The Influence of Colour Priming on Consumers' Physiological Responses in a Retail Environment Using EEG and Eye-Tracking

A thesis submitted to the University of Manchester for the degree of
Doctor of Philosophy
in the Faculty of Science and Engineering

2017

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Conference Presentations and Abstracts:

- Trimble, E. V., Wang, Y., *"The Need for Fusing EEG and Eye-Tracking Data to Investigate Consumer Behaviour"*, presentation at the 11th NeuroPsychoEconomics Conference, Copenhagen, June 2015.
- Trimble, E. V., Wang, Y., Kennon, R., *"Analysis of Consumer Behaviour by Fusing EEG and eye-tracking data"*, presentation at the 5th International Workshop f Advanced Manufacturing, Shanghai, October 2015.

Book Chapter:

- Casson, A. J., Abdulaal, M., Dulabh, M., Kohli, S., Krachunov, S., and Trimble, E. V., *"Electroencephalogram"*, in Seamless Healthcare Monitoring, eds. T. Tamura and W. Chen. Amsterdam: Stringer Nature, 2017.

Prizes:

- First place in the Venture Further business category. Awarded for business ideas based on the methods used in this research.

Abstract

Multiple elements of the retail environment can have an impact on a consumer's behaviour and purchase decisions. Much of the influence that the environment has on behaviour often goes unnoticed, as it affects internal processes that happen below the level of conscious awareness. This research aims to explore and quantify the effect a retail environment has on consumers' affective (emotional) and cognitive responses towards products.

Priming is the influence of external stimuli on one's behaviour or response towards target stimuli. This research designed an experiment to prime participants with a particular coloured stimulus (pink, blue, or red) in order to measure the influence of this prime on the participants' purchase decisions. The participants entered a real-world simulated retail shop, and within a guided format they shopped through the available dresses, eventually picking out their three ranked favourites. The participants' physiological responses were measured using an eye-tracker and a portable Electroencephalogram (EEG) recording unit. The eye-tracking data were analysed using the Gaze Cascade Theory, testing for an increase in gaze bias towards preferred and primed products. The EEG data provided information about the participants' brain activity, and were analysed in accordance with Davidson's model of emotion, indicating an approach or withdrawal tendency towards different products.

The results showed that with both eye-tracking and EEG it is possible to measure a difference between the participants' cognitive and affective responses towards the products that they preferred and chose as their favourites, compared with the products they did not choose. The EEG data provided evidence of a difference in neural responses between the prime matching coloured products and the non-prime matching products. However, the eye-tracking responses did not demonstrate a significant difference in eye-movements between the primed and not primed products. Technical innovation was required to allow the recording of EEG data in the semi-controlled shop environment, to allow data free of motion artefacts to be analysed.

These results demonstrate the ability to measure consumers' physiological, neural, and subconscious responses in a real-world retail environment, whilst allowing the participants to move freely and unhindered. A novel methodology for analysing motion artefact free EEG data is presented. The results demonstrate a significant difference in emotional responses, as detected by EEG, in preference towards the prime coloured products, suggesting that priming has an influence in decision making in fashion retail environments.

Declaration of originality

I hereby confirm that no portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

Copyright statement

Acknowledgements

I would like to start by thanking Richard Kennon, who has been on my team and rooting for my success for eight long years now. I would also like to thank Darragh Downey, for both academic and moral support during testing times. My biggest thank you is to Alex Casson, whose patient guidance and constant support were sometimes all that kept me going.

Thanks to my parents, who have instilled in me a belief that I can achieve anything if I put my mind to it, for which I am eternally grateful. A special thanks to my Dad, whose willingness to proof read parallels the love and support he has given my entire life.

Fellow PhD friends; Kathryn, Natalia, Sid, Meera, and Mo. To the F10 office mates, Casson research group and the 'original EEG crew'. This would have been a lonely, boring process without you. Thank you.

Finally, all my thanks to my boyfriend Bradley. For his love and listening.

Chapter 1

Introduction

1.1 Overview

Consumer decision making involves integrating complex cognitive processes, part rational and part emotional, which can potentially be influenced by a variety of stimuli. The research described in this thesis directly measures consumers' cognitive and affective (emotional) physiological responses in a simulated real-world retail environment, to examine the effects that priming has on these responses.

Priming is a phenomenon in which exposure to particular stimuli influences individuals' subsequent actions. In a similar manner, the retail environment heavily influences consumers' emotional states and subsequent behavioural responses. Consumers are often unaware of the influence the environment is having on their behaviour because it happens below the level of conscious awareness (Dijksterhuis et al. 2005a). To better understand how their environment influences consumers this research will employ priming techniques aiming to influence the consumers' decision making behaviour; specifically the impact of colour priming on consumers' responses towards target stimuli will be assessed. This is the first study, to the researcher's knowledge, to test the influence of colour priming on responses towards fashion garments.

