contrast, the short exposure relating to bottom-up attention did not generate visual attention to these elements.

Furthermore, the item with the lowest amount of visual salience relative to other advertising elements was the 5G symbol (Appendix G: Figure 14.4). This was indicated by the lack of yellow colour on the symbol. However, the most attention, as indicated by eye-tracking data across all four advertisements, was on price and product information, the 5G symbol, and the top left corner of the product image (Appendix G: Figure 14.3). Other AOIs on advertisement 1 for instance the boy, brand and the headline showed less attention given by the respondents relative to the price, product information, product

picture, and pictures close to the product (Appendix G: Figure 14.3). Therefore, it could be inferred that DeepGaze IIE can be seen as a good measure of visual saliency but not as a direct measure of visual attention. This is in line with theory as DeepGaze IIE is based on a purely bottom-up system and does not take top-down factors into account. Thus, salient objects may not always have an effect on top-down attentional processes within the consumer decision making process.

#### 5.7.2.7. Advertisement 2

Advertisement 2 is simple, containing only product images, product information, price and brand. Heatmaps for the short exposure (500 ms) of advertisement 2 are presented in figure 15.2 in Appendix G. The heatmaps identified the singular product image as the element that generated the most attention. Lower levels of attention were placed on the contract deals banner (Appendix G: Figure 15.2: 2A & 2c), background (Appendix G: Figures 15.2: 2A, 2B, 2C), the image indicating the colour combinations of the product (Figures 20.2: 2A, 2B & 2C), product information (Appendix G: Figures 15.2: 2B & 2C), price (Appendix G: Figures 15.2: 2A, 2B & 2D) and brand (Appendix G: Figures 15.2: 2A, 2B, 2C, 2D). Overall, attention was placed just left of the centre of the advertisement in the top half of the page. Despite it being a more simplistic advertisement without distractor elements such as faces, emoticons and other branding, visual attention was placed mostly on the product image and some attention was placed on brand and price. Attention was more evenly distributed across the advertisement during the long exposure of the stimuli. The product description (Appendix G: Figure 15.3) that was given attention during the long exposure was not given attention in three of the four advertisements during the short exposure (Appendix G: Figures 15.3: 2A, 2B and 2D). Significant attention was placed on the first price indicated at the top of the prices and gradually decreased going down the page (Appendix G: Figure 15.3). This was the same for data and airtime bundles (Appendix G: Figure 15.3). Furthermore, the product image and first two images of the product colour combination image received high levels of attention (Appendix G: Figure 15.3). Brand also generated attention which was indicated by the green colour. All elements in the advertisement were given attention; however, lower levels of attention were given to the contract deals banner and the bottom of the advertisement (Appendix G: Figure 15.3) .

For advertisement 2, DeepGaze showed the brand logo in the top right corner as the element with the highest visual saliency across all brands (Appendix G: Figure 15.4). This was followed by the product image and then the data bundle and pricing information (Appendix G: Figure 15.4). Brand logos did not generate a large amount of attention for both the short and long exposure of the stimulus (Appendix G: Figure 15.2 & 15.3). Therefore, visual saliency may not always result in the most amount of visual attention. This indicates that bottom-up attention or visual saliency cannot be used alone to explain consumer decision making. However, colour concentration on the product image showing the front of the phone was similar for DeepGaze IIE and the eye-tracking heatmaps of both the long and short exposure across all for variations of advertisement 2. For this advertisement, product information within the image i.e., Samsung A23, was focused upon in both the short and long exposures and identified as visually salient by the saliency model used in this study. Thus, DeepGaze IIE may be useful to identify specific areas of an advertising element and can be incorporated into product images to capitalise on visual attention.

#### 5.7.2.8. Advertisement 3

Advertisement 3 (Appendix G: Figure 16.1) is a busy advertisement with images of multiple children, emoticons and confetti. A heatmap of the short exposure indicated attention around the headline and

the emoticons, the product image and the child in the middle of the advertisement (Appendix G: Figure 16.2). For advertisement 3A the most attention was given to the headline. Price was not given attention in the short exposure across all variations of the advertisement. In addition, brand was also not given attention in advertisements 2B and 2C. In the long exposure more attention was focused on the price and product relative to other elements in the advertisement (Appendix G: Figure 16.3). The brand, the children's faces, the headline, pictures and emoticons garnered some attention. The DeepGaze saliency model did not indicate the product and price as visually salient (Appendix G: Figure 16.4). However, high levels of visual attention were focused on the price and the product. Respondents were not primed to look for any specific features and were only told that they would have to make a decision. Therefore, we can conclude that top-down visual attention does not rely on visual salience to effectively guide consumer attention and communicate marketing information such as products and prices. Price was not given attention and generated very little attention across all heatmaps for advertisements 1 to 3 during the short exposure. However, for longer exposures price was considered one of the factors most given attention. This indicates that respondents will still search for information that may help inform decisions despite the level of saliency given to the displayed element.

Findings indicated a clear difference between DeepGaze IIE output and the eye-tracking heatmaps developed for stimuli shown for 500ms. Eye-tracking heatmaps indicated that bottom-up attention can be generated by high level features such as faces and text as both faces and textual elements were given attention during the short exposures.

To better understand visual attention for short exposures, descriptive statistics were run to identify any prioritisation. Means for TTFF for brand, picture, price and product were 0.334, 0.338, 0.336 and 0.313 respectively. However, means for TFD were 0.007, 0.036, 0.002 and 0.032 for brand, picture, price and product respectively. This revealed that no Area of Interest (AOI) had a TTFF that was drastically different from the others. Therefore, there was equal probability of looking at or attending to any of the given AOIs thus attention was indicative of chance. However, there was a difference in TFD for various features indicating a priority of specific features. Mean total fixation duration was the highest for pictures, followed by product, brand and then price. This showed that during a short exposure, pictures and the product image were attended to for the longest period of time. Furthermore, similar TTFF for features and the prioritisation of specific features shown through TFD shows that DeepGaze IIE is good at predicting attention grabbing power; however, it shows salience alone is not enough to hold the attention (Attention holding power).

Hypothesis 1c compared and analysed the difference between eye-tracking results for short exposures indicative of results for the bottom-up visual attention process against a purely bottom-up saliency map generated using DeepGaze IIE software. The remaining advertisements (Advertisements 4-7) were presented for a longer period of time and respondents were given specific task instructions. Therefore, eye-tracking heatmaps for advertisements 4-7 aimed to provide insight into advertisement navigation regarding the top-down visual attention process. These advertisements were also compared and analysed against DeepGaze IIE results which is discussed below.

#### 5.7.2.9. Advertisement 4

Heatmaps for advertisement 4 provided a visualisation of attention (Appendix G: Figure 17.2). Price, product and the 5G symbol were the three features that generated the most attention across all four advertisements (F Appendix G: figure 17.2: Advertisements 4A,4B,4C and 4D). All other features

generated some attention. Respondents placed attention on the two middle phones in the colour combination image, the product description, other pictures (for example, the Vodacom 4U symbol) and headlines across all four advertisements. The DeepGaze IIE results were different across all four brands; however, they shared some similarities. Overall, DeepGaze IIE results for the MTN advertisement (Appendix G: Figure 17.3: 4D) depicted lower differences in visual salience across all features than the other three brand advertisements despite changes being related to colour and brand material (headlines, brand logos and random pictorial branding). Headlines were the most prominent feature for the Cell-C, Telkom and Vodacom advertisement variations (Appendix G: Figures 17.3: Advertisements 4A, 4B & 4C). Product image, product description and price were not identified as salient features relative to the whole advertisement. Heatmaps provided a denser heatmap indicating high levels of visual attention on product image, price and the 5G symbol. This provided additional arguments in support of hypothesis 1c.

#### 5.7.2.10. Advertisement 5

Upon assessing the heatmaps for Advertisement 5 (Appendix G: Figure 18.2) it was evident that most of the attention was focused on the price, the product information and the product image itself. Furthermore, the brand logo also generated high levels of visual attention for the Telkom (5b) and Vodacom (5c) advertisements with lower levels of attention for the Cell-c (5a) and MTN (5d) advertisements. Advertisement 5b indicated high levels of attention for all elements excluding the contract deals banner and Terms and Conditions. DeepGaze IIE results for advertisement 5 (Figure 18.3) identified the man's face and brand as the most visually salient features in the advertisement. Price and product were less salient than the aforementioned features and price was more prominent in the Cell-C and MTN advertisements (Appendix G: Figures 18.3: Advertisements 5A & 5D). Despite having lower levels of visual salience according to DeepGaze IIE, product image and price generated the most attention during a visual search where respondents were instructed to view the advertisement considering individual preference for the most important factor in their decision-making process (product, price or brand).

#### 5.7.2.11. Advertisement 6

Similar to Advertisements 4 and 5, the 6<sup>th</sup> advertisement heatmap (Appendix Figure 19.2) also represented high levels of visual attention on the price and product. Images and symbols directly next to the product and price were also given high levels of interest. Respondents also paid some attention to faces, the headline, brand and other symbols. The DeepGaze saliency map showed that the product was not predicted as an area with a high level of salience (Figure 19.3). Despite this, high levels of attention were placed on the product. Furthermore, DeepGaze IIE results for variations of Advertisement 6 (Appendix G: Figure 19.3) identified features such as faces and the price. DeepGaze IIE results did not distinguish large levels of visual salience across all elements in advertisement 6 with the exception of the Cell-C variation presented in Figure 19.3: Advertisement 6A.

#### 5.7.2.12. Advertisement 7

Advertisement 7 heatmaps (Appendix G: Figure 20.2) indicated high fixation densities on product and price. Faces, the headline and the brand were also given some attention. Despite the advertisement including the sun, a flower, a surfboard and other features, very little or no attention was given to these features. The DeepGaze IIE output (Appendix G: Figure 20.3) highlighted faces, the headline and brand

as the most visually salient features. As the only difference in the advertisement variation was attributed to the brand logo, DeepGaze II results were more consistent across all four advertisement variations.

## **5.8. CONCLUSIONS**

Chapter 5 has provided a presentation and interpretation of the findings of this study. This chapter outlined the results of both the qualitative and quantitative analyses used in this study. In particular, descriptive statistics were presented followed by inferential statistics and the results of hypothesis testing. Finally, the results of the qualitative data analysis were discussed. Chapter 6 will provide an outline of the conclusions and recommendations of this study. This includes a summary of the findings, the limitations and future research avenues.

## 6. CHAPTER SIX: CONCLUSION AND RECOMMENDATIONS

### 6.1. INTRODUCTION

The following sections provide a summary of the findings of the present research study. The research findings are discussed with regard to the research objectives and hypotheses as well as prior literature. The research objectives and findings are addressed to provide answers to the research question: *What is the role of top-down and bottom-up attentional processes in consumer decision-making as determined by eye-tracking?*

### 6.2. Summary of Findings

The results and findings of the study provided insights and conclusions regarding the role of the two visual attention processes in consumer decision to achieve the primary and secondary research objectives. The following section discusses the secondary objectives set out for this research study.

#### 6.2.1. Primary Objective

The current study aimed to meet the following primary objective: *To ascertain the role of top-down and bottom-up attentional processes in consumer decision-making as determined by eye tracking.*

Hypothesis 1A assessed the correlation between total fixation duration on Areas of Interest (AOIs) related to choice and consumer decision to purchase. Overall, there was no significant difference between total fixation duration and decision made when looking at all areas of interest on the stimuli (pictures, price, product and brand). However, there was a significant difference between total fixation duration (TFD) on features that were used to provide customers with the context of the advertisement such as brand, price and product. Furthermore, when respondents were provided with instructions and primed to view an advertisement with a particular factor in mind, a positive relationship was identified between preferred factors and total fixation duration as well as decision for preferred factors and total fixation duration.

Hypothesis 1b identified a significant relationship between factor importance that provides contextual relevance for decision making and TFD. However, there was no significant relationship between first fixation duration (FFD) and fixation count and features of contextual importance.

Qualitative data was used to assess hypothesis 1c. The qualitative analysis found that attention was mainly focused on product and price across all advertisements shown for 6 seconds. However, when advertisements were shown for 500ms visual attention was depicted on other advertising elements and little attention was drawn to brand logos, product images and price. Furthermore, levels of attention indicated by the heatmaps differed based on the level of complexity for each advertisement. Upon conducting the comparative analysis of the advertisements and DeepGaze saliency maps it could be inferred that visual attention was not evenly distributed across an advertisement based on salient visual elements. Thus, we can confirm hypothesis 1c and conclude that during a visual search task mobile eye tracking presents a denser heatmap with greater fixation densities on items of importance when compared with a purely bottom-up system (DeepGaze IIE).

Hypothesis 2A found that salient objects determined by time to first fixation (TTFF) do not negatively relate to the accuracy of memory recall. Respondents were able to recall features despite them not being visually attended to. Therefore, visual salience did not have an impact on what was remembered by respondents. Furthermore, this hypothesis was conducted and based on results of short exposures to stimuli in Experiment 2A. Heatmaps revealed that items that may contextually drive decisions such as price, product and brand were not attended to by the majority of the respondent population during short exposures to stimuli. Fixations during short exposures were placed mainly on pictorial elements such as headlines by some of the respondents. As respondents did not visually attend to them, it is not plausible to conclude that salient objects determined by time to first fixation do not have a negative relationship with the accuracy of memory recall on those items. Furthermore, mean TTFF for respondents who recalled and did not recall features were 2ms apart. Thus, bottom-up attention may not play a significant role in decision making.

Hypothesis 2B assessed whether more salient objects determined by total fixation duration and heatmaps showed a positive relationship with the accuracy of memory recall of those same items determined by items recalled during the recall task. Results showed that total fixation duration was significantly different for features recalled and not recalled. This hypothesis was based on the notion that the longer items are attended to the more likely they are to be recalled by memory.

Hypothesis 3A assessed whether primed features for a visual search task produced different heatmaps, greater fixation durations, first fixation durations and fixation counts compared to salient features or objects seen during a free search task. This hypothesis aimed to identify any differences in eye-tracking metrics for free search tasks and a primed visual search task. Eye-tracking heatmaps produced showed that visual attention was placed on primed features (product, price and brand) regardless of whether respondents were primed with a task instruction or not. This may be as a result of learned processes used to navigate an advertisement and factors typically influencing consumer decision-making. Results indicated that there was a significant difference in TFD and fixation count and preference for a factor (product, price or brand) used to prime respondents viewing. Furthermore, results indicated no significant difference between first fixation duration and preferred priming factors. The following section discusses the findings of each secondary objective set out for this research study in more detail.

#### 6.2.1.1. Bottom-up visual attention and consumer decision making

Results of this study provide insight into the first research objective: *To determine whether bottom-up eye-tracking alone can explain consumer decision-making.*

Findings of the present study deduced that bottom-up eye-tracking alone cannot explain consumer decision making. Based on both heatmaps, and descriptive and inferential statistics it is evident that there was no correlation between eye-tracking metrics such as TFD and TTFF on areas of interest (AOIs) and consumer decision-making. Furthermore, heatmaps for short exposures showed that visual attention was not placed on elements such as product, price and brand, which are factors typically used in the consumer decision-making process. In addition to heatmaps and inferential statistics, fixation percentages on short exposures used to measure bottom-up visual attention processes were low, with the majority of respondents not fixating on product, price and brand.

Despite the assumption that areas with higher levels of visual attention will be more readily recalled there was no significant relationship between memory recall and time to first fixation. Findings showed

that respondents did not attend to elements influencing consumer decision-making such as product, price, and brand despite the ability of some respondents to recall these features. A study by Onișor & Ioniță (2021) corroborates this finding due to similar results relating to memory. The study concluded that users who paid the smallest amount of attention to the advertising area had the best advertisement memory in comparison to those who paid the most amount of attention. This does not indicate an inverse relationship between visual attention and memory; however, the findings showed that brands were recalled despite not being looked at all. Respondents were able to identify and remember brands although they did not attend to these elements thus minimal information was gathered through peripheral vision and understood from memory (Onișor & Ioniță, 2021), thus indicating that brand identity elements are ingrained in consumers' minds and can be reconstructed into memory even if they are unseen (Onișor & Ioniță, 2021). For example, elements such as product name, logo/symbols, typography, and slogans can be representative of brands or elements in the mind of the consumer (Onișor & Ioniță, 2021). The same can be applied to the present study as respondents were familiar with the brands as indicated by descriptive statistics, thus may have had colours, logos and slogans ingrained in their minds. Furthermore, presentation of products and prices are typically similar across advertisements thus participants could have been able to recognise these elements from peripheral vision without directly focusing attention on them.

Furthermore, as previously stated, bottom-up attention is unlikely to be a sufficient condition of consciousness as past literature and the findings of this study have provided evidence for bottom-up attention operating unconsciously (Pinto *et al.*, 2013). Based on observations by the researcher and the research assistants, the respondents often appeared confused and stated that they “did not think they looked at anything”. Despite this, respondents were able to recall features during the memory recall task and eye-tracking data was recorded. Therefore, respondents may have been able to recognise various factors based on peripheral vision and prior knowledge of features use in advertisements. This finding indicates that bottom-up visual attention may be a cause of consciousness that is used in consumer decision-making. However, top-down visual attention is a conscious process used in consumer decision-making which is corroborated by eye-tracking metrics on primed and unprimed features.

This study found that bottom-up attention may not play a significant role in decision making. Therefore, utilising bottom-up attention as a measure for impact on decision making will not be beneficial to marketing managers and researchers. Instead, bottom-up attention can be used in other marketing contexts. For example, bottom-up attentional processes may be used to optimise products, advertisements and other marketing material by identifying visually salient elements. This can be beneficial in identifying how products stand out from competitor products as well as how to highlight the right elements to convey marketing messages.

#### 6.2.1.2. The role of bottom-up and top-down visual attention processes in consumer decision making

This section provides insight into the results obtained to confirm the second secondary research objective: *To examine the contribution of bottom-up and top-down visual processes in consumer decision making.*

Based on findings of this research study it is evident that eye-tracking metrics recorded for bottom-up visual attention cannot be used to contribute to the understanding of consumer decision-making. However, eye-tracking metrics for top-down visual attention processes do contribute to consumer

decision-making. The bottom-up visual attention process was found to have little to no involvement in the consumer decision-making process. This was indicated by the differences between items fixated on and not fixated on for short (500ms) and long (6 seconds) exposures. Consumer decision-making factors, price, product and brand were not fixated on by the vast majority of respondents in the 500ms exposure. However, the longer exposures resulted in a shift with fixations increasing on these same elements over time. Furthermore, regardless of whether respondents were provided with task instructions or not, heatmaps generated were relatively similar with visual attention placed on the contextual features in the advertisements. Therefore, it can be concluded that top-down factors play a role regardless of whether respondents were given an instruction or not. This may be attributed to the need to search for factors that may influence consumer decision-making such as price.

### 6.2.1.3. The effect of visual salience on visual attention and consumer decision making

Findings of the third secondary research objective are discussed in this section: *To assess the effect of salient objects on both bottom-up and top-down attentional processes within the consumer decision-making processes.*

Advertisements include product information, images, text, brand information and price information as well as other features used to get consumer attention and convey the marketing message. For example, an advertisement for a Toyota Hilux may depict a “masculine man in order to convey the message that the cars are driven by “real men”, in addition to product imagery and price information. Thus, consumers may focus on how the product is being portrayed and the associations with the product and brand instead of other factors used in consumer decision-making. This concept emphasizes the importance of context in advertisements and the effect on visual attention processes and consumer decision-making. The present research study concluded that context is an important factor for navigation of advertisements as even if something is visually salient or is not visually salient it may still be attended to if it provides the relevant information and context to aid consumer decision-making.

Marketers may highlight specific features in advertisements by making some features stand out more than others. Therefore, even if an item is visually salient, it may not aid consumers in decision-making as it may not be relevant in the context of decision-making. For example, images of children were visually salient in the present research studies advertisements and generated visual attention during short exposures; however, they did not provide any context to the product offering being shown. In the current research study, features indicative of context are product, price and brand as they are contextually relevant features that may help a consumer choose to purchase a product. In general, the advertisements used in this study included the aforementioned contextual features and other features which are not associated with the use of cell phones such as images of children and a surfboard. Stimuli used in this study had varying ranges of complexity with some stimuli containing only features such as product, product descriptions, price and brand and others including more pictorial elements and headlines.

Results of the study showed that contextually relevant features typically related to choices (product, price, and brand) did not show any attention markers (fixations shown through graph and heatmap) during short exposure (500ms). Thus, as bottom-up attention was employed and measured during the short exposures it was concluded that bottom-up processes did not play a role in consumer decision-making. However, top-down visual attention as determined by both eye-tracking metrics and heatmaps was seen to contribute to consumer decision-making. The most salient features as determined by

DeepGaze IIE saliency maps were not always corroborated by heatmaps generated through eye-tracking for measurements of both bottom-up and top-down visual attention processes. DeepGaze IIE provided saliency maps predicting the overall saliency distribution of an image. Short exposures were used to identify visually salient elements as bottom-up attention had been found to occur in earlier fixations. Eye-tracking heatmaps for short exposures and saliency maps generated different depictions of visual salience. The complexity of the advertisements had an effect on saliency maps. Saliency maps indicated higher levels of visual salience on high-level semantic features such as faces, objects and text with increasing advertisement complexity, whereas more simple advertisements showed a more even distribution of salience across all features in the advertisement.

In the present study, items of contextual importance such as the product image were presented on a similar background colour to the image. This was done to show that despite items being less visually salient, even amongst distractor variables, features portraying context for decision-making will still generate consumer attention. For the advertisements used in the short exposure, DeepGaze IIE results did not depict the product, price and brand as the most salient features when other features such as faces, emoticons and headlines were included in the advertisements. Furthermore, only some attention was given to price, product and brand in complex advertisements (advertisements including distractor features) and most of the attention was placed on product for the simpler advertisements shown during the short exposure. However, when respondents were provided with a longer period of time to view the stimuli visual attention was generated on contextually relevant items. This is important to note as one may deduce that even if an item is not visually salient, that same item may still generate visual attention if the feature is important to task goals or motivations.

Furthermore, despite the visual complexity of the advertisement, product information such as price and product are attended to when given more viewing time. Therefore, top-down visual attention can override salient features and bottom-up visual attention in garnering attention to items relevant to task goal or motivation.