A large proportion of what influences consumers' decisions happens below their level of conscious awareness (Calvert and Brammer 2012), and therefore consumers are often unable to accurately recall their experiences or provide direct insight into why specific decisions were made. This inability to accurately recount their activities highlights a need for more quantitative measurements of the psychological processes in marketing research (Custdio 2010). In order to overcome consumer bias and memory recall limitations, as well as to get a clear understanding of consumers' subconscious responses, this research is going to use EEG and eye-tracking to measure the physiological responses of the consumers in a realistic shopping environment.

This chapter begins by outlining the research aims and objectives in section 1.2. Following this, section 1.3 provides relevant background information to help set the premise for the thesis. Finally, section 1.4 describes the structure for the thesis.

1.2 Aims and Objectives

The key aim of this research is to measure consumers' physiological responses towards fashion garments, and measure how these internal responses can be altered by the colour priming effect, in as natural an environment as possible.

A key objective of the current research is to ensure that the participants' responses are as close to what their responses would be when they are shopping in real life. This research will apply lab-tested methods to a realistic setting, allowing participants to be free moving, providing ecological validity and a key novelty of this research.

Two further objectives of this research are to evaluate both the consumers' cognitive and affective responses during the EEG and eye-tracking studies. Eye-tracking data will be analysed using the Gaze Cascade Theory to indicate the participant's cognitive responses during the experiment. The Gaze Cascade Theory is discussed in more detail in section 3.3.5. To evaluate the participant's affective (emotional) responses, the Electroencephalogram (EEG) data will be analysed based upon Davidson's model of emotion. Davidson's model of emotion is discussed in more detail in section 3.4.6.

The use of physiological measures to explore consumer behaviour can provide marketers with invaluable information that is not obtainable through traditional marketing methods (Ariely and Berns 2010). Studies of this nature are commonly conducted in unrealistic laboratory settings, with tasks designed on computer screens, which cause concern for the ecological validity of the findings (Ladouce et al. 2017). A key motivation for the research presented in this thesis is to overcome these current ecological issues. The retail environment has a large impact on consumers' decisions (Dijksterhuis et al. 2005b) and colour is an important evaluative criteria for consumers when making fashion purchases (Forney et al. 2005). A combination of these factors provides a second motivation for the research presented in this thesis. Improving the understanding of how environmental cues can influence responses towards different coloured fashion products could provide valuable information about how retail environments could be used to improve sales for specific products.

1.3 Background

1.3.1 Introduction

The classical view of consumer behaviour was in line with economic theory, and made significant assumptions about consumers' market knowledge and computational capabilities when it came to making purchase decisions. Thanks to ground breaking pieces of work from Nobel laureates such as Herbert Simon (1955) and Daniel Kahneman and

Tversky (1979) , it is now well established that consumers are not rational beings, and their decision making capabilities cannot be calculated and easily predicted (Dijksterhuis et al. 2005b). This section will begin with an introduction of how consumer behaviour theories have shifted from the field of economics, to more behaviourist theories.

It is important to understand how the human subconscious mind operates on a basic systems level, so the concepts of *System 1* and *System 2* will be introduced in section 1.3.3. These terms characterise what has been proposed as a dual brain system, which is the basis of understanding the way priming can influence behaviour subconsciously (Kahneman 2011) . Following this, priming is introduced in section 1.3.4, using our understanding of the brain, within the dual brain system framework and vast associative memory systems, to explain the phenomenon.

1.3.2 Consumer Behaviour Theories

The origins of consumer behaviour theories fall within the realm of theoretical economics. The first theory of consumer choice determined that the decision-maker should chose the option which gives the highest *'expected value'*, however this fails to account for individuals' personal circumstances. Neumann and Morgenstern (1947) introduced the *'expected utility theory'*, which proposes that for every choice there are objective payoffs, with a corresponding psychological value and a probability of the outcome. The theory was developed to account for the quantity of wealth that the individual already possesses, and therefore the decision maker should choose the option with the highest *'expected utility'*.

The field of theoretical economics portrays an ideal world of perfect competition in which consumers would be aware of all product alternatives, be able to correctly rank the alternatives considering their advantages and disadvantages, and be able to make the most sensible choice (Schiffman et al. 2012). The expected utility theory was built in this realm of theoretical economics, postulating a hypothetical *"economic man"* who is entirely rational (Simon 1955). However, the perfectly rational consumer does not exist. Herbert Simon (1955) first introduced this notion with his theory of *"Bounded Rationality"*. He determined that decision makers are limited by small working memories and minimal computational capabilities (Simon 1955). Consumers are just as likely to be influenced to purchase something by their mood, situation or emotion, as much as they may be influenced by family, friends or advertisements and are therefore not entirely rational (Smith and Rupp 2003). Bounded rationality acknowledged that consumers didn't have computational capabilities, full market knowledge, or clear understanding of their own true preferences.

The Theory of Buyer Behaviour (Howard and Sheth 1969) was built on the assumption that consumers' behaviour is rational within the bounds of their available information and cognitive capabilities, as Herbert Simon posited (Simon 1955). This theory shaped the academic field of consumer behaviour for over four decades (Martin and Morich 2011). However, more recent research from complimentary disciplines, such as cognitive neuroscience, has demonstrated that human behaviour is comprised of many subconscious mental processes (Martin and Morich 2011; Bargh and Chartrand 1999; Dijksterhuis et al. 2005b; Dijksterhuis and Nordgren 2006; Wood and Neal 2009; Bargh and Morsella 2010). These subconscious processes can influence consumers to make entirely *irrationational* decisions. The research presented in this thesis will investigate whether these subconscious influences can alter consumers' responses towards fashion garments in a simulated real-world retail environment.

1.3.3 Dual Brain System

System 1 and *System 2* are the labels given to the two key forms of human cognitive processing, which roughly correspond to reasoning and intuition (Kahneman 2003; Stanovich and West 2000). System 1 is our intuition, it works automatically and at very high speed. We do not realise System 1 is working because it uses no conscious mental effort and we have no control over its operation (Kahneman 2003, 2011). System 2, on the other hand, is framed as our reasoning and cognitive process, and does require conscious mental effort in tandem with unconscious processes. We are aware of when we are using our System 2, because this is our conscious thought. System 2 is believed to be responsible for making our final decisions and choices, deciding what to think about and what we should do (Kahneman 2011).

In his book "Thinking, Fast and Slow" Daniel Kahneman (2011) uses many examples to demonstrate the different cognitive processes. The processes that System 1 controls are automatic, such as listening to a simple conversation in one's native language, locating the source of a sudden sound, or recognising anger or frustration in another human's face. System 1 includes the intuitive skills that we (like other animals) are born with, the skills that we use to identify the world around us and avoid danger. It also includes mental processes that become automatic over time, due to extensive repetition and practice, such as reading, or knowing 2+2 = 4 (Kahneman 2011). System 2 processes are not automatic and require one's attention; they are on the whole controlled and can be interrupted if one becomes distracted. Examples of System 2 processes include answering a complicated multiplication problem, searching memory for the name of a holiday destination you visited as a child, and comparing two products for overall value (Kahneman 2011). It is our System 2 processes that are limited by low capacity; this is why we often cannot multi task on tasks that require attention. For example, an experienced driver could easily hold a conversation with their passenger whilst cruising down an empty motorway, which are both two low attention activities. However, as the driver approaches a complicated roundabout or passes a wide truck on a narrow road, their attention will be directed towards the driving task, and temporarily away from their conversation, no matter how interesting it is. The limited capacity of our System 1 is the basis of the Unconscious Thought Theory, which is discussed in more detail in section 2.2.4.

1.3.4 Priming

Another of the skills that the System 1 has ascribed to it is the ability to automatically associate ideas. Kahneman (2011) describes *ideas* quite broadly, explaining that they can be expressed as a noun, verb or an adjective, or even a physical metaphor such as a clenched fist. Ideas can be thought of as nodes in a vast network, each linked to many others, which are also linked to many others, forming an associative chain of memory. Kahneman (2011) explains that the link between ideas can take a number of forms, such as a cause being linked to an effect (i.e freezing temperatures $\rightarrow$ ice), an item being linked to its properties (i.e. football $\rightarrow$ round) or an item being linked to the category to which it belongs (i.e. rose $\rightarrow$ flower). Due to the vast nature of System 1, which is not limited by capacity loading like our conscious System 2 is, countless associations can all happen at once. The activation of one idea does not only activate another single idea. Below our level of conscious awareness our System 1 can associate an idea with many others, which all in turn will associate with many other ideas, quickly and efficiently.