#### 6.2.1.4. Visual search

Results of this study provide insight into the fourth secondary research objective: *To identify the effect of visual salience on goal-directed and free-search fixation maps within the consumer decision making process*

Findings of the study indicated that there was no difference between free and goal-directed search when viewing the advertisements. Respondents continued to place more attention on product and price elements compared to headlines, pictures and brand regardless of participating in a primed or non-primed task. Inferential statistics resulted in statistically significant results between eye-tracking metrics such as total fixation duration and decision to purchase for both free-search tasks (Task 2B) and a primed visual search task (Task 3). Therefore, it may be inferred that despite a lack of instructions, consumers may utilise top-down processes such as prior knowledge of advertisement layout or learned processes of information search as longer exposure time resulted in fixations on all advertising elements, in particular factors such as product and price. Product and price are features that provide the consumer with the context of the advertisement and are given more visual attention than other factors such as pictures and brand regardless of intention to purchase or the task instruction.

#### 6.2.1.5. Visual salience and visual search

This section provides insight into the findings of the study used to assess the fifth secondary research objective: *To explore the effect of salience on goal-directed visual search.*

Visual salience was not found to be an important factor influencing consumer decision-making as respondents attended to pictorial features such as headlines and faces more during short exposures than on features indicative of product offerings such as product, price and brand. Thus, salient features could be distracting for the consumer. Salient items identified by DeepGaze IIE results were attended to. However, items important to decision-making received higher levels of attention. As seen in the heatmaps, salient items indicated by DeepGaze IIE were given some attention; however, top-down factors relating to goals resulted in more visual attention being placed on contextual elements, in particular, product image and price. Therefore, it can be concluded that salience can be overridden by a goal-directed visual search. However, salient items are still attended to.

#### 6.2.1.6. Bottom-up visual attention vs. context

Finally, both qualitative and quantitative findings provided results obtained to achieve the sixth secondary objective set out for this study: *To compare the difference in eye tracking data between bottom-up features (contrast, brightness, colour) and context (faces, text and symbols).* Bottom-up features were identified through the visual saliency model DeepGaze IIE.

A saliency map provided an overall view of the relative salience of all elements within a visual field. In comparison, the short exposure aimed to identify elements which received attention from a bottom-up perspective. Bottom-up attention is driven by salience; however, not all salient elements can be attended to as indicated by the brain's limited processing capacity resulting in the selection of, and inattention to, information (Orquin, Perkovic & Grunert, 2018). The stimuli used in the present study ranged from simple to more complex thus introducing items that may distribute salience and distract attention.

Despite feature salience based on bottom-up features, contextual features (brand, product and price) were more readily attended to. For example, all images of children or adult faces were attended to. High level features (faces, objects symbols, text) were attended to in short exposures. This corroborates past literature stating that high-level and low-level features can be utilized by both bottom-up and top-down attention processes. Past research introduced the notion that low-level feature performance declines over time and that low-level features are better predictors of early fixations. This was corroborated by eye-tracking results of this study as well as differences between eye-tracking heatmaps and DeepGaze IIE saliency maps. Eye-tracking identified salient objects through a short exposure of 500ms and DeepGaze IIE. Results of experiment 2A and 2B indicated which specific areas of interest were fixated on by participants overall. This was given as a percentage of participants who did not fixate on the AOIs and a percentage of participants who did fixate on the AOI per advertisement. The advertisements shown in Experiment 2A and 2B were the same; however, exposure time to the advertisement was 500ms and 6 seconds respectively. Across all three elements that typically influence consumer decision making (product, price and brand) it is evident that the majority of respondents did not fixate on these features in the advertisements during short exposures. However, during longer exposures fixations occurred on all AOIs. In particular, AOIs that generated the most visual attention were product and price which aid consumers' decision making. DeepGaze IIE results for some advertisements did not

identify product and price as visually salient thus low-level features (colour, contrast and brightness) were not used to inform top-down visual attention processes of feature locations.

### **6.3. PRACTICAL MANAGERIAL IMPLICATIONS AND RECOMMENDATIONS**

Marketers are constantly trying to generate attention as well as retain and maintain customer relationships. Through a better understanding of consumers marketers can create and develop strategies which will allow them to achieve specific goals. Consumer neuroscience technology allows market researchers to delve deeper into the unconscious mind of the consumer. Results of this study provided insights into role of visual attention process with regards to salience and consumer decision making. This resulted in several managerial implications that can be used by marketing managers and researchers in the development of future strategies and research methods as well as theoretical foundations for the role of bottom-up and top-down visual attention and consumer decision making.

Eye-tracking metrics for bottom-up visual attention processes cannot be used to determine consumer decisions; however, there are still practical uses for bottom-up visual attention for marketing managers. Bottom-up visual attention processes indicate how stimuli are attended to based on external factors. Marketing managers can utilise this visual attention process in order to understand which elements are generating attention in advertisements and packaging and adapt marketing material to highlight product information or marketing messages. Bottom-up attentional processes may be used to optimise products, advertisements and other marketing material by identifying visually salient elements. This can be beneficial in identifying how products stand out from competitor products as well as how to highlight the right elements to convey marketing messages. For example, if a company is promoting a sustainable product and targeting environmentally-conscious consumers, researchers could utilise and analyse bottom-up visual attention processes to identify whether elements such as recyclable icons stand out to the consumer. Furthermore, bottom-up visual attention and eye-tracking could be used to understand marketing material and packaging relative to competitor offerings through a comparative analysis of eye-tracking and self-report data. For example, researchers could assess whether certain product packaging would stand out on the shelf in comparison to competitor packaging.

Furthermore, there may be an overemphasis on the importance of bottom-up visual attention processes used in neuromarketing applications. Too much emphasis on bottom-up attention and favouring neurological models of decision-making may result in neglect of contextual features influencing consumer decision-making such as price. There are limitations to using eye-tracking to determine decision-making. For example, recalled previous prices and other contextual factors may influence consumer decision-making thus it is important to look at consumer decision-making and eye-tracking holistically. Therefore, it is recommended that marketing managers and researchers utilise eye-tracking alongside other market research tools to improve their understanding of consumer decision-making as opposed to using eye-tracking as an all-inclusive measure of consumer decision-making. For example, surveys or qualitative instruments that can provide contextual information.

Both how information is displayed in advertisements and the relevance or context of the information provided impacts decision making. Marketers sometimes utilise features in addition to product, price and brand such as pictures to create connections and associations between the brand or product and the consumer. Furthermore, advertisements are often created to highlight specific information and retract focus on other areas of the advertisement. As a result of this some advertisements are more complex than others. The present study assessed a variety of advertisements ranging from simple (no distractor

features) to complex (distractor features included in stimuli). Despite level of advertisement complexity, the inclusion or exclusion of distractor variables and irrespective of task instruction, respondents continuously focused on product and price. Thus, understanding how consumers visually navigate and attend to features presented on an advertisement or product is important for marketing managers. This may be as a result of prior learning or familiarity (Takano et al., 2021) with advertisements and how consumers navigate advertisements. Therefore, it is suggested that marketing managers or researchers assess how consumers visually navigate advertisements as well as identify and assess top-down features that inform context within an advertisement. Furthermore, marketing managers can develop marketing material and strategies to focus on these features.

The present study assessed bottom-up attention and visual salience against memory recall. Despite short exposures and little to no fixations on all elements of the stimuli respondents were able to recall these features. Although a negative relationship was expected between TTFF and memory recall, results of this study showed no significant relationship between shorter time to first fixations and memory recall. This may be as a result of peripheral vision.

Moreover, the results of the present study attempted to operationalise eye-tracking metrics with regard to consumer decision making. Results of the study showed a positive relationship between total fixation duration and factors used to inform decision making and preferred primed factors used in decision making. Therefore, marketers can utilise TFD to understand consumer navigation of advertisements and elements used in decision making. Furthermore it was determined that TFD and fixation count are greater for preferred primed features than other features presented on a stimulus. These findings are corroborated by past research by past research (Krajbich, Armel, & Rangel, 2010; Zuschke, 2020). However, FFD for preferred primed factors was not greater in comparison to other non-primed features presented in the stimulus. Further analysis found that fixation count was different for preferred items however did not differ for TFD and FFD for preferred, primed features.

Overall, the role of the two visual attention processes is different for consumer decision making. Visual salience and bottom-up visual attention may be used and targeted by marketers to highlight relevant marketing messages and direct some visual attention initially. However, despite high or low levels of visual salience and non-primed (free search) or primed tasks (visual search), respondents continued to use top-down factors such as familiarity and prior learning to navigate the advertisements and more attention was placed on factors informative of decisions.

#### **6.4. LIMITATIONS OF THE STUDY**

This section outlines the limitations of this research relating to sample, data collection procedures and key constructs of the present study.

The first limitation arose as a result of a smaller sample size being used in this research. Data was collected at the Neural Sense offices in Claremont, Cape Town as well as at the University of Cape Town on upper campus. Data collection was restricted to a month-long period between 9am and 4pm due to the use of office space and a reserved room in the Menzies Building at UCT from Monday the 15th of May to Monday the 12th of June. Due to the time restriction of working hours for data collection this restricted the sample size as some prospective participants were unavailable within these fixed time periods. The data collection allowed for multiple findings; however, time restrictions, location and the nature of this research resulted in a smaller sample size. The complex nature of consumer neuroscience

studies subjects participants to a time-consuming experimental process. These kinds of studies may have low ecological validity as they are conducted in a laboratory environment and not a natural world setting. Furthermore, the respondents needed to travel to the research venue, which further limited the time they had available for participation in the research. Also, as this research was not incentivised it was difficult to recruit a larger group of participants. A larger sample size may have provided more robust results; however, this was unattainable given the circumstances of the present research study. In addition to the sample size, location and time restrictions imposed a further limitation on demographic data such as age. The majority of the participants were between the ages of 18 and 35 despite the target sample age being between 18 and 60.

Secondly, since the data could only be collected at a specific location, it limited the geographic dispersion of the participants. This resulted in a small disparity distribution of participant origins across the Cape Town metropolitan area. In addition, participants were limited to citizens residing in the Cape Town metropolitan area as the research was undertaken in this area. Generalisability of findings may be difficult to larger population groups.

Furthermore, due to the objectives of the present study and the influence of familiarity and other factors such as purchase intention and buying power on top-down processes, respondents who were not actively involved in the process of buying a new cell phone contract formed the target audience. For example, respondents with a higher level of motivation may focus on and process task relevant information more thoroughly (Zuschke, 2020). In comparison, respondents with lower involvement or familiarity may experience less effortful decision making and limited information processing (Zuschke, 2020). A more homogenous sample could be used in future research to provide further insights into the visual attention processes and consumer decision making incorporating the effects of familiarity. For example, respondents used are in the process of purchasing a product.

In addition to this, the present study assessed consumer decision making based on utilitarian value (Maduku & Thusi, 2023). In particular, brand value, price and product offerings (Maduku & Thusi, 2023). However, prior literature has identified hedonic values as another motivational influence on consumer behaviour (Maduku & Thusi, 2023). There is opportunity for future research to include hedonic values (adventure, idea, roles, social, value and gratification) in the analysis in the context of South Africa to gain a better understanding of factors influencing visual attention and decision-making processes (Maduku & Thusi, 2023).

Moreover, the study focused solely on telecommunications brands (MTN, Vodacom, Telkom, and Cell-C) and two cell-phone product brands (Apple and Samsung). Thus, the data generated through this study were limited to telecommunications brands and product brands as well as related advertisements. The use of various brands across multiple sectors may provide more generalised results. Advertisement variations such as differences in background colours and headlines were identified as another limitation in this research when using DeepGaze IIE software as a measure of comparison between advertisements. Although the advertisements were the same, brand elements such as logos, headlines and colours were changed to reflect advertising material for each brand. DeepGaze IIE output differed across variations of the advertisements as some brand colours stood out more in comparison to others.

In addition, eye-tracking was the only neuromarketing tool used in this research study. The eye-mind link allows for the generation of behavioural insights from eye movements. Associations between eye movements and visual processing allows researchers to gather insights regarding visual attention cognitive processes and reactions (“Psychology and neuroscience research”, n.d.). There has been

debate regarding whether eye-tracking is a pure neuroscience or brain-based measurement, or a behaviour measurement of eye movements associated with visual processing. Additional neuroscience tools could be used alongside eye-tracking to achieve further insight into the role of visual attention in consumer decision-making. For example, EEG and fNIRS or fMRI which are all alternative measures of attention.

Further limitations arose due to treatment stimuli and research design. Respondents were presented with five images and seven advertisements. Four of the five images were shown for 500ms. The fifth image was shown for 6 seconds. Furthermore, three of the seven advertisements were randomly displayed for 500ms followed by an instruction and exposure of 6 seconds. The remaining four advertisements were shown for 6 seconds. Due to the short exposure of 500ms some respondents reported they initially struggled to divert their gaze to the image following the presentation of the fixation cross. Future research could utilise additional stimuli or advertisements (practice exercises or dummy exercises) to allow participants enough time to familiarise themselves with the shift in eye movement to the stimuli. Furthermore, timing related to bottom-up and top-down visual attention processes is not clearly defined in past and current literature. Thresholds relating to timing of bottom-up and top-down visual attention may be explored and defined in future research for different marketing material such as point of sale material and advertisements.

Furthermore, respondents were asked to make a decision that typically involves complex decision-making processes and it takes time to evaluate all the factors and alternatives. This introduces a further limitation to this study as participants were restricted to a limited period of time in which to make a choice. Buying a cell-phone may be a more complex decision making process therefore it may be useful to conduct this research across different types and stages of the decision making process.

Despite the aforementioned limitations, the present study achieved the research objectives resulting in useful recommendations and a greater understanding of the role of visual attention in consumer decision-making. Furthermore, the limitations outlined in this research study provide future research avenues which are discussed and outlined in the following section.

## **6.5. RECOMMENDATIONS FOR FUTURE RESEARCH**

This section outlines future research avenues and recommendations with regard to visual attention and consumer decision-making as a result of both the findings and limitations of this research. The findings of this research were limited to respondents from the age of 18 to 60 residing in the Cape Town metropolitan area, South Africa. As the majority of the participants fell within the age range of 18-35, inferences could be made for generations Y and Z. Furthermore, age and education level were the only demographic factors recorded in this research project. Future research could place focus on streamlining results with regard to demographic factors such as age, gender, race and location to provide a cross-sectional analysis and further insight for marketing managers. For example, future research may compare the responses of different genders and generations to advertising material that is suitable to the target population. Furthermore, it is recommended that this research is conducted in the future with a larger sample size as this was not possible due to the nature of this study.

Respondents used in this study were familiar with the brands and mobile operating systems provided in the advertisements. Future research can include advertisement variations accounting for associations with brands or create a new brand with zero associations. In addition to this, future research may utilise

different stimuli and marketing material to provide a better understanding of visual attention and consumer decision-making and how this influences navigation of relevant marketing material. In addition to various types of marketing material, future research could utilise advertisements or other marketing material for different brands and industries. This may be useful as visual attention in relation to consumer decision-making is likely to change across industries. For example, the fashion industry would have different requirements to the motor industry.

In addition, future research could utilise advertisements for various products to compare consumer buying decisions against the visual attention processes. The current research study assessed the role of visual attention processes in consumer decision-making for complex buying behaviour. Therefore, it may be of use to future researchers to understand the role of visual attention processes and consumer decision-making for other buying behaviours such as habitual buying behaviour.

The present research study utilised advertisements that included more pictorial elements than product information. Results were calculated and analysed which included and removed pictorial elements as there were more pictures than product, price and brand features. Furthermore, pictures were excluded in some parts of the analysis due to focus of preference on factors influencing consumer decision-making during top-down experimental tasks. Future research may be broadened by utilising an equal number of elements per category and varying the number of elements per category to assess differences across outcomes to understand how pictorial elements not relating to product information influence respondent navigation of advertisements and consumer decision-making.

Moreover, to the best of knowledge literature based on the two visual attention processes and visual salience remains limited due to confusion resulting from blurred definitions and understandings of timing related to deployment and disengagement of both bottom-up and visual attention. The present research study utilised long and short exposures to assess top-down and bottom-up visual attention; however, there is limited literature regarding the timeline of the two processes and whether they operate in isolation or together. Improved understanding of time related to the visual attention processes will allow marketing managers and researchers in various fields to streamline their research and experimental designs.

Furthermore, a combination of neuroscience tools could be used to generate further understanding of visual attention and consumer decision-making as well as how consumers navigate advertisements, for example, facial coding, Galvanic Skin Response (GSR) and Electroencephalogram (EEG). EEG allows for additional information linking attention and emotions (Santos *et al.*, 2015).

In addition to utilising other neuroscience tools, future research could utilise DeepGaze III to understand predicted fixations based on fixation history. DeepGaze III is a new model that predicts spatial location of consecutive fixations in a free-viewing scan path over static images (Kümmerer, Bethge & Wallis, 2022). This is a deep learning model that combines image information and fixation history information that predicts where a respondent may fixate on next (Kümmerer, Bethge & Wallis, 2022). When viewing static scenes fixations occur where gaze fixates on an image location with little movement and saccades occur where gaze moves from one fixation to the next (Kümmerer, Bethge & Wallis, 2022). However, this was not commented on in the present research study. Furthermore, future research could assess the visual attention processes in relation to consumer decision-making using another saliency model. For example, a study by Guo *et al.* (2023) built a vision backbone VAN which allows for image classification, object detection, and semantic segmentation.

Finally, future research may examine these processes in a more naturalistic setting with higher ecological validity as well as replicate research conclude and corroborate the findings of the present research study.

## **6.6. Summary**

The role of visual attention processes for consumer decision-making as determined by eye-tracking was identified in the present research study. It was evident that eye-tracking metrics indicative of bottom-up visual attention do not play a significant role in consumer decision-making as features used to decipher choice were not depicted during measurement of bottom-up exposures despite being recalled. However, eye-tracking metrics for top-down visual attention played a significant role in determining and understanding consumer decision-making. It is thus evident that regardless of priming, contextually relevant factors are visually attended to when viewing advertisements. Overall, it can be concluded that eye-tracking alone should not be utilised to understand consumer decision-making. Instead, eye-tracking and the visual attention process should be used alongside other market research tools to aid understanding of consumer decision-making.

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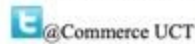
APPENDIX A: Ethics & DSA Approval, Language Certificate, Turnitin Score, Cover Letter & Questionnaire

## Ethics Approval:



### Faculty of Commerce

Private Bag X3, Rondebosch, 7701  
2.26 Leslie Commerce Building, Upper Campus  
Tel: +27 (0) 21 650 4375/ 5748 Fax: +27 (0) 21 650 4369  
E-mail: [jacques.rousseau@uct.ac.za](mailto:jacques.rousseau@uct.ac.za)  
Internet: [www.uct.ac.za](http://www.uct.ac.za)



@Commerce UCT



UCT Commerce Faculty Office

13 12 2022

Rebecca Perrott  
School of Management Studies  
University of Cape Town  
REF: REC 2022/12/009

**Is it top-down or bottom-up? Processes involved in salience and decision making in eye-tracking consumer neuroscience research**

We are pleased to inform you that your ethics application has been approved. Unless otherwise specified this ethical clearance is valid until 31-Dec-2023 .

Your clearance may be renewed upon application.

Please be aware that you need to notify the Ethics Committee immediately should any aspect of your study regarding the engagement with participants as approved in this application, change. This may include aspects such as changes to the research design, questionnaires, or choice of participants.

The ongoing ethical conduct throughout the duration of the study remains the responsibility of the principal investigator.

We wish you well for your research.

Signed by candidate 2022.12.15  
14:24:03 +02'00'

**Jacques Rousseau**  
Commerce Research Ethics Chair  
University of Cape Town  
Commerce Faculty Office  
Room 2.26 | Leslie Commerce Building

Office Telephone: +27 (0)21 650 2695 / 4375  
Office Fax: +27 (0)21 650 4369  
E-mail: [jacques.rousseau@uct.ac.za](mailto:jacques.rousseau@uct.ac.za)  
Website: <http://www.commerce.uct.ac.za/com/Ethics-in-Research>

"Our Mission is to be an outstanding teaching and research university, educating for life and addressing the challenges facing our society."

## DSA Approval:



# RESEARCH ACCESS TO STUDENTS

# DSA100

### NOTES

- This form must be FULLY completed by all applicants who want to access UCT students for the purpose of research or surveys.
- Return the fully completed (a) DSA 100 application form by email, in the same word format, together with your: (b) research proposal inclusive of your survey, (c) copy of your ethics approval letter / proof (d) informed consent letter to: Nadierah.Pienaar@uct.ac.za. Your application will be attended to by the Executive Director, Department of Student Affairs (DSA), UCT.
- The turnaround time for a reply is approximately 10 working days.
- NB: It is the responsibility of the researcher/s to apply for and to obtain ethics approval and to comply with amendments that may be requested; as well as to obtain approval to access UCT staff and/or UCT students, from the following, at UCT, respectively:
  - Ethics: Chairperson, Faculty Research Ethics Committee' (FREC) for ethics approval, (b) Staff access: Executive Director: HR for approval to access UCT staff, and (c) Student access: Executive Director: Student Affairs for approval to access UCT students.
- Note: UCT Senate Research Protocols requires compliance to the above, even if prior approval has been obtained from any other institution/agency. UCT's research protocol requirements applies to all persons, institutions and agencies from UCT and external to UCT who want to conduct research on human subjects for academic, marketing or service related reasons at UCT.
- Should approval be granted to access UCT students for this research study, such approval is effective for a period of one year from the date of approval (as stated in Section D of this form), and the approval expires automatically on the last day.
- The approving authority reserves the right to revoke an approval based on reasonable grounds and/or new information.