Until the 1980s the only tool researchers had for studying associations was to ask people questions about which words they associated with others, for example when asked about the word “day”, participants might reply “night”, “sunny” or “long” (Kahneman 2011). However, a major change in associative memory research happened when psychologists learned that exposure to one word will change the ease with which other words will come to mind. It was discovered that by provoking one idea it is possible evoke related ideas; this is what is known as a priming effect. A common example of priming is a simple experiment in which a participant is asked to complete the word SO_P (Kahneman 2011). If the participant is first exposed to the word “EAT” they are most likely to complete the word as “SOUP”, as there is a clear link between eat and soup. Alternatively, if the participant has been exposed to the word “WASH” then they are most likely to complete the word as “SOAP”. In this example the word “EAT” has primed the participant to think of the word “SOUP, and the word “WASH” has primed the word “SOAP”.

Due to the countless links in our associative memory between ideas, the introduction of one idea will prime many subsequent ideas. Using the word “EAT’ as our example again, this will not only prime an individual to think of soup, but it may also make them think about other food-related concepts, such as “fork, hungry, fat, diet and cookie” (Kahneman 2011, pg. 53). Our associative memory is a vast network of ideas, in which the activation of one idea causes the activation of many ideas, and these in turn activate many other ideas. Through these associative links, a primed idea can prime many ideas, which in turn (although to a lesser extent) can prime the next tier of ideas.

Priming is not limited to influencing responses to word and sentence tasks, it can also have an influence on an individual's emotions and actions. Bargh et al. (1996) conducted an experiment that demonstrated the influence of lexical priming on secondary behaviour. In principle their experiment was simple, starting with participants completing a scrambled word task. There were two separate condition groups: half of the participants performed the tasks using neutral words, whereas the other half were primed by using words that related to the elderly. The words used included "old", "retired", "wrinkle", "knits" and "grey". After the initial scrambled word task, the participants were asked to walk down the corridor to another room to perform a different task. Unbeknown to the participants, it was the speed at which they walked down the corridor that was of interest to the investigators. Despite prime words not including anything about speed, the primed participants walked more slowly down the corridor than their non-primed counterparts. The idea of the elderly had primed associated ideas, such as walking slowly, and this had changed their behaviour.

1.3.5 Implications for This Research

The field of consumer behaviour has evolved from believing that consumers are linear and rational, to understanding that various psychological factors have an influence on buying behaviour. *System 1* and *System 2* provide the underlying framework for understanding human processes, which are necessary to demonstrate how priming can influence individuals below their level of conscious awareness. Building from this brief overview, this thesis will explore the existing literature regarding subconscious influences on consumer behaviour, motivating the work and contributions of this thesis. A key contribution of this research is exploring the effects of colour priming on consumers' responses towards fashion products. The specific link between priming and consumer preferences will be explored in more detail in section 2.3.

1.4 Thesis Structure

The thesis is structured as follows:

Chapter 2 - Subconscious Influences on Consumer Behaviour

Chapter two provides an introduction to the psychological background of consumer behaviour research. This chapter introduces the concepts of the non-conscious consumer, priming and consumer emotions. An overview of previous academic research in these areas is provided, critiqued and existing gaps in the current literature are highlighted.

Chapter 3 - Physiological Measurement for Understanding Consumer Behaviour

Following the understanding of the non-conscious consumer, and the subconscious influence that the retail environment can have on a consumer, chapter three evaluates the use of the physiological measures eye-tracking and EEG. Both techniques provide valuable insight into consumers' subconscious responses, that cannot be obtained through traditional marketing research methods. The theories and methods for doing so are reviewed in this chapter.

Chapter 4 - Hypotheses and Experimental Design

This chapter begins by outlining the research hypotheses, which investigate the consumers' physiological responses to evidence preference and the priming effect. The overarching theoretical framework for the research is the Stimulus-Organism-Response (S-O-R) framework, which is widely used in environmental psychology research, and is a proposed basis for consumer behaviour research in a retail environment. Details of the equipment and data collection methods used are described in this chapter.

Chapter 5 - Eye-Tracking Methods and Results

This is the first of two chapters exploring the results of the experiments, in order to test the research's preference and priming based hypotheses. This chapter focusses on the eye-tracking data, beginning with a detailed overview of the data preparation methods required. Thereafter the data are statistically compared to identify a difference in responses between participants' chosen dresses and the not chosen dresses, and between the prime matching coloured dresses and the not prime matching coloured dresses. Furthermore, this chapter explores the level of cognitive control of the participants' eye-movements, based on visualisations of eye-gaze data. The findings are discussed in depth, and explanations for the findings are presented. The use of eye-tracking to monitor the influence of colour priming on consumers' behaviour is a novelty of this research.