### SECTION A: RESEARCH APPLICANT/S DETAILS

Position	Staff / Student No	Title and Full Name	Contact Details (Email & Cell / Land line)
A.1 Student Number	PRRREB002	Miss Rebecca Perrott	Prrreb002@myuct.ac.za 0834172540
A.2 Academic / PASS Staff No.			
A.3 Visitor/ Researcher ID No.			
A.4 University at which a student or employee	UCT	Address if <u>not</u> UCT:	
A.5 Faculty & Department/School	School of Management Studies, Faculty of Commerce		
A.6 APPLICANTS DETAILS If different from above	Title and Name	Tel.	Email

### SECTION B: RESEARCHER/S SUPERVISOR/S DETAILS

Position	Title and Name	Tel.	Email
B.1 Supervisor	Dr Pragasen Pillay	021 6507368	p.pillay@uct.ac.za
B.2 Co-Supervisor/s	Dr David Rosenstein Dr Ashraf Vahed	084 210 1630 078 511 2786	david.rosenstein@neuralsense.co.za ashraf.vahed@neuralsense.co.za

### SECTION C: APPLICANT'S RESEARCH STUDY FIELD AND APPROVAL STATUS

C.1 Degree – if applicable	MbusSci Marketing		
C.2 Research Project Title	Is it top-down or bottom-up? An evaluation of processes involved in salience and decision making utilising eye-tracking consumer neuroscience research		
C.3 Research Proposal	Attached:	Yes <input checked="" type="checkbox"/>	No <input type="checkbox"/>
C.4 Target population	UCT students residing in the cape town metropolitan area between the age of 18-60		
C.5 Lead Researcher details	If different from applicant:		
C.6. Will use research assistant/s	Yes <input type="checkbox"/>	No <input checked="" type="checkbox"/>	If yes: provide a list of names, contact details:
C.7 Research Methodology and Informed consent	Research methodology: Quantitative questionnaire and Screen Based Eye-tracking Informed consent: Cover letter provided to participant upon research invitation and before questionnaire		
C.8 Ethics clearance status from UCT's Faculty Ethics in Research Committee /Chair (EIRC)	Approved by the UCT EIRC: Yes <input checked="" type="checkbox"/>	With amendments: Yes <input type="checkbox"/>	No <input checked="" type="checkbox"/>
	(a) Attach copy of your UCT ethics approval. Attached: Yes <input checked="" type="checkbox"/>	No <input type="checkbox"/>	
	(b) State date / Ref. No / Faculty of your UCT ethics approval: 13/12/2022 Ref. / Faculty: REC 2022/12/009		

### SECTION D: APPLICANT/S APPROVAL STATUS FOR ACCESS TO STUDENTS FOR RESEARCH PURPOSE (To be completed by the ED, DSA or NOMINEE)

D.1 APPROVAL STATUS	Approved / With Terms / Not	* Conditional approval with terms		Applicant/s Ref. No.:
	(i) Approved <input checked="" type="checkbox"/> (ii) With terms <input type="checkbox"/> (iii) Not approved <input type="checkbox"/>	a) Access to students for this research study must only be undertaken after written ethics approval has been obtained. b) In event any ethics conditions are attached, these must be complied with before access to students.		
D.2 PREPARED BY:	Designation	Name	Signature	Date of Approval
	Personal Assistant	Nadierah Pienaar	Signed by candidate	12/05/2023
D.3 APPROVED BY:	Designation	Name	Signature	Date of Approval
	Executive Director Department of Student Affairs	Mr Pura Mgolombane	Signed by candidate	12/05/2023

**Language Edit Certificate:**

To whom it may concern:

Re: Masters Dissertation entitled:

Is it top-down or bottom-up? An evaluation of processes involved in salience and decision-making utilising eye-tracking consumer neuroscience research

Submitted in fulfilment of the requirements for the degree of  
**Master of Business Science in Marketing**  
by **Rebecca Perrott**.

Declaration:

I have edited this document in terms of language usage and grammatical correctness.

I am an experienced editor and proof reader and have edited several dissertations/theses.

My qualifications are as follows:

Bachelor of Arts (English and Afrikaans)

University Education Diploma (UED)

Diploma in Translation (Unisa)

[Signed]

**Michael Vermeer**  
**Editor/Proof reader**

**20 November 2023**

**Turnitin Score:**

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ORIGINALITY REPORT

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**15%**  
SIMILARITY INDEX

**12%**  
INTERNET SOURCES

**10%**  
PUBLICATIONS

**3%**  
STUDENT PAPERS

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## Cover Letter and Questionnaire:



UNIVERSITY OF CAPE TOWN  
**FACULTY OF COMMERCE**  
Igniting Knowledge and Opportunity



To the respondent:

This research will be conducted by a Master of Business Science specialising in Marketing student at the University of Cape Town. The aim of this research is to improve the understanding of the role of visual attention as well as saliency allowing for better and more robust neuromarketing research.

This research has been approved by the UCT Faculty of Commerce Ethics in Research committee.

Participation in this study requires you to answer a questionnaire that will take approximately **5 minutes** to complete, as well as a **25 minute** eye-tracking experiment. Both the questionnaire and experiment will take approximately **30 minutes** to complete. This research will take place at the Neural Sense offices in Claremont. The eye tracking experiment will use a Tobii screen based eye-tracking device. This is non-invasive and records eye movements from a distance. Please note that this research will be excluding the participation of minors. Participation is **voluntary**, responses are **anonymous and confidential** and will be used solely for the purpose of this research. Participants will not need to reveal personal details such as names, contact information or a physical address as this is not relevant to the study. The participants will be given a participant ID (e.g. Participant 1) to keep track of proceedings. All the data captured will be kept on a secure laptop and there will be no links back to the participants. Participants need to be between the ages of 18 and 60 to be eligible for the study. The study should take no longer than 30 minutes and COVID screening and protocols will be conducted prior to the testing. By participating in this study, you as a respondent: Consent to participate in this study (Questionnaire and eye-tracking experiments), are aware that participation is voluntary and understand that you may withdraw from the study at any point in time without penalty.

If you are interested in participating please email: [PRRREB002@myuct.ac.za](mailto:PRRREB002@myuct.ac.za)

Should you have any questions regarding the study, please do not hesitate to contact the following researcher:

Rebecca Perrott: [PRRREB002@myuct.ac.za](mailto:PRRREB002@myuct.ac.za)

Supervisors:

Dr Pragasen Pillay: [P.Pillay@uct.ac.za](mailto:P.Pillay@uct.ac.za)

Dr David Rostenstein: [david.rosenstein@neuralsense.co.za](mailto:david.rosenstein@neuralsense.co.za)

Mr Mark Drummond: [mark.drummond@neuralsense.co.za](mailto:mark.drummond@neuralsense.co.za)

Your participation will be greatly appreciated.

Kind regards

Rebecca Perrott: [PRRREB002@myuct.ac.za](mailto:PRRREB002@myuct.ac.za)



**Rebecca Perrott PRRREB002**

**Title: Is it top-down or bottom-up? An evaluation of processes involved in salience and decision making in eye-tracking consumer neuroscience research**

**QUESTIONNAIRE**

1. What is your education level ?

Primary
Secondary
Tertiary
Other
Prefer not to answer

2. How old are you ?

e.g., 18
Prefer not to answer

3. Please select the brands you are familiar with from the following list:

- MTN
- Vodacom
- Telkom
- Cell-C

4. Please indicate whether you are a customer of the following brands;

- MTN
- Vodacom
- Telkom
- Cell-C
- Not a customer

5. Please select the brands you are familiar with from the following list:

- Apple
- Android
- None

6. Please indicate whether you are a customer of the following brands;

- Apple
- Android
- None

APPENDIX B: Procedures

**Procedures:**

**Figure 1: Tobii Pro X2-30**



(“Tobii Pro X2-30 screen-based eye tracker.”, 2015)

**Figure 2: Placement of Tobii Eye tracker at base of screen**

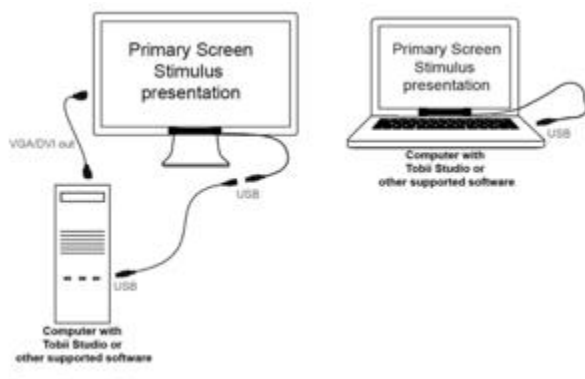
Figure 2.1:

(“User`s Manual Tobii X2-30 Eye Tracker | Manualzz”, n.d.)



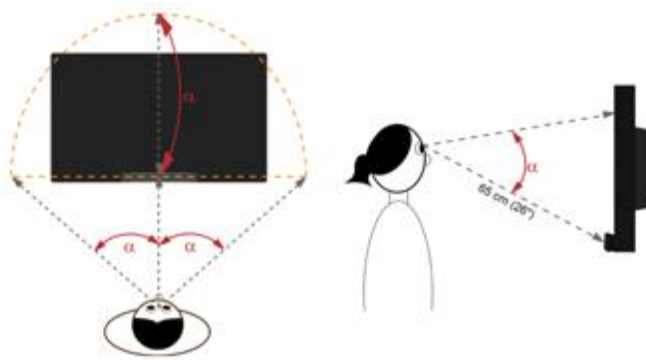
(“Easy to use, small, portal eye tracker - Tobii Pro Nano”, 2018)

Figure 2.2:



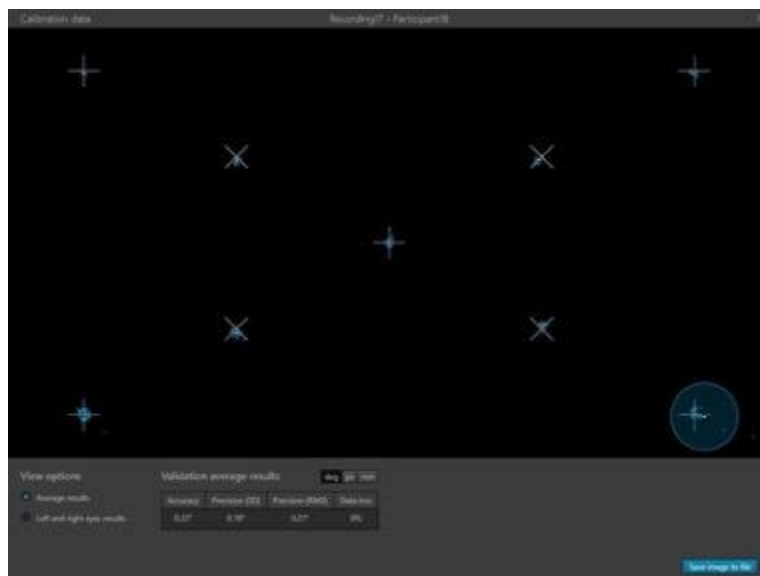
(“User`s Manual Tobii X2-30 Eye Tracker | Manualzz”, n.d.)

**Figure 3: Participant distance from screen**



(“User`s Manual Tobii X2-30 Eye Tracker | Manualzz”, n.d.)

**Figure 4: Eye-Tracking Calibration**



(“How to calibrate and validate in Tobii Pro Lab”, 2022)

APPENDIX C: Overview of Eye Tracking Study Including an example for each task

## Overview of Study Design:

Figure 5.1: Overview of Study design

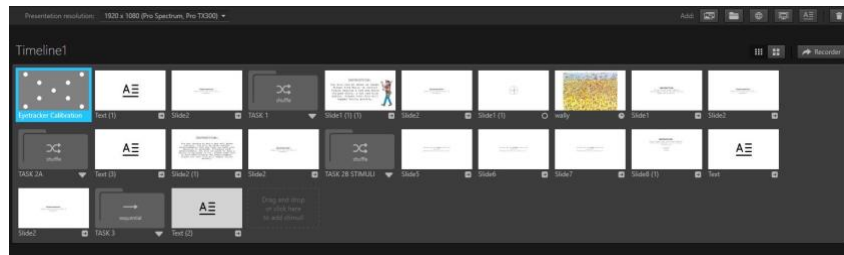


Figure 5.2: Fixation Cross with Gaze block

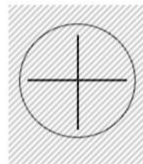


Figure 5.3: Fixation Cross examples for task 2 & 3

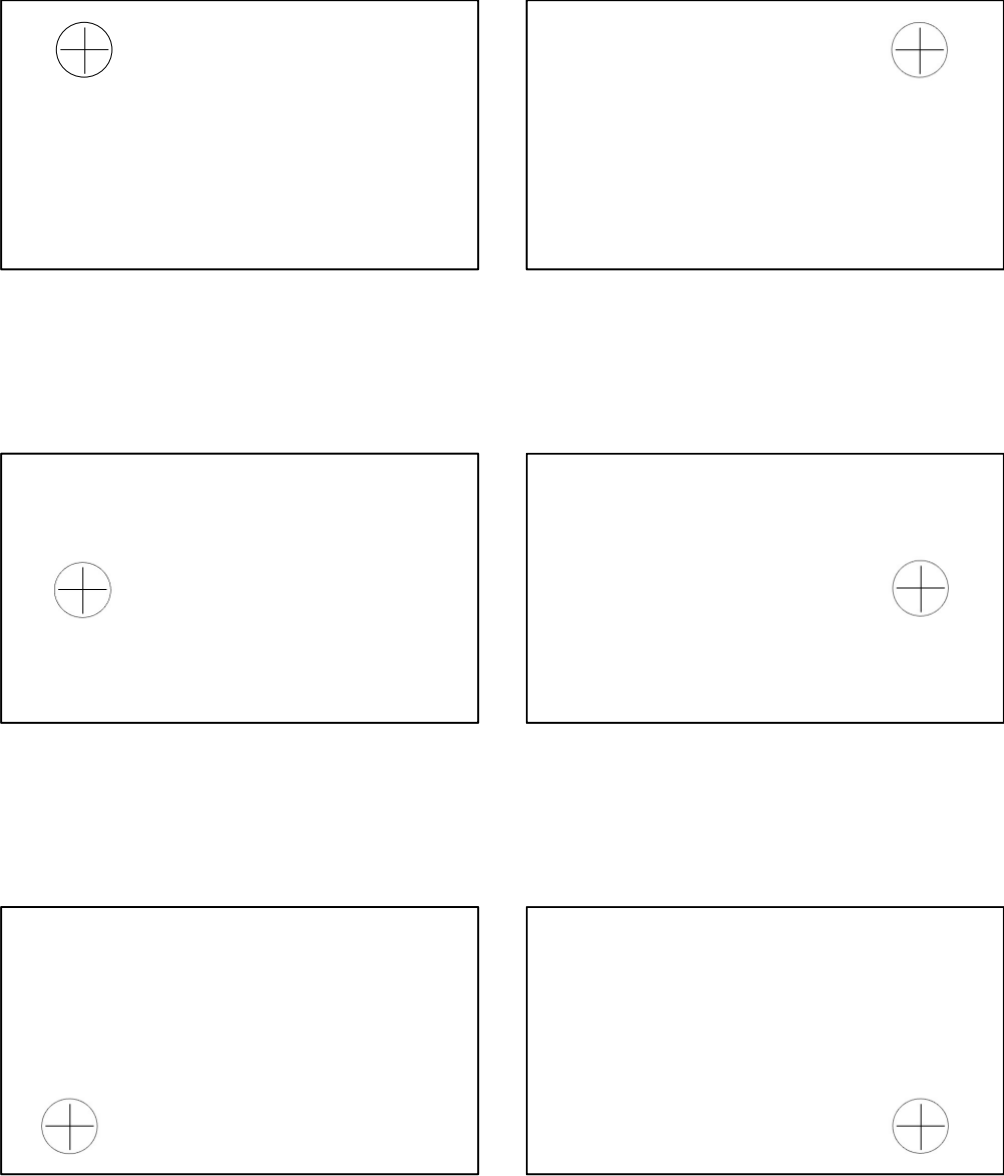


Figure 5.4: Task 1 study design

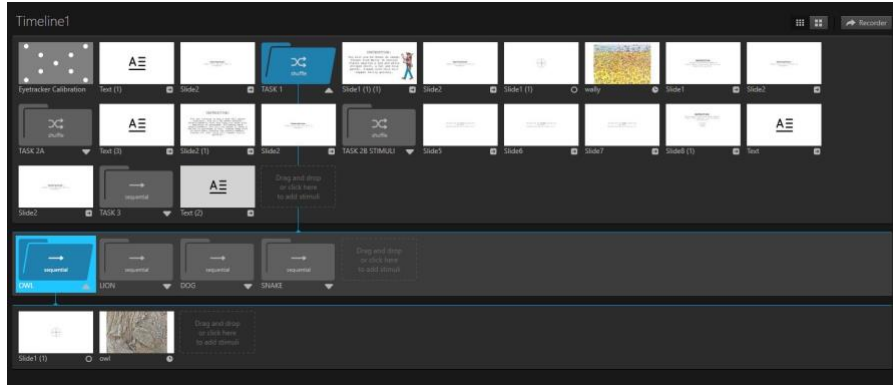


Figure 5.5: Task 1 Instruction

**INSTRUCTION:**  
You will now be shown a number of  
advertisements. Please note that this will  
happen fairly quickly.

Figure 5.6: Crosshair Instruction

**Instruction:**  
Please look at the cross until it  
disappears.

Figure 5.7: Fixation Cross

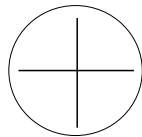
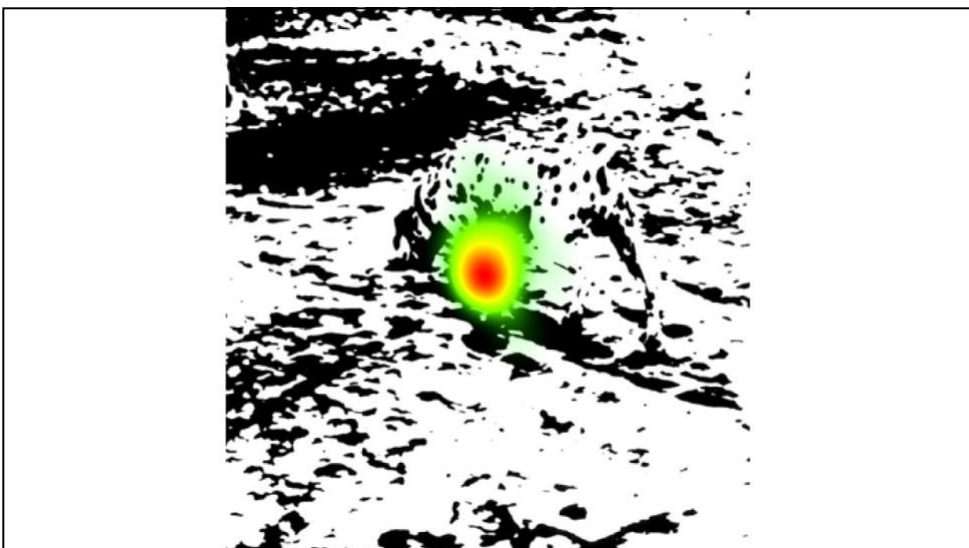


Figure 5.8: Task 1 Stimuli Gestalt Dog




Figure 5.9: Eye Tracking Heatmap for Task 1 Stimuli Gestalt Dog



**Figure 5.10:** Task 1 Instruction for “Where is Wally?” Stimulus

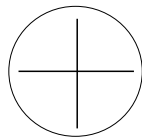
**INSTRUCTION:**  
You will now be shown an image.  
Please find Wally (A cartoon figure wearing a red and white striped shirt, a hat and blue pants). Please note this will happen fairly quickly.

A cartoon illustration of Wally G from the movie 'Finding Nemo'. He is wearing his signature red and white striped shirt, blue pants, a red hat, and a brown tool belt. He is holding a wrench and a pencil, and has a friendly expression.

**Figure 5.11:** Fixation Cross instruction

**Instruction:**  
Please look at the cross until it disappears.

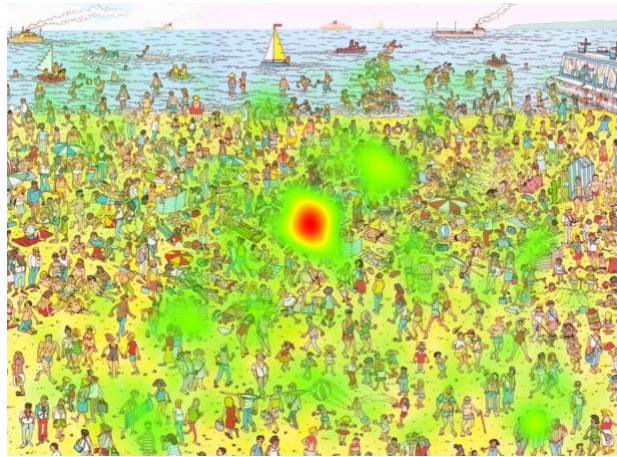
**Figure 5.12:** Fixation Cross



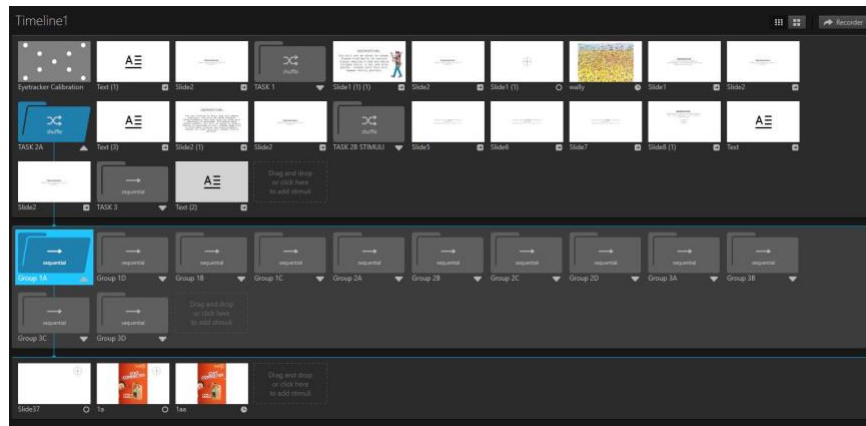
**Figure 5.13:** “Where is Wally?” Stimulus



**Figure 5.14:** Eye Tracking Heatmap for “Where is Wally?” Stimulus



**Figure 5.15:** Overview of Task 2A



**Figure 5.16:** Eye Tracking Heatmap with Fixation Cross



**Figure 5.17:** Eye Tracking Heatmap for Fixation Cross and Stimulus



**Figure 5.18:** Advertisement 3c Stimulus



**Figure 5.19:** Eye Tracking Heatmap Advertisement 3c (500ms)

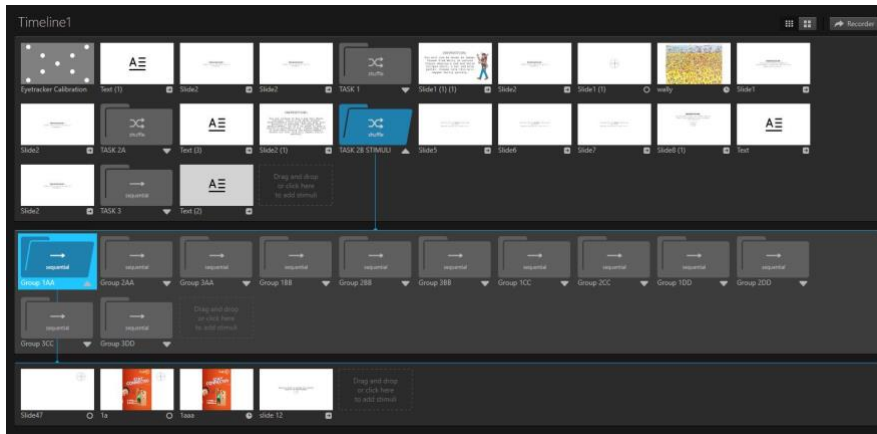


**Figure 5.20: Memory Recall Instruction**

What do you remember seeing in the advertisement?

- a. Product
- b. Price
- c. Brand
- d. Pictures
- e. All of the above
- f. None of the above

**Figure 5.21: Task 2B Study Design**



**Figure 5.22:** Task 2B Instruction

INSTRUCTION:

You are looking to buy a new cell phone contract. You will be shown several advertisements that may help you make your decision to purchase. Following each advertisement, you will be asked to make a choice to purchase or not. Please keep this in mind when viewing the advertisement. Please note that this will happen fairly quickly.

**Figure 5.23:** Eye Tracking Heatmap with Fixation Cross



**Figure 5.24:** Eye Tracking Heatmap for Fixation Cross and Stimulus



**Figure 5.25:** Advertisement 3c Stimulus



**Figure 5.26:**Eye Tracking Heatmap Advertisement 3c (6 Seconds)



**Figure 5.27:** Respondent Decision Instruction

Would you choose to purchase this contract  
based on the advertisement?  
a. Yes  
b. No

**Figure 5.28: Likert Scale Contextual Importance Instruction (Price)**

How much did the **price** inform your  
decision?  
indicate this by on a scale of 1-5

**Figure 5.29: Likert Scale Contextual Importance Instruction (Product)**

How much did the **product** inform your  
decision?  
indicate this by on a scale of 1-5



**Figure 5.32: Task 3 Instruction**

**INSTRUCTION:**

You are looking to buy a new cell phone contract. You will be shown several advertisements and then be asked to make a decision. Please keep your previous choice (a. Product, b. Price or c. Brand) in mind when viewing the advertisements. Please note this will happen fairly quickly.

**Figure 5.33: Task 3 Factor Importance Choice**

**INSTRUCTION:**

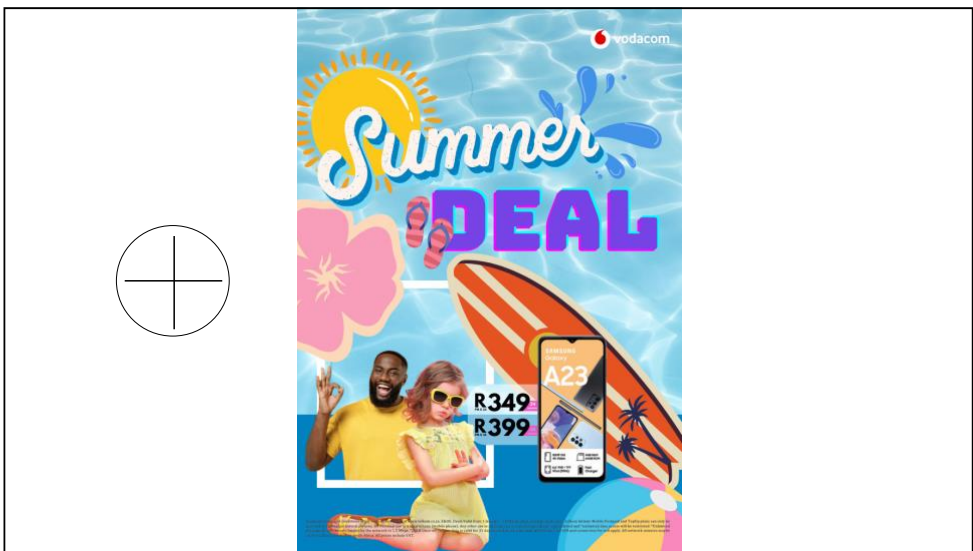
You are going to buy a cell phone contract.  
What is more important to you in making  
this decision?

- a.Product
- b.Price
- c.Brand

**Figure 5.34: Fixation Cross**



**Figure 5.35: Fixation Cross and Advertisement 7c Stimulus**



**Figure 5.36:** Advertisement 7c Stimulus



**Figure 5.37:** Eye Tracking Heatmap for Advertisement 3c Stimulus (6 Seconds)



**Figure 5.38:** Respondent Decision Instruction

Would you choose to purchase this contract  
based on the advertisement?  
a. Yes  
b. No

## APPENDIX D: Stimuli

**Contextual Stimuli:**

Figure 6.1: Lion Stimulus



(Kelly, 2014)

Figure 6.2: Owl Stimulus



*(‘The camouflage and concealment strategies of various animal species...’,2022)*

Figure 6.3: Snake Stimulus



(Nowak, 2023)

Figure 6.4: Gestalt Dog Stimulus



(Kadish, 2015)

Figure 6.5: “Where is Wally” Stimulus



*(Where's the brains behind Wally?, 2011)*

Advertisement Stimuli:

Figure 7.1: Advertisements 1-3 (500ms & 6 seconds)



Figure 7.2 : Advertisements 4-7 (6 seconds)



## AREAS OF INTEREST

Figure 8.1 : Areas of Interest for Advertisement 1



Figure 8.2: Areas of Interest for Advertisement 2



Figure 8.3: Areas of Interest for Advertisement 3



Figure 8.4: Areas of Interest for Advertisement 4



Figure 8.5: Areas of Interest for Advertisement 5



Figure 8.6: Areas of Interest for Advertisement 6



Figure 8.7: Areas of Interest for Advertisement 7



Figure 8.8: Areas of Interest for Lion Contextual Stimulus



Figure 8.9: Areas of Interest for Owl Contextual Stimulus



**Figure 8.10:** Areas of Interest for Snake Contextual Stim



**Figure 8.11:** Areas of Interest for Gestalt Dog Contextual Stimulus



**Figure 8.12:** Areas of Interest for “Where is Wally?” Contextual



APPENDIX E: Descriptive Statistics

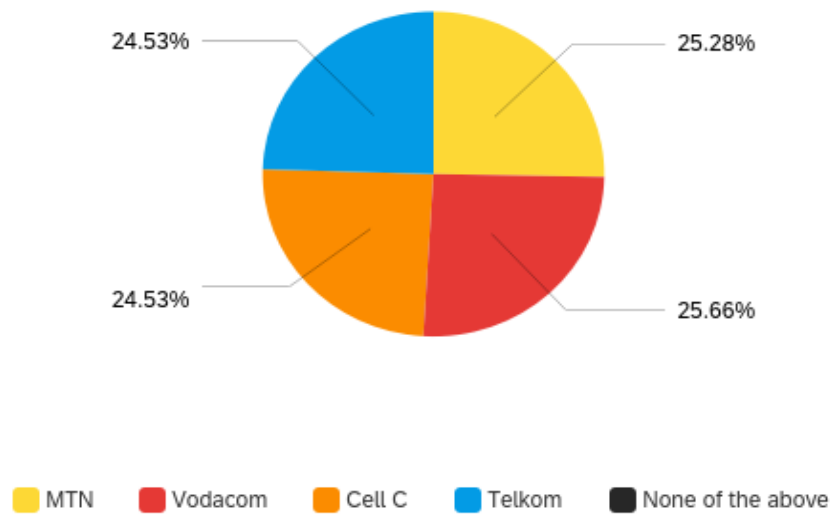
**Table 1:** Question 2 Survey Response: Respondent Age

#	Answer	%	Count
1	18-35	95.71%	67
2	36-60	4.29%	3
3	Click to write Choice 3	0.00%	0
	Total	100%	70

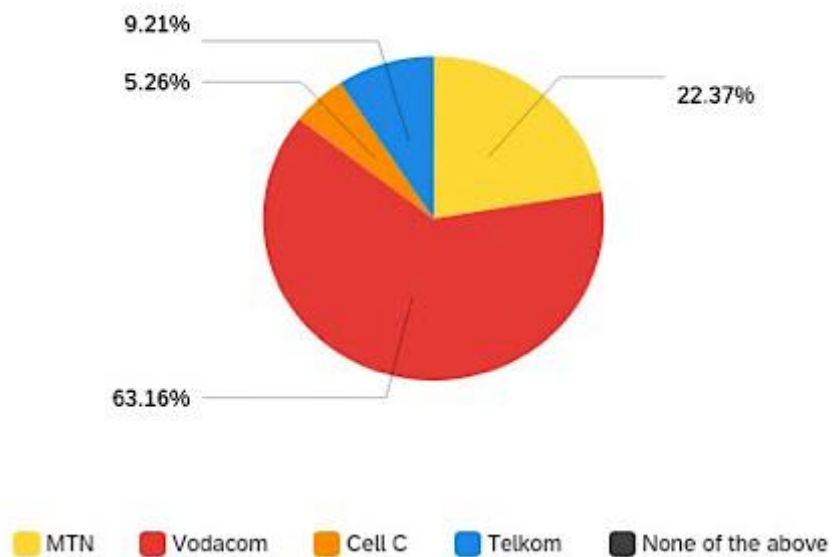
**Table 2 :** Question 3 Survey Response: Respondent Education Level

#	Answer	%	Count
1	Primary	0.00%	0
2	Secondary	4.29%	3
3	Tertiary	95.71%	67
4	Other	0.00%	0
5	Prefer not to answer	0.00%	0
	Total	100%	70

**Figure 9.1:** Question 4 Survey Response: Familiarity of participants with telecommunications brands (MTN, Vodacom, Telkom, Cell-C)



**Figure 9.2:** Question 5 Survey Response: Telecommunications brand users



**Table 3: Question 5 Survey Response: Telecommunications brand users**

#	Answer	%	Count
1	MTN	22.37%	17
2	Vodacom	63.16%	48
3	Cell C	5.26%	4
4	Telkom	9.21%	7
5	None of the above	0.00%	0
	Total	100%	76

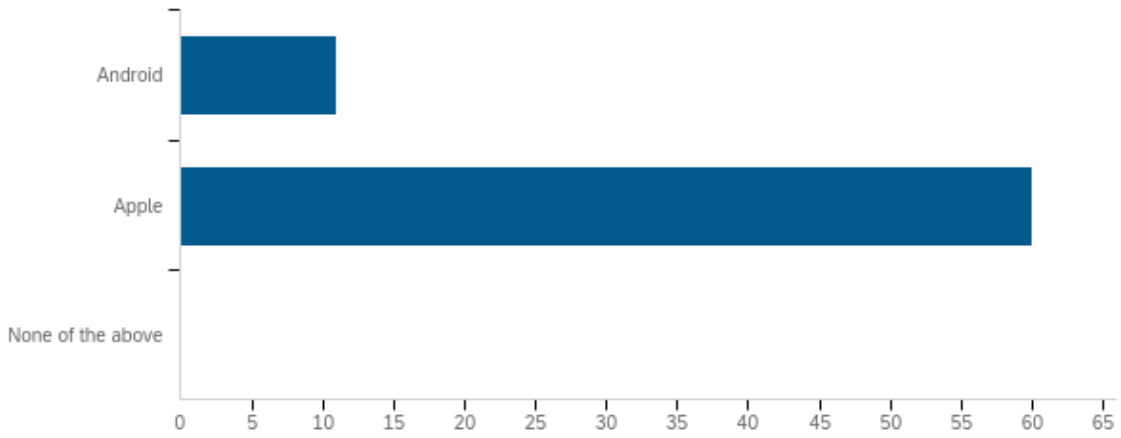
**Table 4: Question 6 Survey Response: Familiarity with Mobile operating system/product**

#	Answer	%	Count
1	Android	45.61%	52
2	Apple	54.39%	62
3	None of the above	0.00%	0
	Total	100%	114

**Table 5: Question 7 Survey Response: Mobile operating system/product users**

#	Answer	%	Count
1	Android	15.49%	11
2	Apple	84.51%	60
3	None of the above	0.00%	0
	Total	100%	71

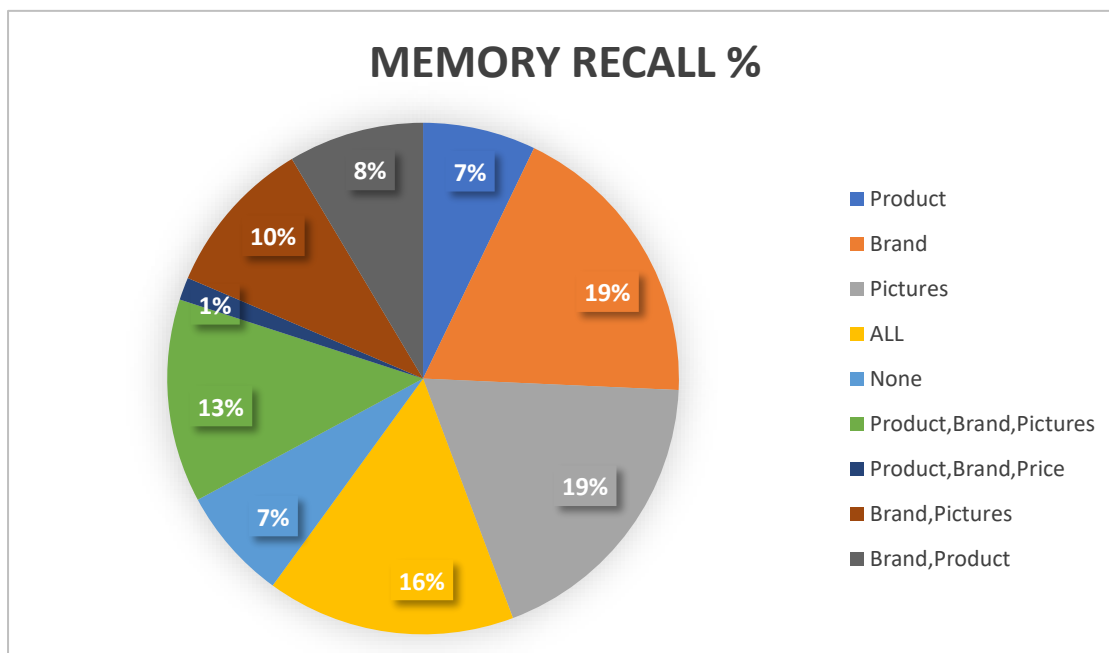
**Figure 9.3:** Question 7 Survey Response: Mobile operating system/product users



**Table 6:** Memory recall responses for Task 2A

	Product	Brand	Pictures	All	None	Product, Brand, Pictures	Product, Brand, Price	Brand, Pictures	Brand, Product
<b>MEMORY RECALL %</b>	7%	19%	19%	16%	7%	13%	1%	10%	8%

**Figure 9.4:** Pie chart of the factors recalled by memory recall in Task 2A

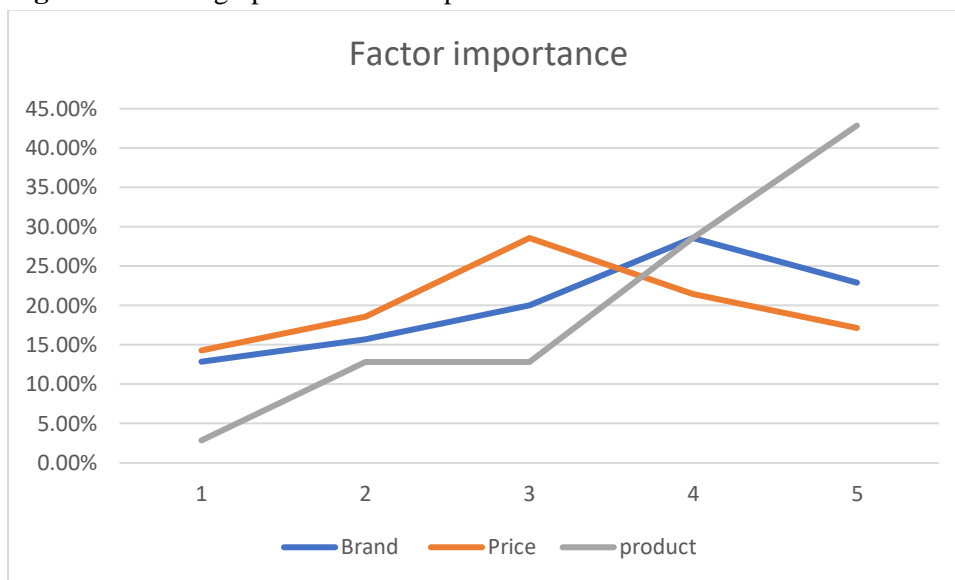


**Table 7:** Factor importance as indicated by Likert scale Questions in Task 2B

<b>FACTOR IMPORTANCE</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>
Brand	12,86%	15,71%	20,00%	28,57%	22,86%
Price	14,29%	18,57%	28,57%	21,43%	17,14%
product	2,86%	12,86%	12,86%	28,57%	42,86%

<b>FACTOR IMPORTANCE</b>	<b>Likert Scale Rating</b>					<b>Grand Total</b>
	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	
Brand	9	11	14	20	16	70
Price	10	13	20	15	12	70
Product	2	9	9	20	30	70
<b>Grand Total</b>	<b>21</b>	<b>33</b>	<b>43</b>	<b>55</b>	<b>58</b>	<b>210</b>

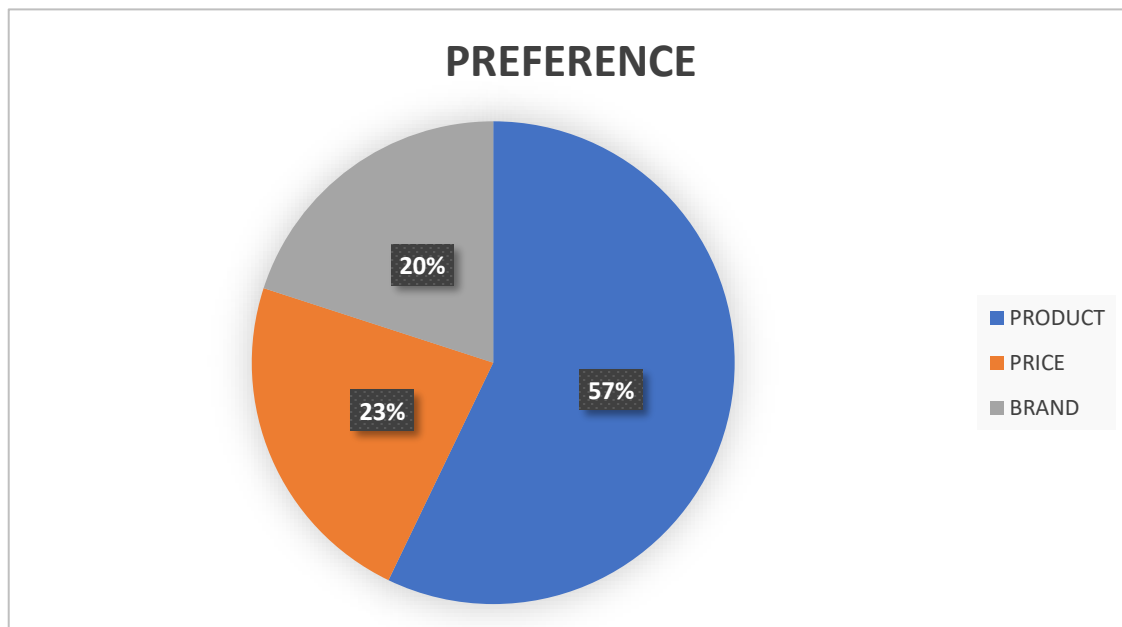
**Figure 9.5:** Line graph for Factor Importance



**Table 8:** Factor importance indicated by preference

	<b>PRODUCT</b>	<b>PRICE</b>	<b>BRAND</b>	<b>Grand Total</b>
PREFERENCE	57,14%	22,86%	20,00%	100,00%

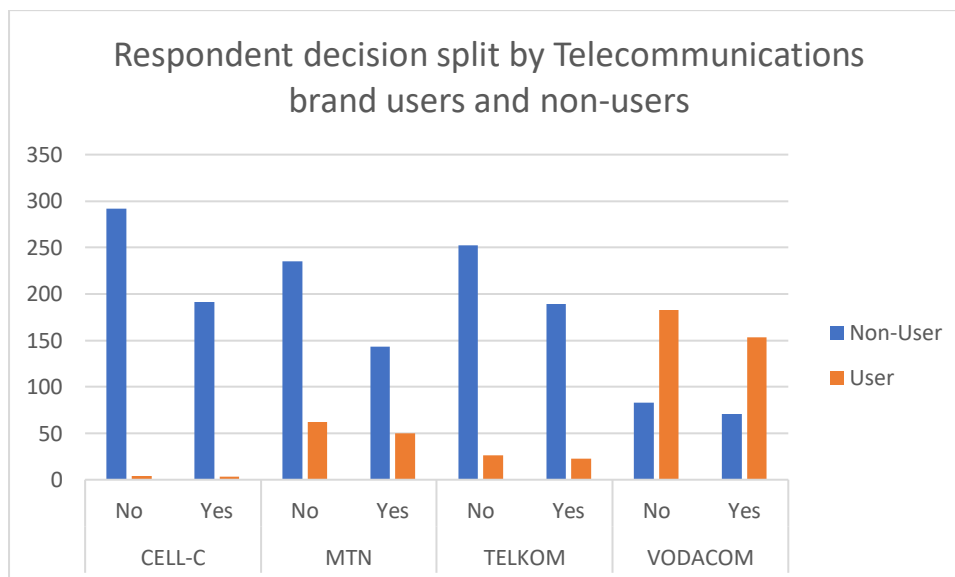
**Figure 9.6:** Pie Chart indicating preference for factors influencing consumer decision making