Chapter 6 - EEG Methods and Results

This chapter extends the eye-tracking analysis to include EEG data. A novel approach is introduced to overcome the technical challenge of the synchronisation of the EEG data with the fixation timings from the eye-tracking data. In order to analyse the correct epochs of EEG data, temporal synchronisation was critical as the fixation times are short, therefore a small misalignment of the signals could cause the incorrect segments of EEG data to be analysed. The techniques for temporally aligning the signals are discussed in this chapter. Once the correct EEG epochs had been identified, an algorithm based on Davidson's model of emotion was applied, to determine the participants' level of approach or withdrawal tendencies towards different groups of products. As with the eye-tracking data, the participants' responses towards chosen and not chosen dresses were compared, as well as responses towards prime coloured and not prime coloured dresses. The results are discussed in line with the research hypotheses, and show that mobile EEG is a suitable method for analysing consumer responses. The use of EEG to monitor responses towards fashion garments, influenced by colour priming, is a novel contribution of this thesis.

Chapter 7 - Conclusions

This chapter provides an overview of the findings of the whole thesis. The research hypotheses are revisited, and the contributions to knowledge of the thesis are outlined.

Chapter 2

Subconscious Influences on Consumer Behaviour

2.1 Introduction

Consumer behaviour research has developed since it was first established in the field of economics and now benefits from largely psychology-based advancements. This chapter provides an overview of consumer subconsciousness, priming, and emotion. These are key factors that influence the way the retail environment influences consumers' behaviour, and are therefore central to this thesis.

Section 2.2 introduces the concept of consumers making decisions that are subliminally influenced by factors within their environment, defines the different levels of consumer awareness, and demonstrates how Unconscious Thought Theory (UTT) has changed the consumer behaviour research field. Section 2.3 provides a thorough overview of priming and demonstrates how priming can change individuals' behaviour, including examples of the influence of colour priming. Finally, section 2.4 establishes the role that emotions play in decision making, and provides an overview of existing research regarding the influence of emotions of a consumer's shopping experience. The research presented in this thesis is exploring consumers' subconscious physiological responses towards elements of the retail environment, therefore it is important to review the literature regarding such consumer psychology, and how these factors influence consumer behaviour.

2.2 Consciousness

2.2.1 Introduction

The aim of this section is to demonstrate the state of the art in our understanding of how the consumers' subconscious minds influence their purchasing decisions. This research will focus on consumers' subconscious responses, as well as the impact of priming techniques on these responses. Firstly, section 2.2.2 considers the effect unconscious processes can have on consumers' behaviour, then section 2.2.3 carefully critiques the use of the term "unconscious" to ensure the correct terminology is being applied. Following this an explanation of the Unconscious Thought Theory (UTT) will be provided, which defines the importance of subconscious processes for optimal decision making, in section 2.2.4. The section finishes with an overview of responses to the unconscious thought theory in section 2.2.5, where the literature will be critically reviewed.

2.2.2 The Unconscious Consumer

Many consumer behaviour theories and studies have been based on the assumption that consumers are rational, albeit within their available knowledge and cognitive capabilities (Simon 1955; Bargh 2002). However, much interdisciplinary research has now shown that human behaviour is more commonly influenced by unconscious mental processes than being consciously controlled (Martin and Morich 2011; Bargh and Chartrand 1999; Dijksterhuis et al. 2005b; Dijksterhuis and Nordgren 2006; Wood and Neal 2009). The unconscious influence that environmental cues have on consumers' responses is a key focus of this research.

Fitzsimons et al. (2002) presented their belief that the unconscious mind plays an important role in understanding consumer psychology at a choice symposium in 2002. When they did so, they discovered that many of their peers were also conducting research centred around consumers' non-conscious processes, but had also faced strong resistance to the idea from many editors and editorial boards (Chartrand and Fitzsimons 2011). Dijksterhuis et al. (2005a) noted that there has always been resistance towards researchers investigating unconscious psychology, due to the fact that many people do not want to believe that subliminal perception exists. They imply that this unwillingness to believe in subliminal perception is due to fear that we are not truly in control of our own behaviour, and the belief that our consciousness should be able to control everything we do, particularly when faced with important decisions (Dijksterhuis et al. 2005a).

The 2002 choice symposium can be considered a turning point for the growth of research into the non-conscious processes that affect consumer choice, and since then there has been a large upsurge in the number of published papers regarding consumption being driven by non-conscious processes (Chartrand and Fitzsimons 2011). It is now almost taken for granted in the literature that consumer choice is a combination of both conscious and non-conscious processes (Fitzsimons et al. 2002).

Dijksterhuis et al. (2005b) authored a paper arguing that subtle environmental cues have a substantial influence on consumer behaviour. They began by demonstrating this principle with a simple supermarket example. Their hypothetical consumer spends 20 minutes wandering the aisles of the supermarket, collecting items to purchase in their shopping basket. When they reach the till, Dijksterhuis et al, argue the hypothetical consumer will have difficulty explaining exactly why each item has ended up in their basket. Some choices will be easier than others; buying detergent was an obvious choice because they remembered that they had run out, and need to clean shirts for a conference they will soon be attending. However other choices will be harder to explain; *"Ice cream? Well I really felt like ice cream, I guess"* (Dijksterhuis et al. 2005b, pg. 193).

Dijksterhuis et al. (2005b) claim that the reason these choices cannot be explained is because they are made unconsciously or mindlessly. Whilst the hypothetical consumer was perusing the supermarket shelves and selecting items to purchase, the amount of information processing they engaged in was minimal or virtually non-existent. Traditional consumer behaviour theories, rooted in cognitive psychology, suggest that before people choose any product they engage in conscious information processing (Chaiken 1980; Petty et al. 1983). Understanding the role of information processing is very useful; however, solely focusing on information processing portrays consumers as conscious decision makers who are able to accurately base their decisions on the pros and cons of any particular product (Dijksterhuis et al. 2005b). Since Simon (1955) introduced the concept of bounded rationality, challenging the principles of utility theory, it has been acknowledged that consumers are not always able to make such accurate, rational decisions. For more details of Herbet Simon's theory of bounded rationality, please see section 1.3.2. There are some occasions, particularly when the product is either important or expensive, that consumers will engage in extensive conscious information processing to carefully make their choice, however often this is not the case (Dijksterhuis et al. 2005b).

Dijksterhuis et al. (2005b) explain that one reason why shoppers make decisions unconsciously is because the particular decision has become highly habitualised. A consumer's attitude towards a product can become automatically activated when they see a product because of their memories, or previous information processing. No new information processing is happening with these kinds of choices, they are simply influenced by memory. Impulse purchases are unconscious decisions that consumers make with little engagement in information processing. It is impulse purchases that are most commonly strongly influenced by cues in the retail environment (Dijksterhuis et al. 2005b).

2.2.3 Awareness and Automatic Processes

Before discussing unconscious decisions further, it is important to clarify what this thesis means by the term *"unconscious"*. Generally, we mean that the consumer has not engaged in any information processing that they are aware of, and that their decision has been influenced by environmental factors outside of their awareness. Chartrand (2005) has been critical of Dijksterhuis's lack of a clear definition of awareness in this context, and offers more accurate descriptions of levels of consumer awareness. She notes that Dijksterhuis et al, categorise consumer decisions in a black and white manner, as either involving conscious information processing, or being a completely "unconscious" decision. However, she argues that the consumer's choice is not entirely unconscious, they know that they have made a decision, what they are not aware of is the internal automatic process that influenced their choice (Chartrand 2005).

A common sequence of human behaviour is that environmental features trigger an automatic process, which produces an outcome (see Figure 2.1) (Chartrand 2005). Environmental features include tangible places and objects, and also include the social aspects of a scene, such as the current event or the presence of other people. There are many automatic processes that can occur as a response to environmental stimuli. Chartrand (2005) lists some of these as automatic evaluation and emotion, automatic trait and stereotype activation, attitude activation, non-conscious goal pursuit and non-conscious behavioural mimicry. The outcomes of automatic processes can include the individual's behaviour, judgements, motivations, decisions or emotions. When investigating consumer behaviour it is the consumer's choice which is often the outcome of interest (Chartrand 2005); however, in this research it is the internal processes (B) that relate to that outcome, which are of key interest. The internal processes are measured using mobile eye-tracking and EEG devices, and will be discussed in chapters five and six.

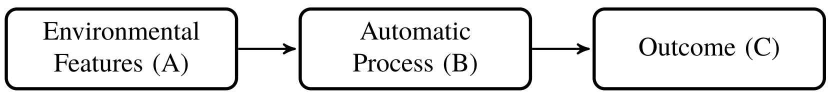

Figure 2.1: Model of automatic processes. Adapted from Chartrand (2005)