**Table 9:** Consumer decision based on brand use for stimuli for each brand

Stimulus Brand	Brand User		Grand Total
	Non-User	User	
<b>CELL-C</b>	<b>483</b>	<b>7</b>	<b>490</b>
No	292	4	296
Yes	191	3	194
<b>MTN</b>	<b>378</b>	<b>112</b>	<b>490</b>
No	235	62	297
Yes	143	50	193
<b>TELKOM</b>	<b>441</b>	<b>49</b>	<b>490</b>
No	252	26	278
Yes	189	23	212
<b>VODACOM</b>	<b>154</b>	<b>336</b>	<b>490</b>
No	83	183	266
Yes	71	153	224
<b>Grand Total</b>	<b>1456</b>	<b>504</b>	<b>1960</b>

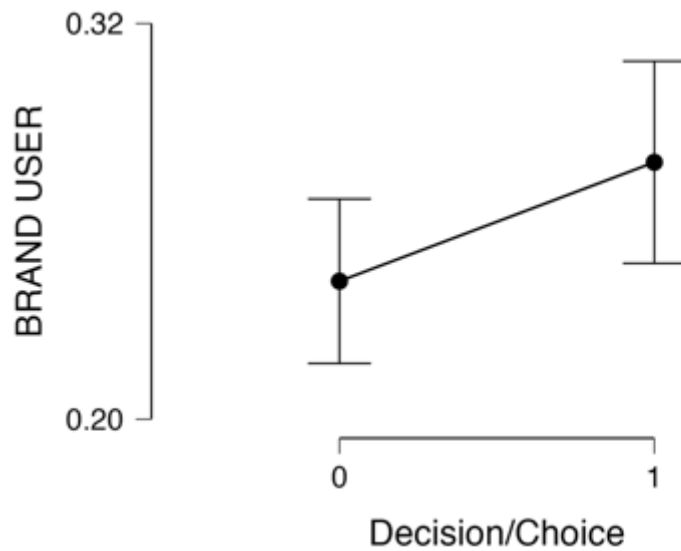
**Figure 9.7:** Consumer decision based on brand use for stimuli for each brand



**Table 10:** Descriptive statistics for brand users and decision

	Group	N	Mean	SD	SE	Coefficient of variation
Brand User	0	1137	0.242	0.428	0.013	1.771
	1	824	0.278	0.448	0.016	1.613

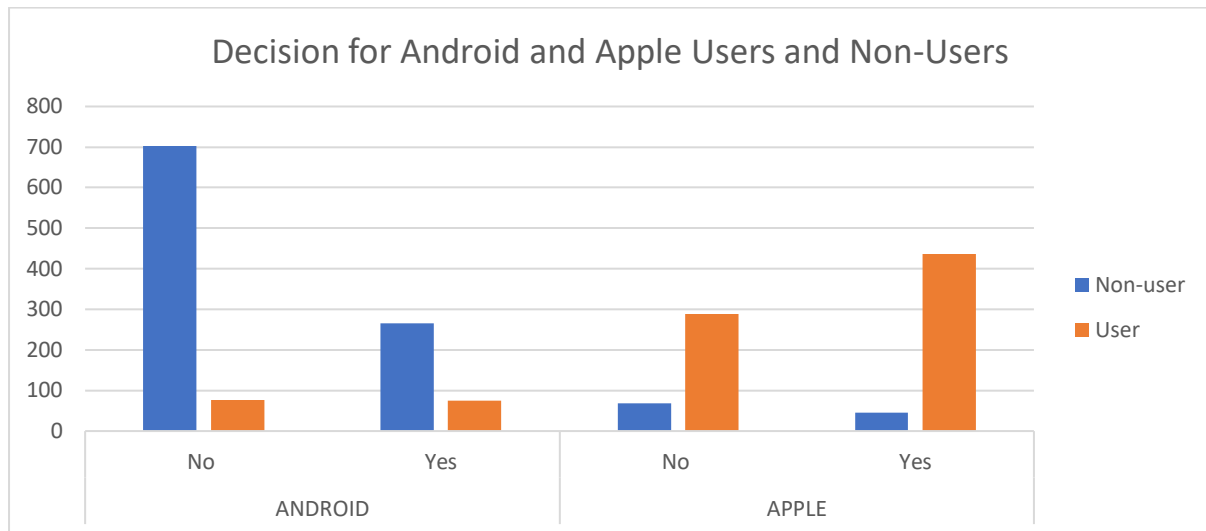
**Figure 9.8:** Descriptive plot for brand users and decision



**Table 11:** Consumer decision based on mobile operating system/product use for stimuli for each brand

Stimulus Product	Mobile operating system user		
	Non-user	User	Grand Total
<b>ANDROID</b>	<b>968</b>	<b>152</b>	<b>1120</b>
No	702	77	779
Yes	266	75	341
<b>APPLE</b>	<b>114</b>	<b>726</b>	<b>840</b>
No	69	289	358
Yes	45	437	482
<b>Grand Total</b>	<b>1082</b>	<b>878</b>	<b>1960</b>

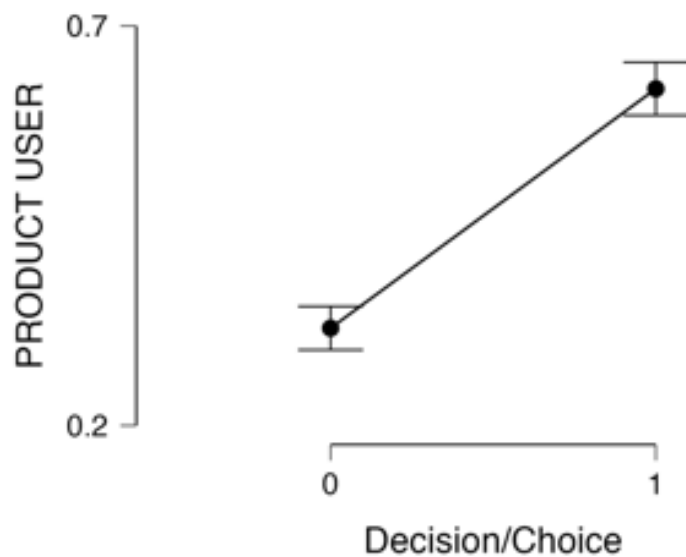
**Figure 9.9:** Consumer decision based on mobile operating system/product use for stimuli for each brand



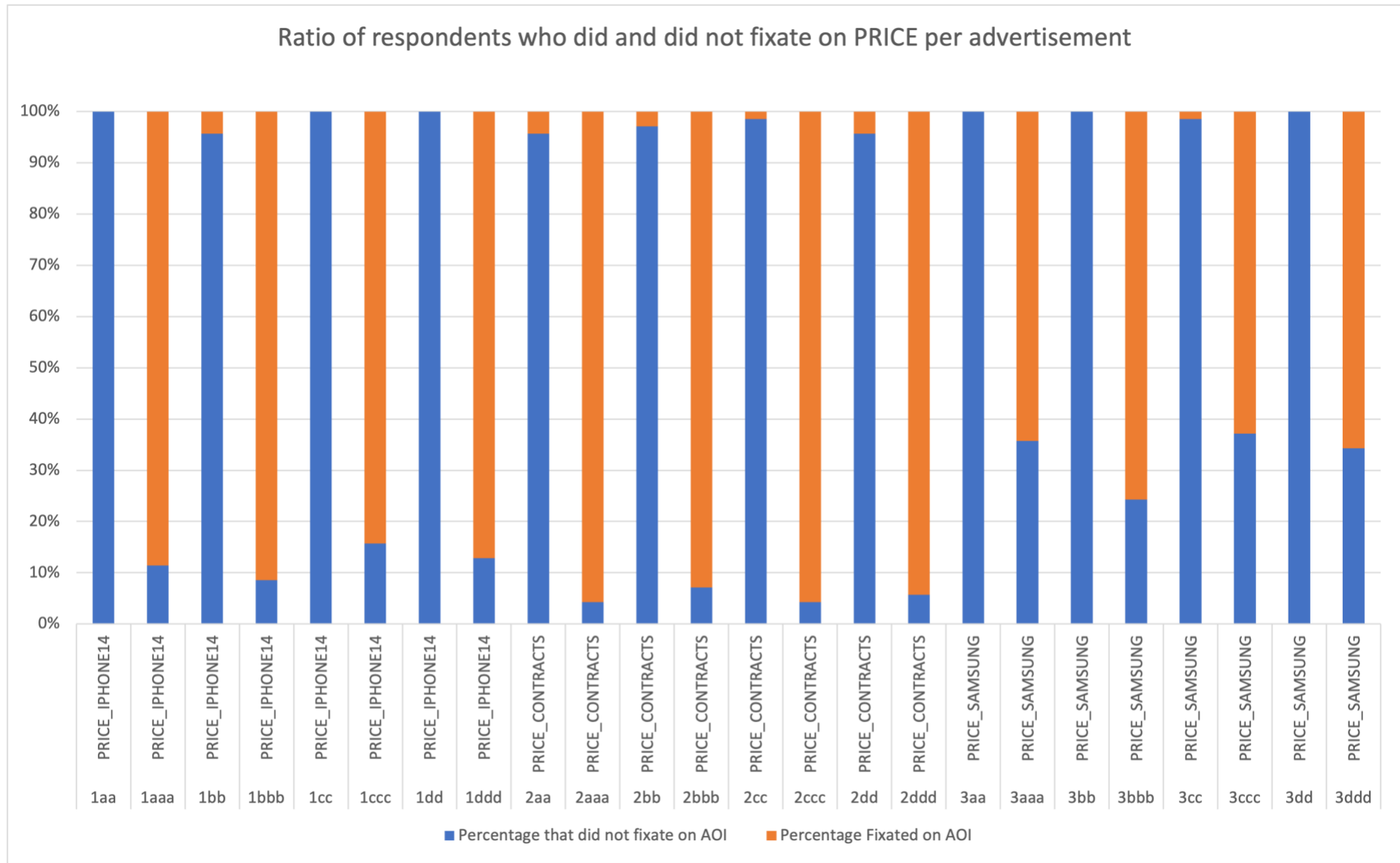
**Table 12:** Descriptive statistics for mobile operating system/product users and decision

	Group	N	Mean	SD	SE	Coefficient of variation
Product	0	1137	0.322	0.467	0.014	1.452
User	1	824	0.621	0.485	0.017	0.781

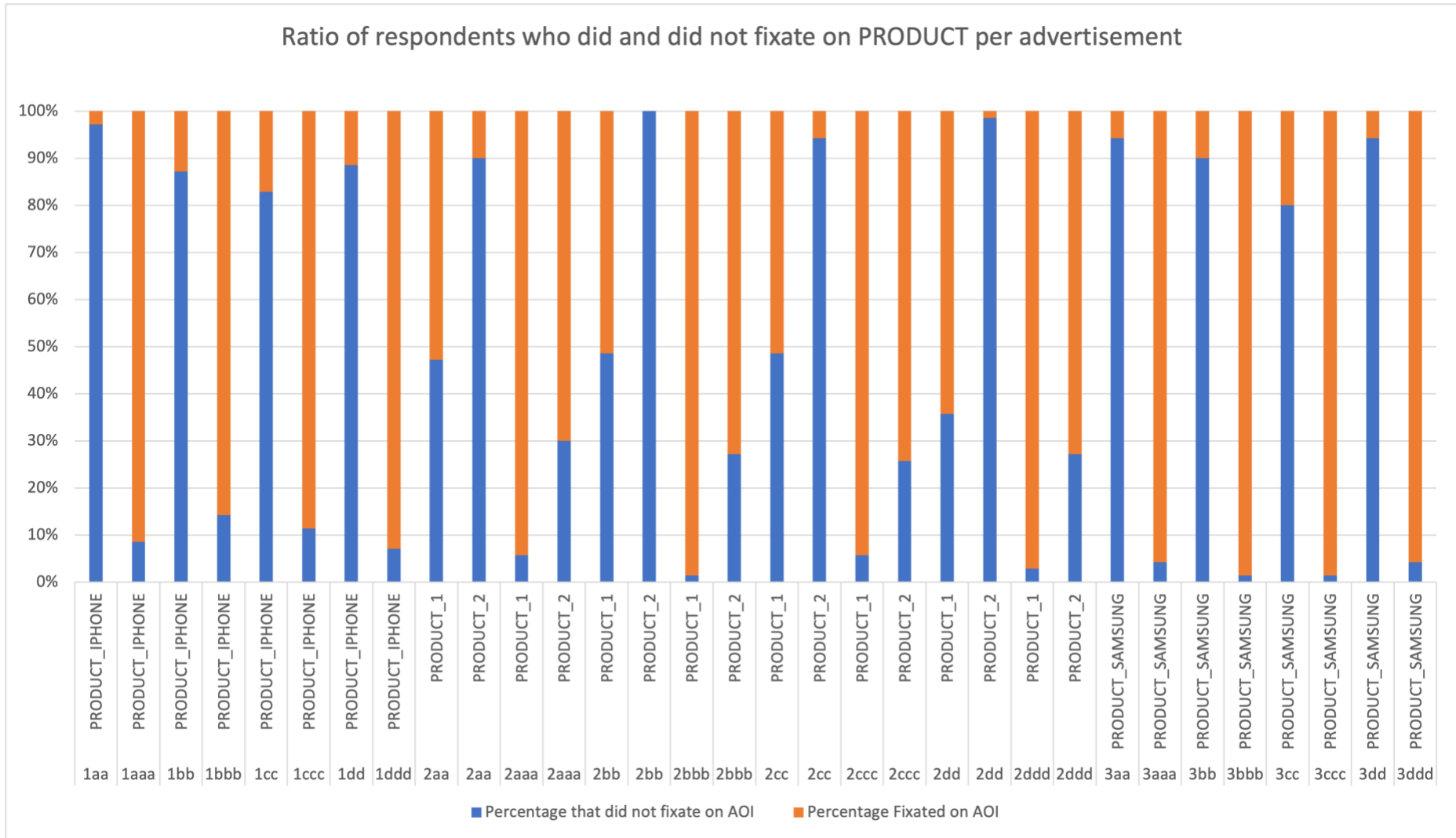
**Figure 9.10:** Descriptive plots for b mobile operating system/product users and decision



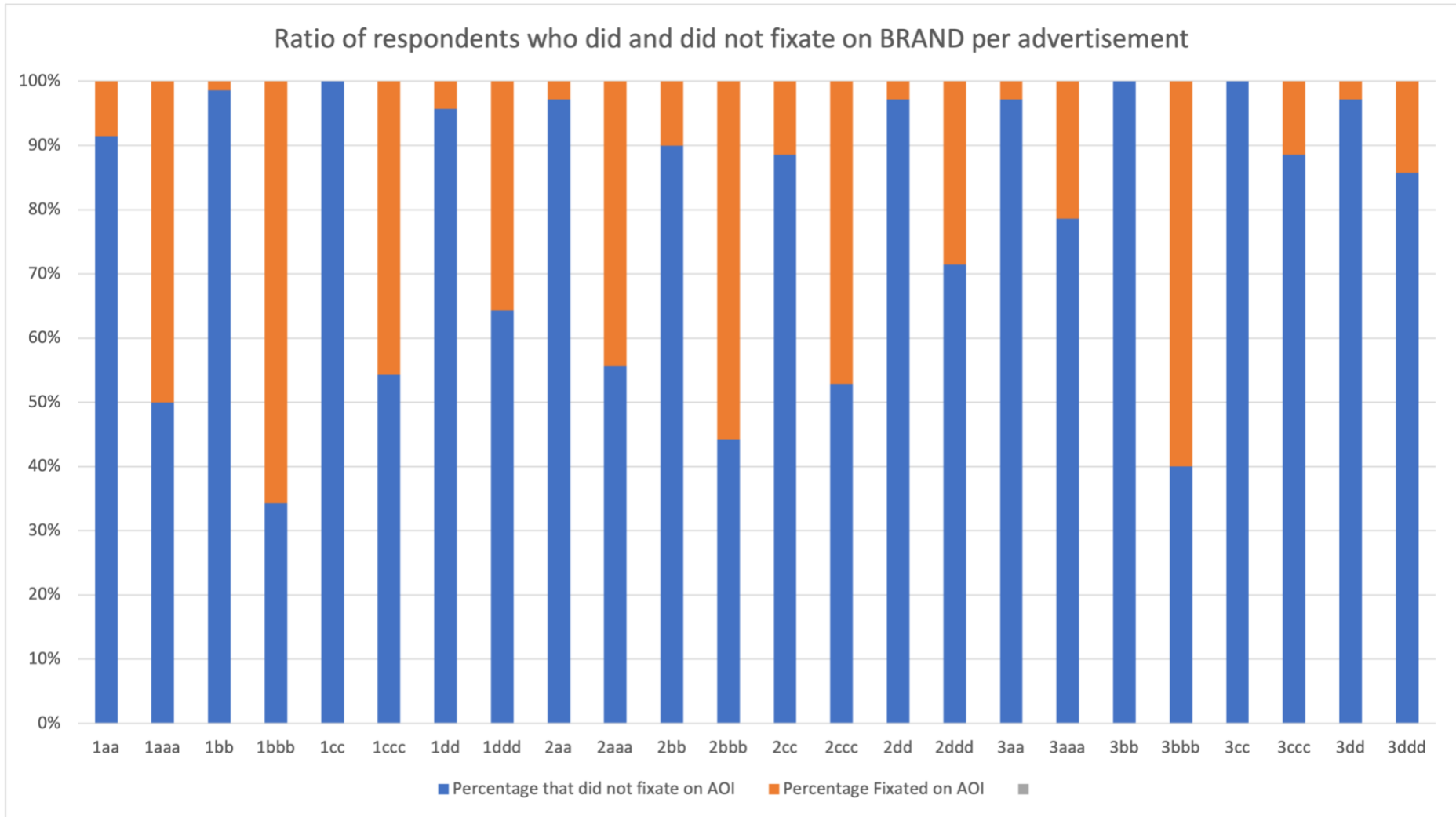
**Figure 9.11.1:** Stacked bar graph showing the ratio of respondents who did and did not fixate on **price** per advertisement



**Figure 9.11.2:** Stacked bar graph showing the ratio of respondents who did and did not fixate on **product** per advertisement

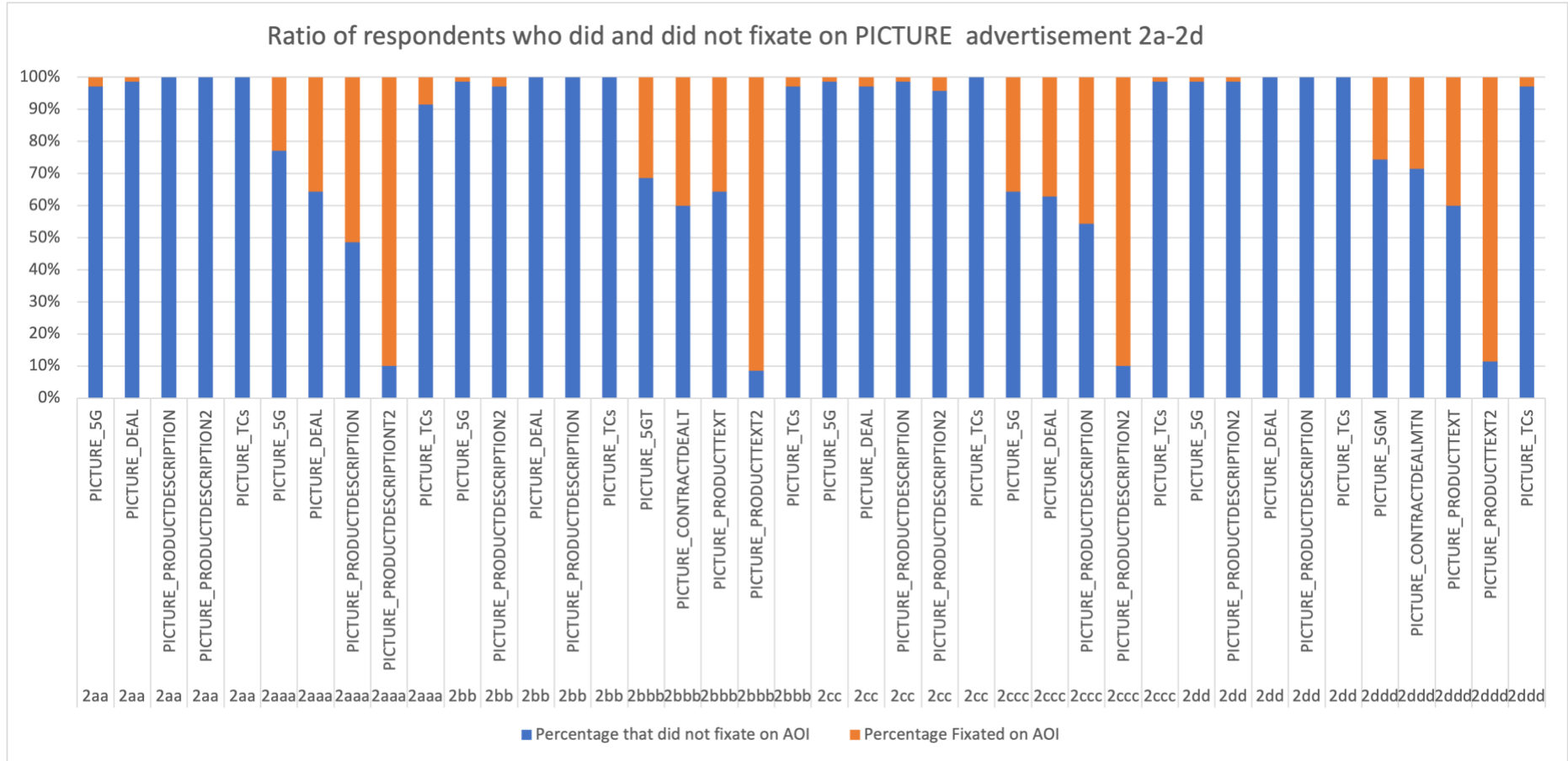


**Figure 9.11.3:** Stacked bar graph showing the ratio of respondents who did and did not fixate on **brand** per advertisement