At any of these three stages one might be aware, or unaware, of what is happening. Consumers might not notice the environmental cues that are influencing them, they could be unaware of the automatic process that they are going through internally, or they may not even acknowledge their outcome (Chartrand 2005). Most commonly in consumer behaviour, the decision maker is aware of the outcome (C), as this is the product that they have picked up and chosen to purchase. They are often, but not always, aware of the environmental features (A) around them, such as the visual merchandising displays or the music playing overhead. Despite being aware of the presence of the environmental features, they may not realise the impact these features are having on them. Even if the consumer is aware of the environmental features (A) and the outcome (C), they are rarely aware of the automatic process (B) that has prompted their decision. Most people aren't even aware that there is an automatic process influencing their decision, because they cannot imagine their behaviour as being anything other than completely consciously controlled. They thought about buying something, and then they bought it, therefore they think it was their independent thoughts that caused them to buy it (Williams and Poehlman 2016). It is important to clarify which stages are inside or outside of the consumer's awareness because it affects our understanding of how the consumer's behaviour has been influenced. In this research the participants will be aware of the retail environment that they are in (A), and they will be aware of the dresses that they choose (C), however they will not be aware of the subconscious influence (B) that the colour priming stimuli within the environment will have on their responses. For this reason physiological data will be recorded using mobile eye-tracking and EEG devices, to try to measure the subconscious internal processes that occur.

2.2.4 Unconscious Thought Theory

Dijksterhuis et al. (2006) introduced the Unconscious Thought Theory (UTT), in which they state that there are two different but interrelated modes of thought: conscious and unconscious. They define conscious thought as *"object-relevant or task-relevant cognitive or affective thought processes that occur while the object or task is the focus of one's conscious attention"*, which put simply is what laypeople would refer to as "thought" (Dijksterhuis et al. 2006, pg 96.). The key way to distinguish between conscious and unconscious thought is attention; conscious thought involves attention, whereas unconscious thought does not (Dijksterhuis et al. 2006).

One of the foundations for the UTT is the limited capacity of consciousness. In the 1950s researchers began attempting to quantify the capacity of consciousness, and the capacity of the whole human sensory system. Nørretranders (1998) summarised these findings about the human processing capacity, with particular interest in comparing the capacity of consciousness with the capacity of all of the senses (Dijksterhuis et al. 2005a). In order to make comparisons possible, information is divided into small, quantifiable chunks, called bits, in the same manner as information in digital computing. For reference, reading silently typically processes 45 bits per second, which equates to a few words (Dijksterhuis et al. 2005a). In some contexts consciousness can process approximately 10 to 60 bits per second, however the human visual system can process 10,000,000 bits per second, and the whole sensory system combined can process around 11,200,000 bits (Dijksterhuis et al. 2005a; Zimmermann 1989). By comparison it can be seen how truly limited the capacity of our human consciousness is, highlighting the importance of understanding how influential our unconscious processes are.

There are many decision theorists who have demonstrated that decision makers are burdened with limited conscious capacity (Bettman et al. 1998; Kahneman 2003; Simon 1955; Tversky and Kahneman 1975; Dijksterhuis and Nordgren 2006). Dijksterhuis and Nordgren (2006)'s Unconscious Thought Theory was motivated by the work of Wilson and Schooler (1991), who explicitly argued that the limited capacity of consciousness is detrimental to decision makers, causing them to make poor choices (Dijksterhuis and Nordgren 2006). Wilson and Schooler's experiments involved participants evaluating various objects under different conditions. In one of the conditions the participants did not put much thought or effort into their analysis, and simply made a quick decision. Where as in another condition the participants were encouraged to think carefully about their analysis, and write down the reasoning for their choice, causing them to engage in conscious thought. The results showed that the additional effort by the conscious thinking participants was not beneficial, as they made less accurate evaluations than the other participants (Wilson and Schooler 1991). The limited capacity of consciousness had caused the over-thinking participants to focus most of their attention on only a handful of attributes, unable to process all of the available attributes. This meant that they over-looked important information whilst only focusing on the number of attributes they could hold in their consciousness. Typically capacity can hold approximately seven discrete items of information at one time (Miller 1956).

Condition 1	Condition 2	Condition 3
Immediate decision	Decision after distraction	Decision after deliberation
Almost no thought	Unconscious thought	Conscious thought

Figure 2.2: The three different conditions used by Dijksterhuis and Nordgren (2006) to test the power of unconscious thought in decision making

Dijksterhuis and Nordgren (2006) expanded on Wilson and Schooler's (1991) experimental set up and added an additional condition in which the participant is distracted by another task before giving their answer. The three conditions Dijksterhuis and Nordgren (2006) used were making an immediate decision (almost no thought), making a decision after distraction (unconscious thought), and making a decision after careful deliberation (conscious thought), as can be seen in Figure 2.2. In one experiment in which these conditions were used, participants were asked to evaluate four apartments after reading 48 pieces of information about each one. The apartment descriptions were designed so that there was a clear most desirable option, which had prominently positive features, and a clear least desirable option, with predominantly negative features. The other two apartments were neutral options. The participants in the distraction and deliberation conditions were either distracted or given time to deliberate for three minutes. The results found that the unconscious thinkers from the distracted condition performed better than those in the other two conditions for being able to pick out the most desirable apartment. Dijksterhuis and Nordgren (2006) provide this as evidence that decision making that happens below the level of consciousness is superior to conscious decision making.