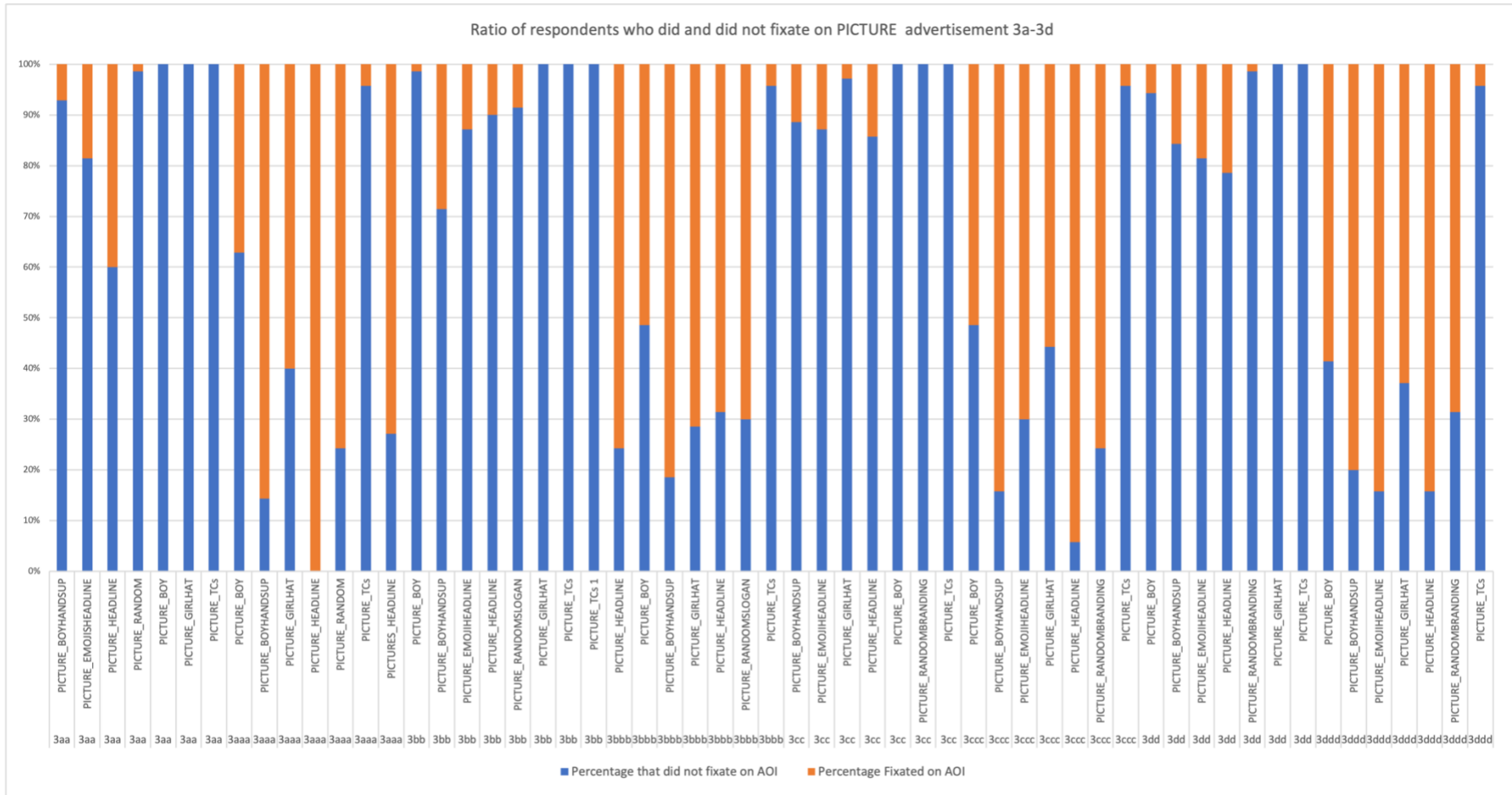




**Figure 9.11.5:** Stacked bar graph showing the ratio of respondents who did and did not fixate on **pictures** in advertisement 2a-2d



**Figure 9.11.6:** Stacked bar graph showing the ratio of respondents who did and did not fixate on **pictures** in advertisement 3a-3d

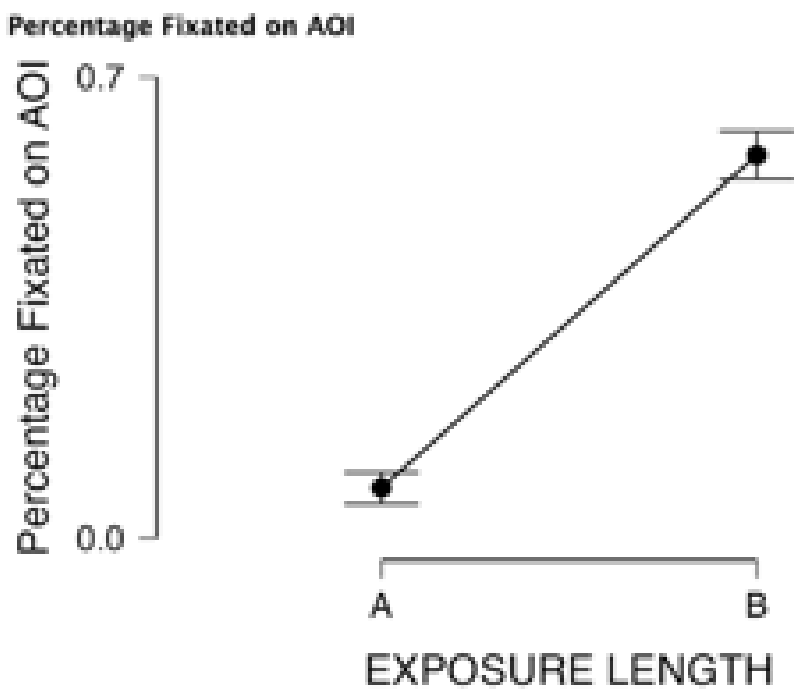


**Table 13:** Descriptive statistics for Percentage of Respondent Fixations on AOIs split by exposure length of Stimulus.

Group	N	Mean	SD	SE	Coefficient of variation
Percentage A	107	0.076	0.126	0.012	1.656
Fixated on AOI B	262	0.582	0.300	0.019	0.515

**Figure 9.12:** Descriptive plots for Percentage of Respondent Fixations on AOIs split by exposure length of Stimulus.

**Percentage Fixated on AOI**



APPENDIX F: Inferential Statistics: Tests for Normality, H1a, H1b, H2a, H2b, H3, User, Exposure  
time

**TESTS FOR NORMALITY**

**HYPOTHESIS 1A: TESTS OF NORMALITY**

**Table 14.1:** Shapiro-Wilk Test for TFD for Task 2 and 3

		<b>W</b>	<b>p</b>
TFD	0	0.809	< .001
	1	0.837	< .001

**Table 14.2:** Shapiro-Wilk Test for TFD for Task 2

		<b>W</b>	<b>p</b>
TFD	0	0.810	< .001
	1	0.859	< .001

**Table 14.3:** Shapiro-Wilk Test for TFD for Task 3

		<b>W</b>	<b>p</b>
TFD	0	0.808	< .001
	1	0.816	< .001

**Table 14.5:** Shapiro-Wilk Test for TFD and Decision for Task 3 excluding pictures

		<b>W</b>	<b>p</b>
TFD	0	0.784	< .001
	1	0.797	< .001

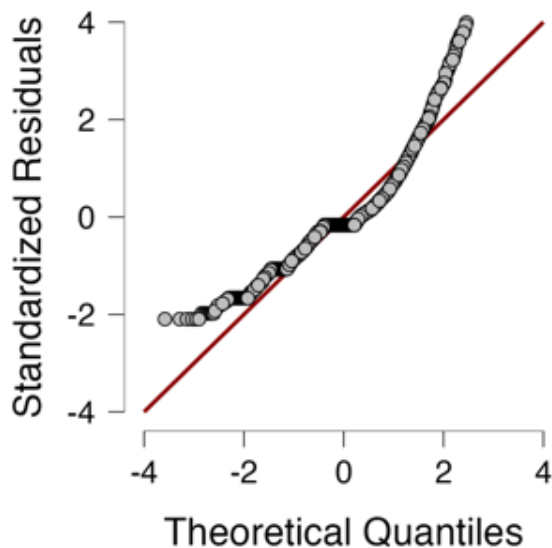
**Table 14.5:** Shapiro-Wilk Test for TFD and Preferred AOIs and Decision to purchase for Task 3

		<b>W</b>	<b>p</b>
TFD	0	0.772	< .001
	1	0.901	< .001

**Table 14.6:** Levene’s test Equality of Variances for TFD

<b>F</b>	<b>df1</b>	<b>df2</b>	<b>p</b>
175.321	5.000	2934.000	< .001

**Figure 10.1:** Q-Q Plot for Total Fixation Duration

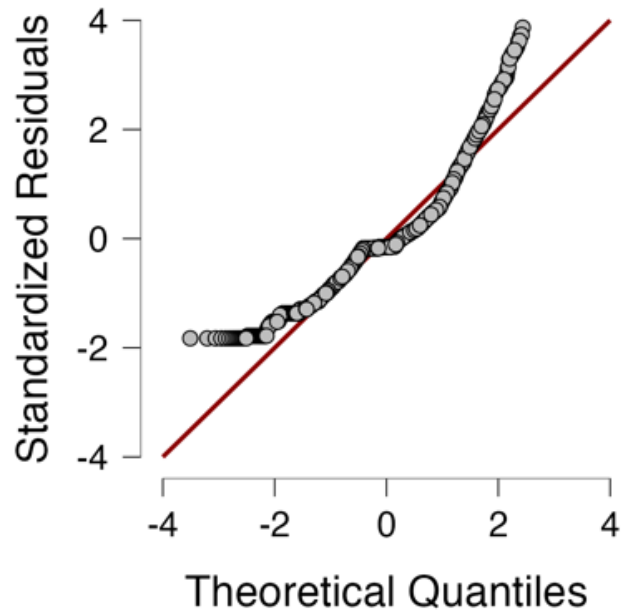


## HYPOTHESIS 1B: TESTS OF NORMALITY

**Table 14.6:** Levene's test Equality of Variances for TFD

<b>F</b>	<b>df1</b>	<b>df2</b>	<b>p</b>
56.491	14.000	2213.000	< .001

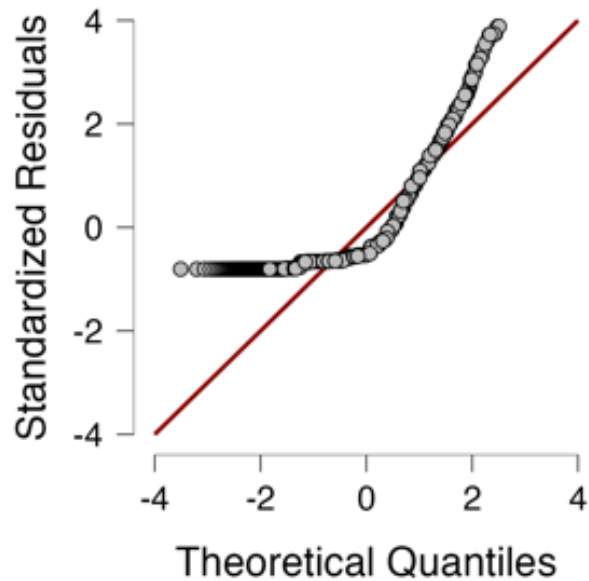
**Figure 10.2:** Q-Q Plot for Total Fixation Duration



**Table 14.7:** Levene's test Equality of Variances for Fixation Count

<b>F</b>	<b>df1</b>	<b>df2</b>	<b>p</b>
2.532	14.000	2213.000	.001

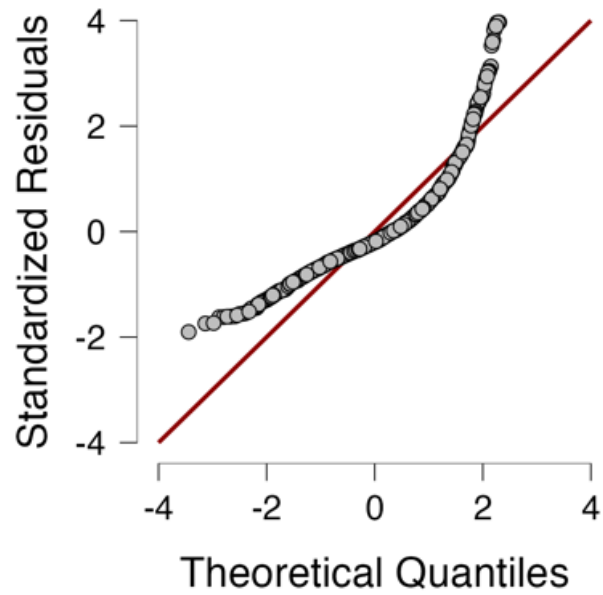
**Figure 10.3:** Q-Q Plot for Fixation Count



**Table 14.8:** Levene's test Equality of Variances for FFD

F	df1	df2	p
20.060	14.000	1722.000	< .001

**Figure 10.4:** Q-Q Plot for First Fixation Duration



## HYPOTHESIS 2A: TESTS OF NORMALITY

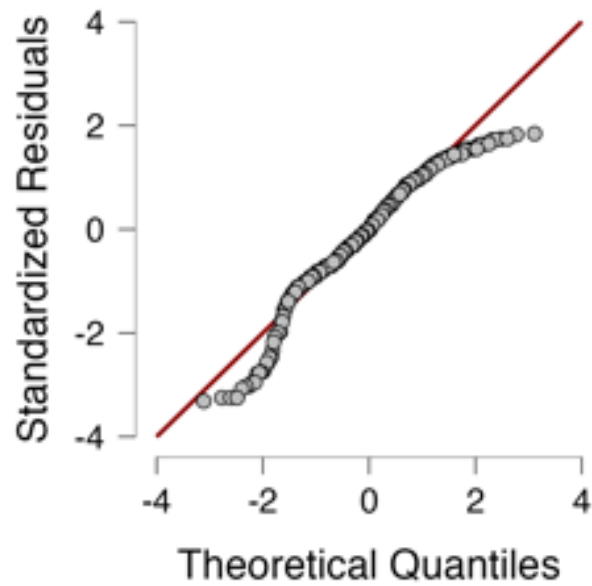
**Table 14.9:** Shapiro-Wilk Test for TTFF and Memory Recall

		<b>W</b>	<b>p</b>
TTFF	0	0.960	< .001
	1	0.955	< .001

**Table 14.10:** Levene's Test for equality of variances for TTFF and Memory Recall

<b>F</b>	<b>df1</b>	<b>df2</b>	<b>p</b>
1.030	7.000	530.000	0.409

**Figure 10.5:** Q-Q Plot for TTFF



## HYPOTHESIS 2B: TESTS OF NORMALITY

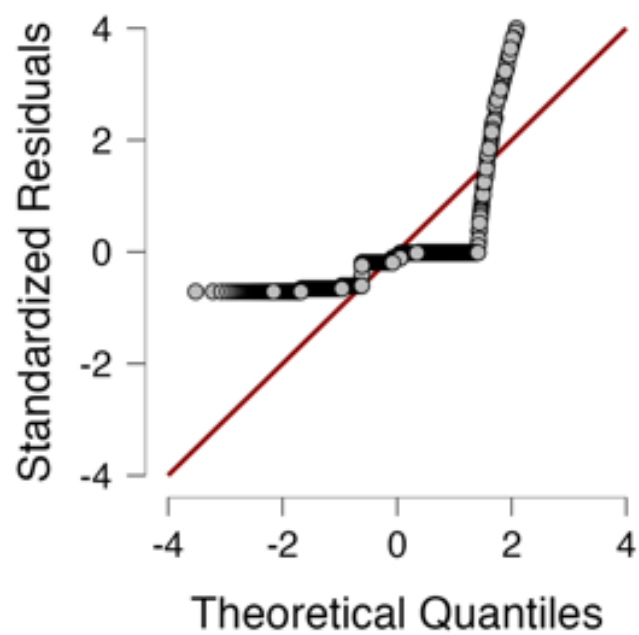
**Table 14.11:** Shapiro-Wilk Test for TFD and Memory Recall

		<b>W</b>	<b>p</b>
TFD	0	0.245	< .001
	1	0.333	< .001

**Table 14.12:** Levene's Test for equality of variance for TFD and Memory Recall

<b>F</b>	<b>df1</b>	<b>df2</b>	<b>p</b>
106.698	7.000	2281.000	< .001

**Figure 10.6:** Q-Q Plot for TFD



### **HYPOTHESIS 3: TESTS OF NORMALITY**

**Table 14.13:** Shapiro-Wilk Test for TFD and Preference

		<b>W</b>	<b>p</b>
TFD	0	0.752	< .001
	1	0.850	< .001

**Table 14.14:** Shapiro-Wilk Test for TFD and Preference

		<b>W</b>	<b>p</b>
Fixation Count	0	0.835	< .001
	1	0.918	< .001

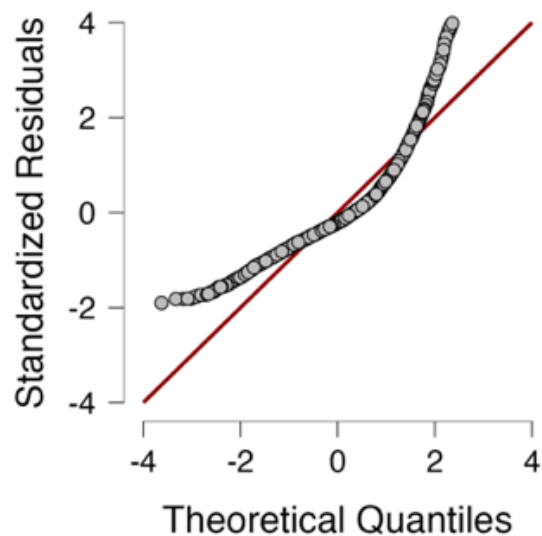
**Table 14.15:** Shapiro-Wilk Test for TFD and Preference

		<b>W</b>	<b>p</b>
FFD	0	0.477	< .001
	1	0.538	< .001

**Table 14.16:** Levene's Test for equality of variances for Total Fixation Duration and Preference

<b>F</b>	<b>df1</b>	<b>df2</b>	<b>p</b>
38.526	11.000	3439.000	< .001

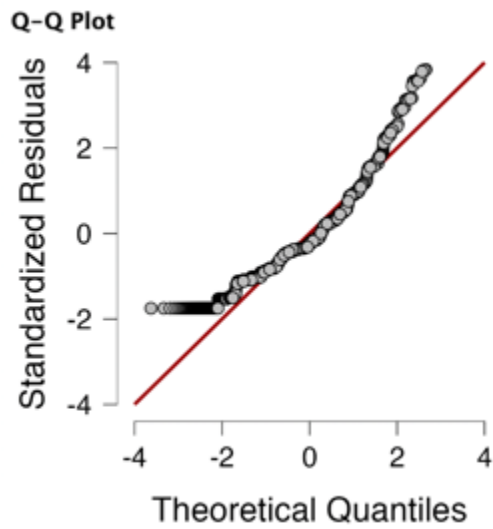
**Figure 10.7:** Q-Q Plot for Total Fixation Duration



**Table 14.17:** Levene's Test for equality of variances for Fixation count and Preference

<b>F</b>	<b>df1</b>	<b>df2</b>	<b>p</b>
31.934	11.000	3439.000	< .001

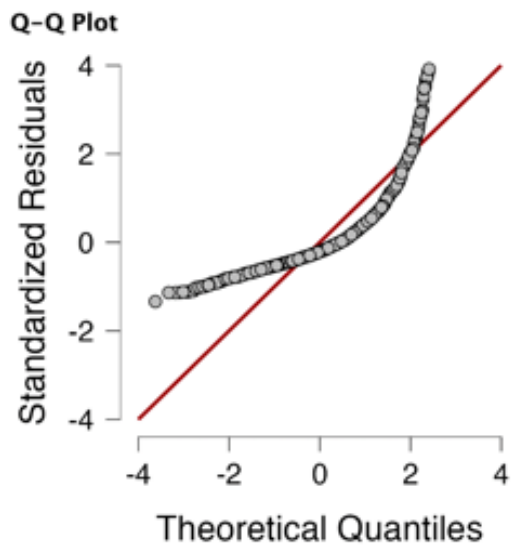
**Figure 10.8:** Q-Q Plot for Fixation Count



**Table 14.18:** Levene's Test for equality of variances for First Fixation Duration and Preference

<b>F</b>	<b>df1</b>	<b>df2</b>	<b>p</b>
6.522	11.000	3439.000	< .001

**Figure 10.9:** Q-Q Plot for First Fixation Duration



**Tests for normality for telecommunications brands and mobile operating system users and exposure time:**

**Table 14.19:** Shapiro-Wilk Test for Normality for product/mobile operating system user and decision

		<b>W</b>	<b>p</b>
PRODUCT USER	0	0.589	< .001
	1	0.615	< .001

**Table 14.20:** Shapiro-Wilk Test for Normality for percentage of fixations on AOI and exposure length

		<b>W</b>	<b>p</b>
BRAND USER	0	0.531	< .001
	1	0.560	< .001

**Table 14.21:** Shapiro-Wilk Test for Normality for percentage of fixations on AOI and exposure length

		<b>W</b>	<b>p</b>
Percentage Fixated on AOI	0	0.643	< .001
	1	0.917	< .001

## Hypothesis 1A

**Table 15.1:** Binomial test for Decision in Task 2B and 3

Variable	Level	Counts	Total	Proportion	p
Decision	0	3283	5509	0.596	< .001
	1	2226	5509	0.404	< .001

**Table 15.2:** Binomial test for Decision and preference in Task 3

Variable	Level	Counts	Total	Proportion	p
Decision	0	1782	2940	0.606	< .001
	1	1158	2940	0.394	< .001
Preference	0	2052	2940	0.698	< .001
	1	888	2940	0.302	< .001

**Table 15.3:** Marginal means for TFD split by Feature type (AOIs) and preference when decided to purchase for Task 3

Preferred and said yes	Type	Marginal Mean	95% CI for Mean Difference		SE
			Lower	Upper	
0	BRAND	0.114	0.072	0.157	0.022
1		0.210	0.064	0.357	0.075
0	PRICE	0.738	0.692	0.784	0.024
1		1.363	1.242	1.484	0.062
0	PRODUCT	1.153	1.101	1.204	0.026
1		1.445	1.334	1.557	0.057

**Table 15.4:** Dunn's Post Hoc Comparisons for TFD for preference when decided to purchase for Task 3

COMPARISON	Z	W <sub>I</sub>	W <sub>J</sub>	P	P <sub>BONF</sub>	P <sub>HOLM</sub>
0 - 1	-10.257	1411.578	1892.774	< .001	< .001	< .001

**Table 15.5:** Dunn's Post Hoc Comparisons for TFD for Feature type (AOIs)

COMPARISON	Z	W <sub>I</sub>	W <sub>J</sub>	P	P <sub>BONF</sub>	P <sub>HOLM</sub>
BRAND - PRICE	-24.792	802.890	1707.126	< .001	< .001	< .001
BRAND - PRODUCT	-33.676	802.890	2084.583	< .001	< .001	< .001
PRICE - PRODUCT	-9.627	1707.126	2084.583	< .001	< .001	< .001

## **Hypothesis 1B**

**Table 16.1:** Dunn's Post Hoc Comparisons for Factor Importance (Total Fixation Duration)

<b>COMPARISON</b>	<b>Z</b>	<b>W<sub>I</sub></b>	<b>W<sub>J</sub></b>	<b>P</b>	<b>P<sub>BONF</sub></b>	<b>P<sub>HOLM</sub></b>
1 - 2	-2.698	930.591	1076.322	0.007	0.070	0.035
1 - 3	-2.766	930.591	1072.763	0.006	0.057	0.034
1 - 4	-4.323	930.591	1146.597	< .001	< .001	< .001
1 - 5	-5.617	930.591	1210.337	< .001	< .001	< .001
2 - 3	0.080	1076.322	1072.763	0.936	1.000	0.936
2 - 4	-1.646	1076.322	1146.597	0.100	0.998	0.261
2 - 5	-3.153	1076.322	1210.337	0.002	0.016	0.011
3 - 4	-1.876	1072.763	1146.597	0.061	0.606	0.242
3 - 5	-3.515	1072.763	1210.337	< .001	0.004	0.004
4 - 5	-1.712	1146.597	1210.337	0.087	0.869	0.261

**Table 16.2:** Dunn's Post Hoc Comparisons for Type (Total Fixation Duration)

<b>COMPARISON</b>	<b>Z</b>	<b>W<sub>I</sub></b>	<b>W<sub>J</sub></b>	<b>P</b>	<b>P<sub>BONF</sub></b>	<b>P<sub>HOLM</sub></b>
BRAND - PRICE	-25.636	561.126	1376.894	< .001	< .001	< .001
BRAND - PRODUCT	-25.914	561.126	1445.986	< .001	< .001	< .001
PRICE - PRODUCT	-2.056	1376.894	1445.986	0.040	0.119	0.040

**Table 16.3:** Dunn's Post Hoc Comparisons for Factor Importance (Fixation Count)

<b>COMPARISON</b>	<b>Z</b>	<b>W<sub>I</sub></b>	<b>W<sub>J</sub></b>	<b>P</b>	<b>P<sub>BONF</sub></b>	<b>P<sub>HOLM</sub></b>
1 - 2	-2.150	1055.656	1165.478	0.032	0.316	0.316
1 - 3	-0.826	1055.656	1095.802	0.409	1.000	1.000
1 - 4	-1.456	1055.656	1124.493	0.145	1.000	1.000
1 - 5	-1.179	1055.656	1111.197	0.238	1.000	1.000
2 - 3	1.660	1165.478	1095.802	0.097	0.969	0.872
2 - 4	1.015	1165.478	1124.493	0.310	1.000	1.000
2 - 5	1.350	1165.478	1111.197	0.177	1.000	1.000
3 - 4	-0.771	1095.802	1124.493	0.441	1.000	1.000
3 - 5	-0.416	1095.802	1111.197	0.677	1.000	1.000
4 - 5	0.378	1124.493	1111.197	0.706	1.000	1.000

**Table 16.4:** Dunn's Post Hoc Comparisons for Type (Fixation Count)

<b>COMPARISON</b>	<b>Z</b>	<b>W<sub>I</sub></b>	<b>W<sub>J</sub></b>	<b>P</b>	<b>P<sub>BONF</sub></b>	<b>P<sub>HOLM</sub></b>
BRAND - PRICE	1.910	1129.554	1072.074	0.056	0.168	0.112
BRAND - PRODUCT	-0.691	1129.554	1151.861	0.490	1.000	0.490
PRICE - PRODUCT	-2.510	1072.074	1151.861	0.012	0.036	0.036

**Table 16.5:** Dunn's Post Hoc Comparisons for Factor Importance (First Fixation Duration)

COMPARISON	Z	W <sub>I</sub>	W <sub>J</sub>	P	P <sub>BONF</sub>	P <sub>HOLM</sub>
1 - 2	1.296	938.468	872.846	0.195	1.000	1.000
1 - 3	1.255	938.468	877.497	0.209	1.000	1.000
1 - 4	1.594	938.468	863.887	0.111	1.000	0.998
1 - 5	2.030	938.468	844.889	0.042	0.423	0.423
2 - 3	-0.114	872.846	877.497	0.909	1.000	1.000
2 - 4	0.232	872.846	863.887	0.816	1.000	1.000
2 - 5	0.741	872.846	844.889	0.458	1.000	1.000
3 - 4	0.380	877.497	863.887	0.704	1.000	1.000
3 - 5	0.935	877.497	844.889	0.350	1.000	1.000
4 - 5	0.587	863.887	844.889	0.557	1.000	1.000

**Table 16.6:** Dunn's Post Hoc Comparisons for Type (First Fixation Duration)

COMPARISON	Z	W <sub>I</sub>	W <sub>J</sub>	P	P <sub>BONF</sub>	P <sub>HOLM</sub>
BRAND - PRICE	-8.529	733.349	1027.266	< .001	< .001	< .001
BRAND - PRODUCT	-1.202	733.349	774.463	0.229	0.688	0.229
PRICE - PRODUCT	9.537	1027.266	774.463	< .001	< .001	< .001

## Hypothesis 2A

**Table 17.1:** Binomial Test for Memory Recall and Type (Time to First Fixation)

Variable	Level	Counts	Total	Proportion	p
Recall	No	234	538	0.435	0.003
	Yes	304	538	0.565	0.003
Type	BRAND	32	538	0.059	< .001
	PICTURE	275	538	0.511	0.635
	PRICE	13	538	0.024	< .001
	PRODUCT	218	538	0.405	< .001

**Table 17.2:** ANOVA Results for Memory Recall and Type (Time to First Fixation)

Cases	Sum of Squares	df	Mean Square	F	p	$\eta^2$
Memory Recall	0.005	1	0.005	0.454	0.501	$8.372 \times 10^{-4}$
Type	0.089	3	0.030	2.806	0.039	0.016
Memory Recall * Type	0.039	3	0.013	1.230	0.298	0.007
Residuals	5.573	530	0.011			

**Table 17.3:** Post Hoc Comparisons for Memory Recall (Time to First Fixation)

		Mean Difference	SE	t	p <sub>tukey</sub>
0	1	-0.015	0.022	-0.673	0.501

**Table 17.4:** Post Hoc Comparisons for Feature Type (Time to First Fixation)

		Mean Difference	SE	t	p <sub>tukey</sub>
BRAND	PICTURE	0.001	0.032	0.034	1.000
	PRICE	0.016	0.043	0.374	0.982
	PRODUCT	0.028	0.032	0.885	0.813
PICTURE	PRICE	0.015	0.030	0.497	0.960
	PRODUCT	0.027	0.009	2.868	0.022
PRICE	PRODUCT	0.012	0.030	0.407	0.977

**Hypothesis 2B**

**Table 18.1:** Binomial Test for Memory Recall and Type (Total Fixation Duration)

<b>Variable</b>	<b>Level</b>	<b>Counts</b>	<b>Total</b>	<b>Proportion</b>	<b>p</b>
Memory Recall	No	1307	2289	0.571	< .001
	Yes	982	2289	0.429	< .001
Type	BRAND	748	2289	0.327	< .001
	PICTURE	147	2289	0.064	< .001
	PRICE	782	2289	0.342	< .001
	PRODUCT	612	2289	0.267	< .001

**Table 18.2:** Dunn's Post Hoc Comparisons for Memory Recall and Type (Total Fixation Duration)

<b>COMPARISON</b>	<b>Z</b>	<b>W<sub>I</sub></b>	<b>W<sub>J</sub></b>	<b>P</b>	<b>P<sub>BONF</sub></b>	<b>P<sub>HOLM</sub></b>
BRAND - PICTURE	-8.774	1101.108	1350.218	< .001	< .001	< .001
BRAND - PRICE	2.228	1101.108	1065.248	0.026	0.155	0.026
BRAND - PRODUCT	-8.754	1101.108	1251.258	< .001	< .001	< .001
PICTURE - PRICE	10.073	1350.218	1065.248	< .001	< .001	< .001
PICTURE - PRODUCT	3.424	1350.218	1251.258	< .001	0.004	0.001
PRICE - PRODUCT	-10.952	1065.248	1251.258	< .001	< .001	< .001

**Table 18.3:** Dunn's Post Hoc Comparisons for Memory Recall (Total Fixation Duration)

<b>Comparison</b>	<b>z</b>	<b>W<sub>i</sub></b>	<b>W<sub>j</sub></b>	<b>P</b>	<b>P<sub>bonf</sub></b>	<b>P<sub>holm</sub></b>
No - Yes	-3.865	1122.962	1174.332	< .001	< .001	< .001

### Hypothesis 3

**Table 19.1:** Dunn's Post Hoc Comparisons for Feature Type (Total Fixation Duration)

COMPARISON	Z	W <sub>I</sub>	W <sub>J</sub>	P	P <sub>BONF</sub>	P <sub>HOLM</sub>
BRAND - PICTURE	-10.365	948.579	1562.987	< .001	< .001	< .001
BRAND - PRICE	-14.640	948.579	1836.421	< .001	< .001	< .001
BRAND - PRODUCT	-18.990	948.579	2080.064	< .001	< .001	< .001
PICTURE - PRICE	-6.144	1562.987	1836.421	< .001	< .001	< .001
PICTURE - PRODUCT	-12.013	1562.987	2080.064	< .001	< .001	< .001
PRICE - PRODUCT	-5.426	1836.421	2080.064	< .001	< .001	< .001

**Table 19.2:** Dunn's Post Hoc Comparisons for Preference (Total Fixation Duration)

COMPARISON	Z	W <sub>I</sub>	W <sub>J</sub>	P	P <sub>BONF</sub>	P <sub>HOLM</sub>
BRAND - PRICE	0.710	1712.718	1676.343	0.478	1.000	0.745
BRAND - PRODUCT	-0.891	1712.718	1751.845	0.373	1.000	0.745
PRICE - PRODUCT	-1.816	1676.343	1751.845	0.069	0.208	0.208

**Table 19.3:** Dunn's Post Hoc Comparisons for Feature Type (Fixation Count)

COMPARISON	Z	W <sub>I</sub>	W <sub>J</sub>	P	P <sub>BONF</sub>	P <sub>HOLM</sub>
BRAND - PICTURE	-11.151	902.513	1556.156	< .001	< .001	< .001
BRAND - PRICE	-14.511	902.513	1772.691	< .001	< .001	< .001
BRAND - PRODUCT	-21.343	902.513	2160.018	< .001	< .001	< .001
PICTURE - PRICE	-4.921	1556.156	1772.691	< .001	< .001	< .001
PICTURE - PRODUCT	-14.187	1556.156	2160.018	< .001	< .001	< .001
PRICE - PRODUCT	-8.722	1772.691	2160.018	< .001	< .001	< .001

**Table 19.4:** Dunn's Post Hoc Comparisons for Preference (Fixation Count)

COMPARISON	Z	W <sub>I</sub>	W <sub>J</sub>	P	P <sub>BONF</sub>	P <sub>HOLM</sub>
BRAND - PRICE	-1.162	1650.045	1708.936	0.245	0.736	0.413
BRAND - PRODUCT	-2.554	1650.045	1760.872	0.011	0.032	0.032
PRICE - PRODUCT	-1.263	1708.936	1760.872	0.207	0.620	0.413

**Table 19.5:** Dunn's Post Hoc Comparisons for Feature Type (First Fixation Duration)

COMPARISON	Z	W <sub>I</sub>	W <sub>J</sub>	P	P <sub>BONF</sub>	P <sub>HOLM</sub>
BRAND - PICTURE	-3.256	1597.210	1790.235	0.001	0.007	0.003
BRAND - PRICE	-3.807	1597.210	1828.069	< .001	< .001	< .001
BRAND - PRODUCT	-0.315	1597.210	1615.957	0.753	1.000	0.790
PICTURE - PRICE	-0.850	1790.235	1828.069	0.395	1.000	0.790
PICTURE - PRODUCT	4.049	1790.235	1615.957	< .001	< .001	< .001
PRICE - PRODUCT	4.723	1828.069	1615.957	< .001	< .001	< .001

**Table 19.6:** Dunn's Post Hoc Comparisons for Preference (First Fixation Duration)

COMPARISON	Z	W <sub>I</sub>	W <sub>J</sub>	P	P <sub>BONF</sub>	P <sub>HOLM</sub>
BRAND - PRICE	1.160	1770.025	1710.550	0.246	0.738	0.668

COMPARISON	Z	W <sub>I</sub>	W <sub>J</sub>	P	P <sub>BONF</sub>	P <sub>HOLM</sub>
BRAND - PRODUCT	1.219	1770.025	1716.509	0.223	0.668	0.668
PRICE - PRODUCT	-0.143	1710.550	1716.509	0.886	1.000	0.886

**Inferential statistics for Telecommunications Brand and Mobile Operating System Users:**

**Table 20.1:** Mann-Whitney U-test for Product User and Decision

	Test	Statistic	df	p
PRODUCT USER	Mann-Whitney	328164.000	1959	< .001

**Table 20.2:** Mann-Whitney U-test for Brand User and Decision

	Test	Statistic	df	p
BRAND USER	Mann-Whitney	451557.500	1959	0.036

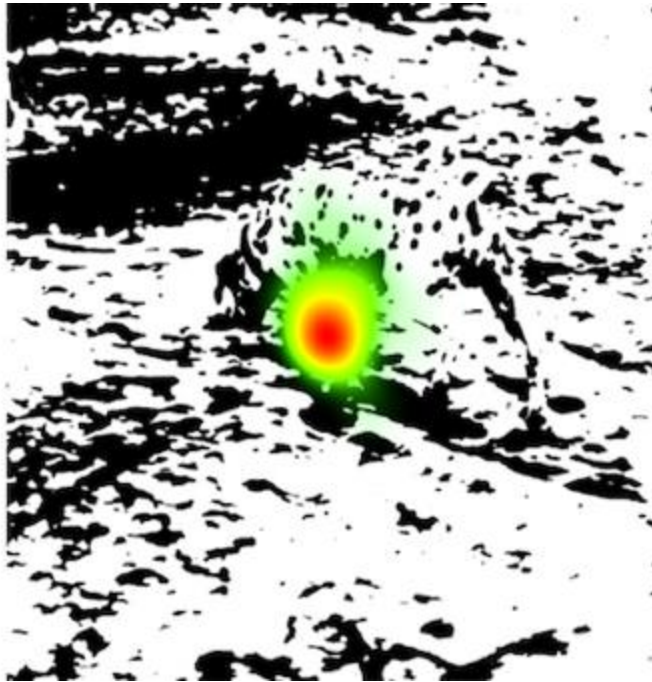
**Inferential Statistics for Exposure Time**

**Table 20.3:** Mann-Whitney U-test for percentage fixated on AOIs during long and short exposures

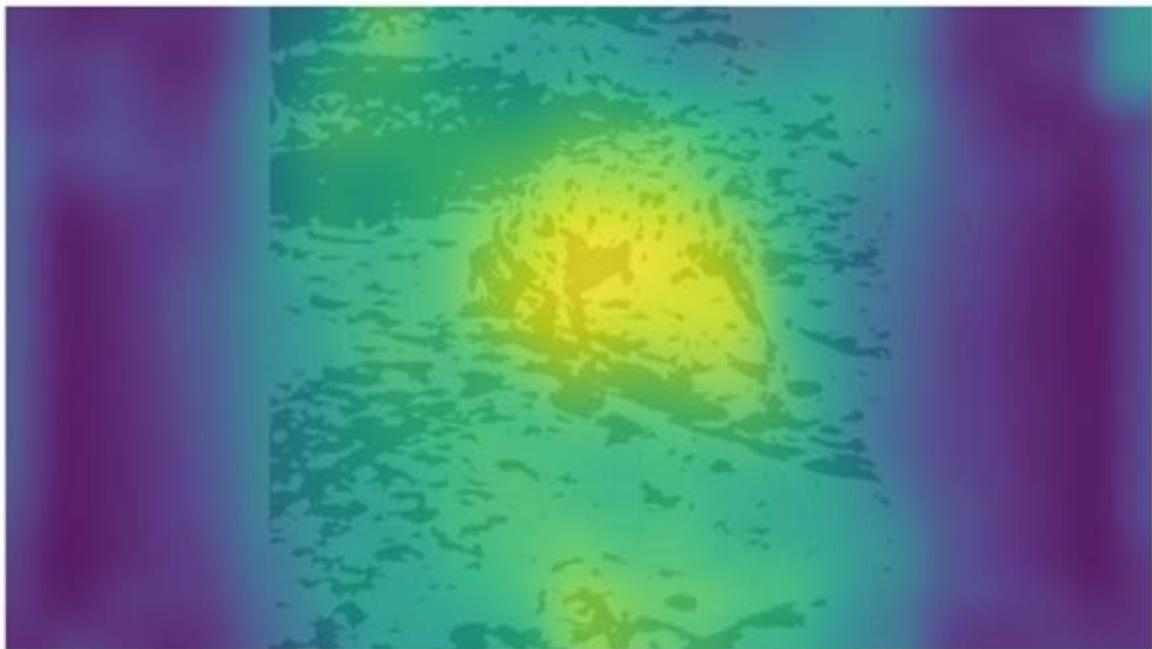
	Test	Statistic	df	p
Percentage Fixated on AOI	Mann-Whitney	2206.500	367	< .001

APPENDIX G: Hypothesis 1c: Heatmaps and DeepGaze IIE Results

**Figure 13.1.1:** Eye tracking heatmap Gestalt image of dog



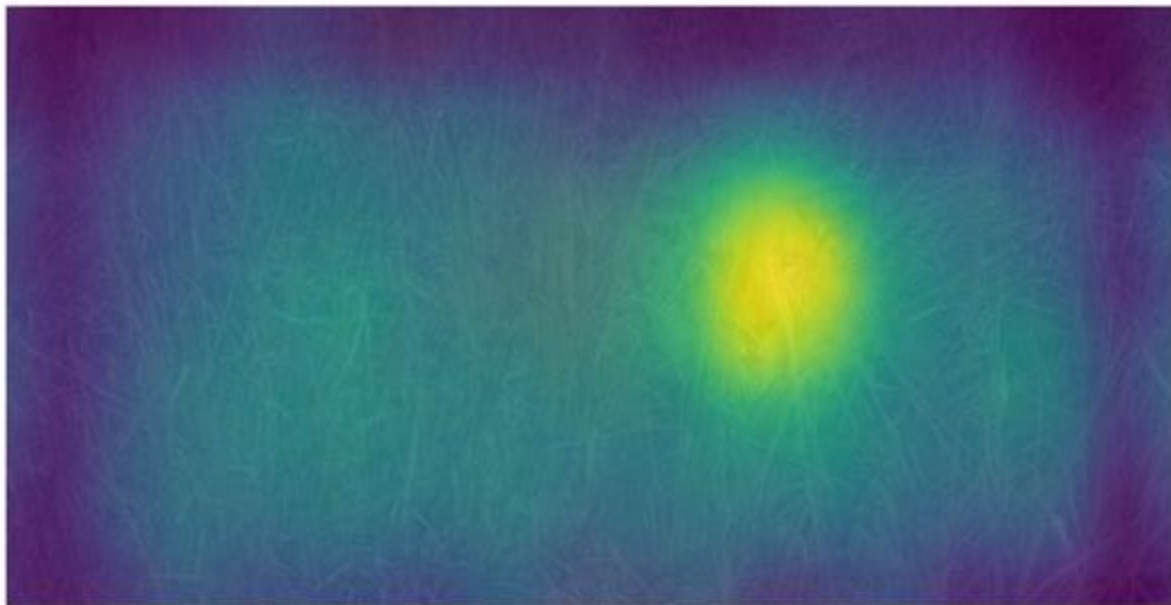
**Figure 13.1.2:** DeepGaze IIE Gestalt image of dog



**Figure 13.2.1:** Eye tracking heatmap lion



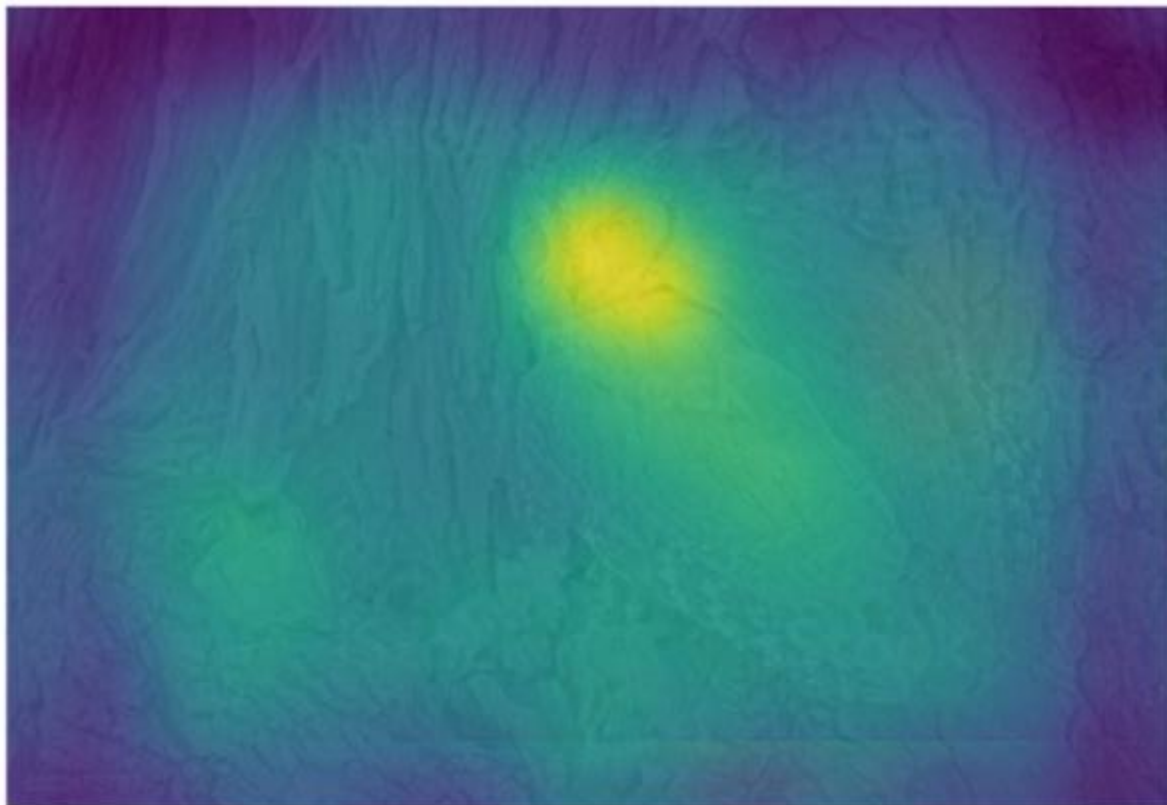
**Figure 13.2.2:** DeepGaze IIE lion



**Figure 13.3.1:** Eye tracking heatmap owl



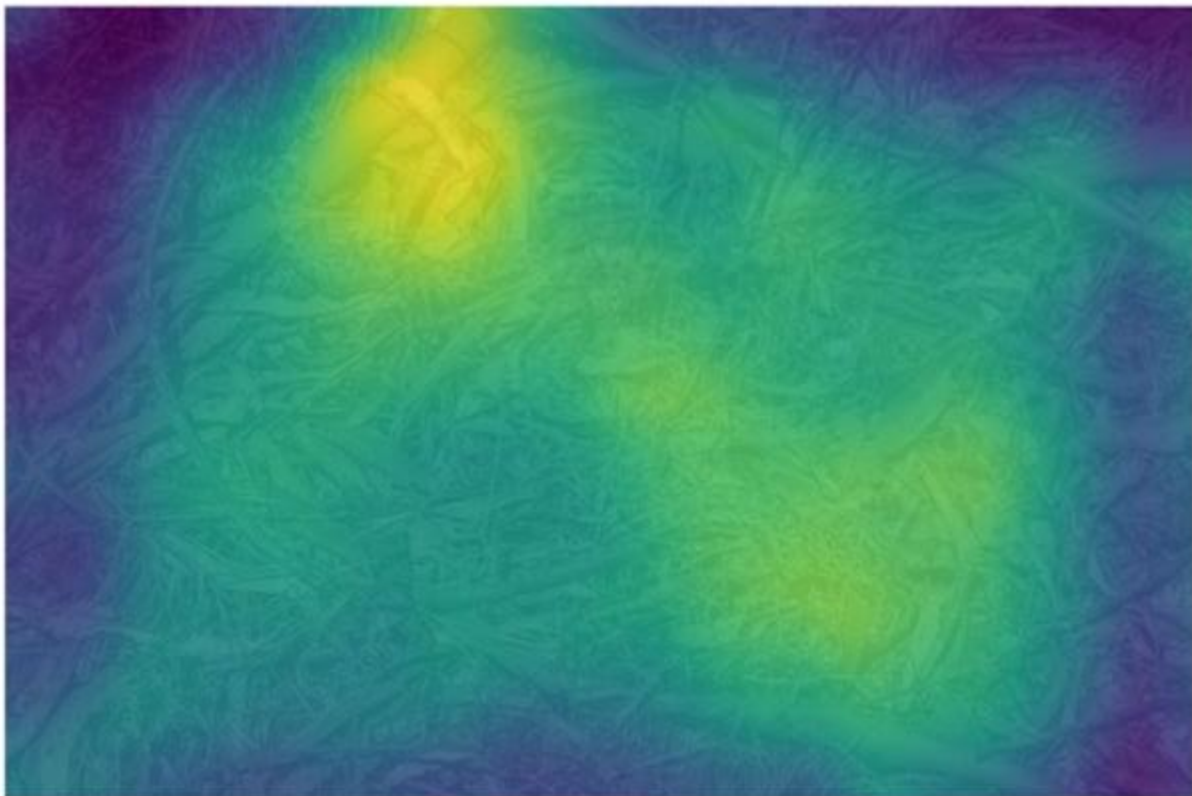
**Figure 13.3.2:** DeepGaze IIE owl



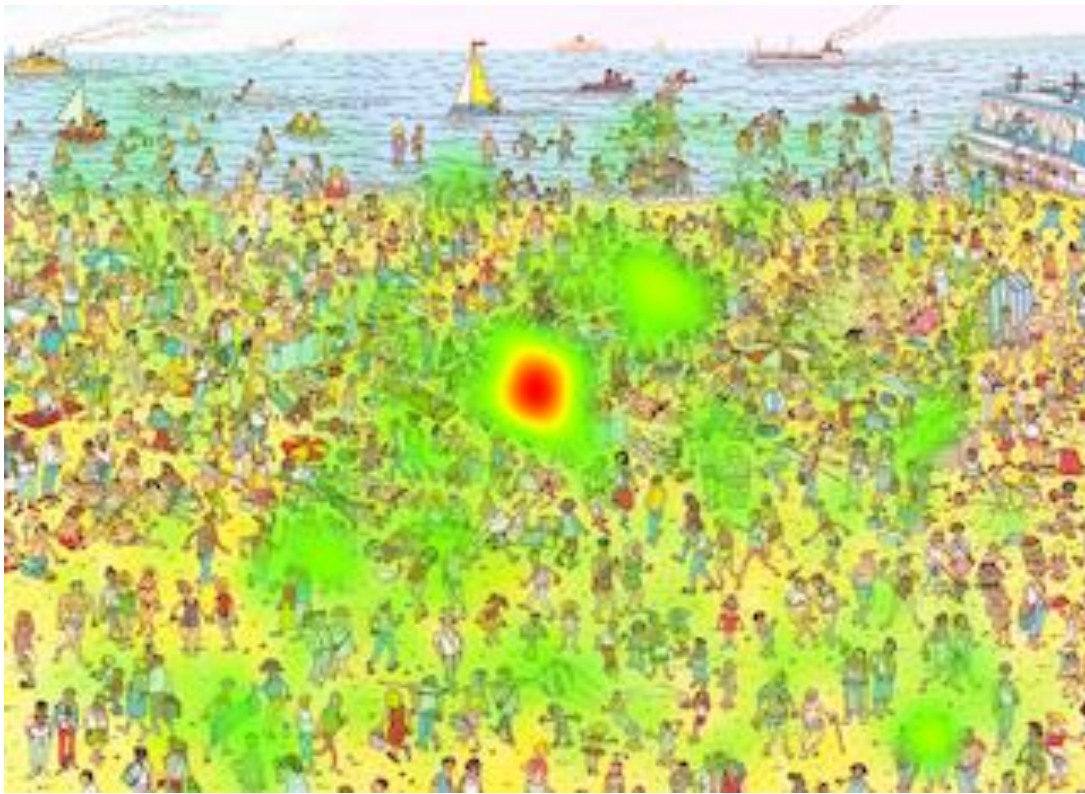
**Figure 13.4.1:** Eye tracking heatmap snake



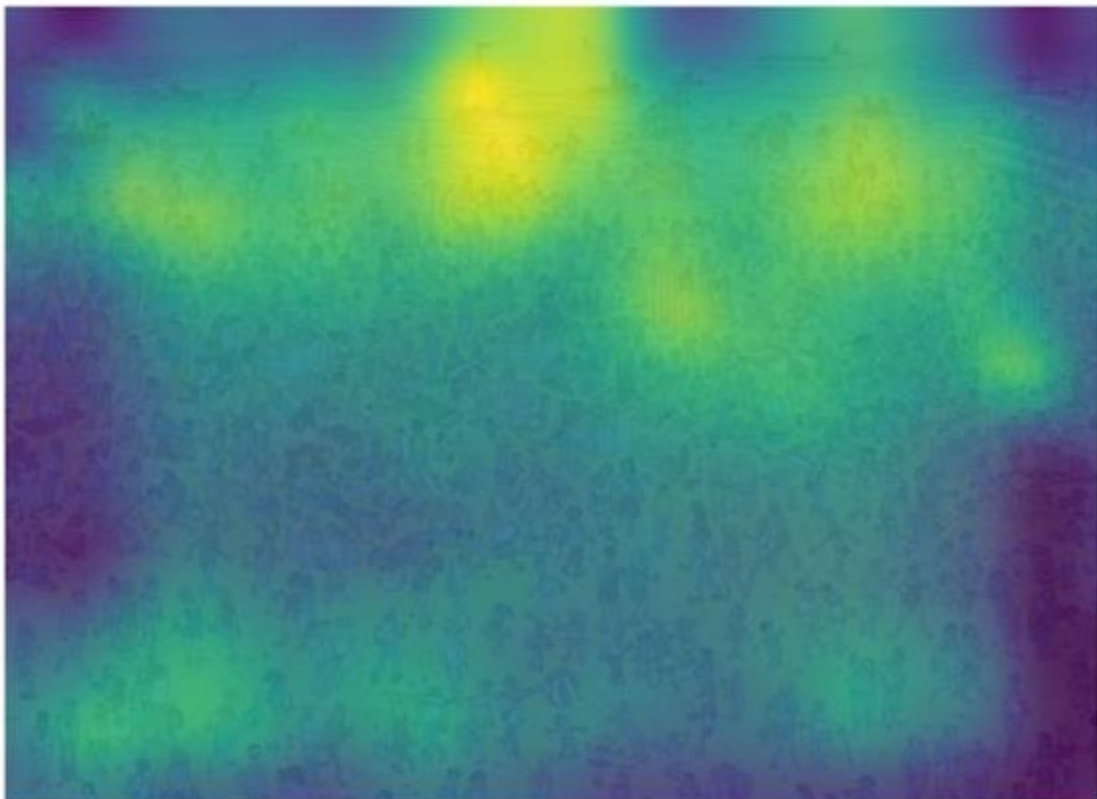
**Figure 13.4.2:** DeepGaze IIE snake



**Figure 13.5.1:** Eye tracking heatmap “Where is Wally?”



**Figure 13.5.2:** DeepGaze IIE “Where is Wally?”



**Figure 14.1:** Advertisement 1 Stimuli



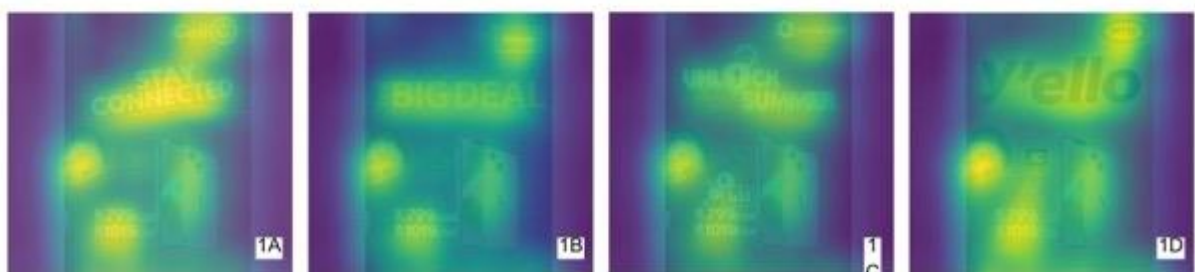
**Figure 14.2:** Eye Tracking Heatmap Advertisement 1 (500ms)



**Figure 14.3:** Eye Tracking Heatmap Advertisement 1 (6 seconds)



**Figure 14.4:** DeepGaze IIE Advertisement 1



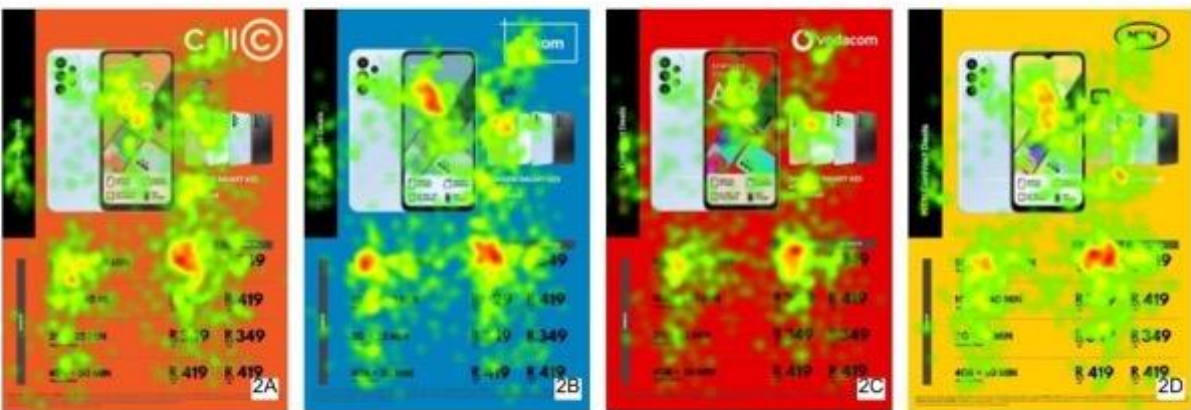
**Figure 15.1:** Advertisement 2 Stimuli



**Figure 15.2:** Eye Tracking Heatmap Advertisement 2 (500ms)



**Figure 15.3:** Eye Tracking Heatmap Advertisement 2 (6 seconds)



**Figure 15.4:** DeepGaze IIE Advertisement 2

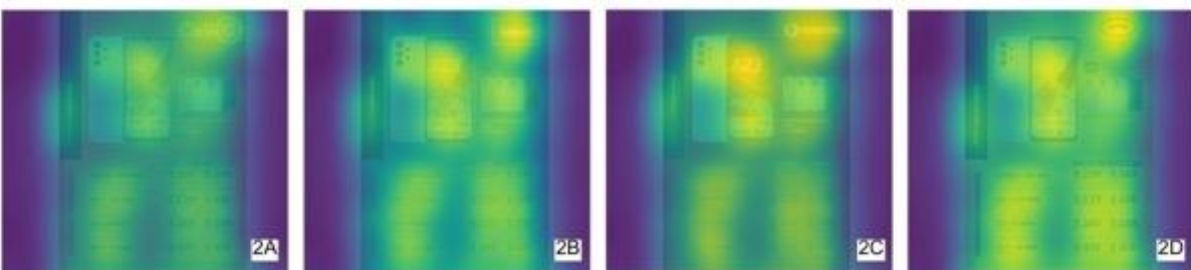


Figure 16.1: Advertisement 3 Stimuli



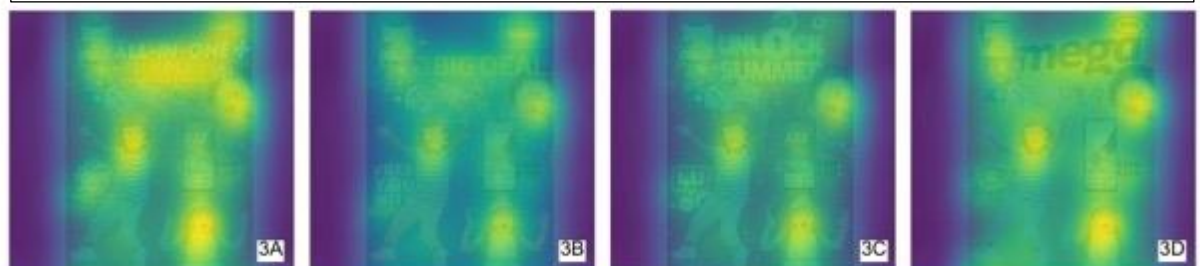
Figure 16.2: Eye Tracking Heatmap Advertisement 3 (500ms)



Figure 16.3: Eye Tracking Heatmap Advertisement 3 (6 seconds)



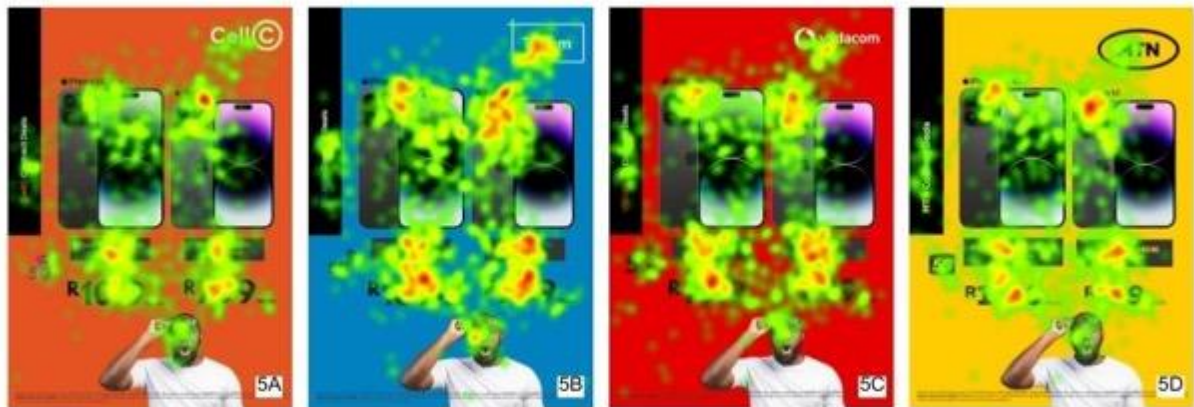
Figure 16.4: DeepGaze IIE Advertisement 3



**Figure 18.1:** Advertisement 5 Stimuli



**Figure 18.2:** Eye Tracking Heatmap Advertisement 5 (6 seconds)



**Figure 18.3:** DeepGaze IIE Advertisement 5

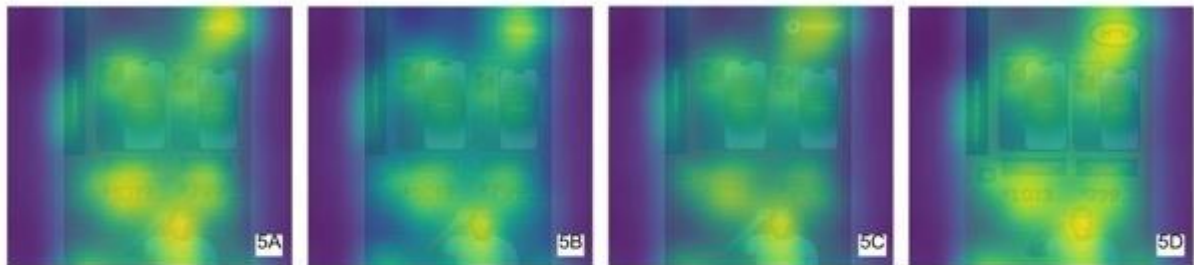


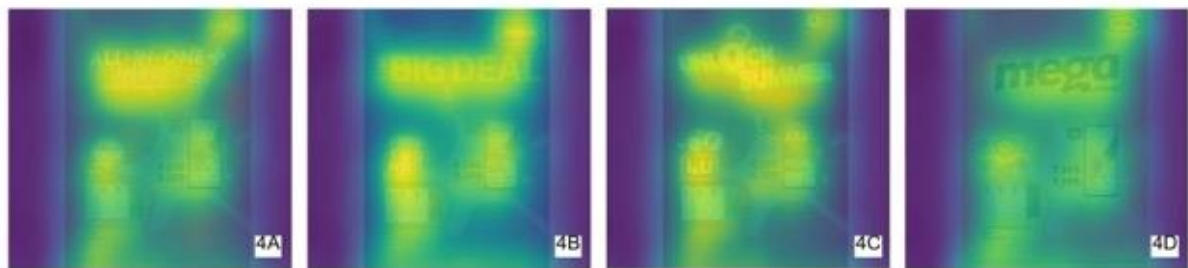
Figure 17.1: Advertisement 4 Stimuli



Figure 17.2: Eye Tracking Heatmap Advertisement 4 (6 seconds)



Figure 17.3: DeepGaze IIE Advertisement 4



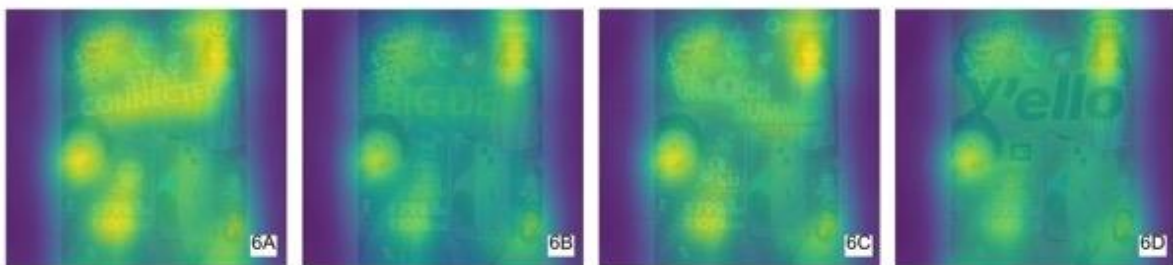
**Figure 19.1:** Advertisement 6 Stimuli



**Figure 19.2:** Eye Tracking Heatmap Advertisement 6 (6 seconds)



**Figure 19.3:** DeepGaze IIE Advertisement 6



**Figure 20.1:** Advertisement 7 Stimuli



**Figure 20.2:** Eye Tracking Heatmap Advertisement 7 (6 seconds)



**Figure 20.3:** DeepGaze IIE Advertisement 7