2.2.5 Responses to the Unconscious Thought Theory

Criticism

Newell and Shanks (2014) produced a thorough critical review of the literature on unconscious influences on decision making, highlighting empirical evidence contradicting those who claim unconscious thought is important and/or superior to consciousness. They believed that a critical review was necessary due to the fact that underlying unconscious influence on behaviour is significant to such a large range of scientific domains, including cognitive neuroscience, experimental psychology and behavioural economics (Newell and Shanks 2014). They urge researchers to conduct more reliable experiments, leaning away from confirmation bias and to consider the experimental and theoretical challenges that they have uncovered (Newell and Shanks 2014).

In their critical review Newell and Shanks provide evidence to unravel Dijksterhuis's claim (Dijksterhuis et al. 2006) that one's unconscious can make better decisions than one's deliberate consciousness. They refute Dijksterhuis's theories due to the lack of reliability and the existence of available alternative explanations for the experimental findings.

Newel and Shanks stress that to clearly demonstrate the superiority of unconscious thought for decision making, participants' choices need to be significantly improved in both the immediate decision condition and the distraction condition. However, according to the literature that they have reviewed this criterion is rarely demonstrated in a single experiment. There are a number of studies that compared the same three conditions as Dijksterhuis et al, and discovered no evidence of an advantage of the unconscious thought condition (Acker 2008; Calvillo and Penaloza 2009; Huizenga et al. 2012; Mamede et al. 2010; Newell et al. 2009; Payne et al. 2008; Rey et al. 2009; Thorsteinson and Withrow 2009; Waroquier et al. 2010). Acker (2008, pg. 292) analysed 17 separate data sets but found *"little evidence"* for the positive effects of unconscious thought. They also noticed a pattern amongst the different findings that the studies with the smallest sample size were the ones that showed the most positive effects of unconscious thought, which is often a sign of publication bias. To further investigate the available findings in unconscious-thought experiments, Newell et al. (2009) conducted a Bayesian analysis of 16 existing studies and discovered overwhelming evidence revealing no difference between conscious thought and unconscious thought. It is on the basis of these studies that Newell and Shanks (2014) believe that the evidence for the benefit of unconscious thought is unreliable.

Another problematic factor with testing the advantage of unconscious thought is that amongst the options given to the participant, there needs to be a clearly superior choice and inferior choice. When deciding which is the best and worst option, attributes can be weighted and scored, so an overall score for the options can be calculated. In their car study, Dijksterhuis et al. (2006) weighted the attributes themselves, and therefore the weighting may not have been reflective of the participants' perceived importance of various car attributes. For example, Dijksterhuis's experiment gave the same weighted value to cup holders as it did to fuel economy (Newell and Shanks 2014), but the participants might have given each of these attributes a different level of importance. Without taking into account participants' individual importance of the various attributes it is not possible to verify whether the *best* choice is actually the most favourable to all participants. To overcome this examiner bias Newell et al. (2009) asked participants to give weight to each of the available attributes, so that they could determine which choice was best for each participant individually based on their idiosyncratic weights. In this more valid approach Newell et al. (2009) found little difference between the accuracy of the participants' choices in any of the three conditions.

Another contradiction to the theories of unconscious thought is that the positive findings in some studies can be discredited and explained by the disadvantages of conscious thought, as opposed to advantages of unconscious thought. Payne et al. (2008) hypothesised that forcing participants to concentrate on one problem for more time than they require, causes them to shift their attention to irrelevant information, leading to poor choices. To test this Payne et al. (2008) added an additional conscious thought condition to his experiments in which the participants were left to deliberate their options for as much time as they wished. In this self-paced conscious thought condition Payne et al. (2008) found that the participants were able to make decisions as accurately as they did in the unconscious thought condition, and both of these conditions were superior to the constrained conscious thought condition.

It is clear that Newell and Shanks are yet to be convinced of the power of unconscious thought in decision-making. The concept of *"sleeping on it"* (pg. 10), meaning to think unconsciously about something whilst you sleep, to improve the decision process has captured the interest of the research community because it is so fascinating and seems fitting with anecdotal experience (Newell and Shanks 2014). However, the debate of the theory's validity is far from settled due to the lack of unequivocal evidence (Newell and Shanks 2014).

Support

Newell and Shanks' criticisms of unconscious thought theory do not appear to be reflective of the whole research community, as many researchers responded to their critical review with opposing ideas. This is an indication of how divided the psychological research community is over the validity of outcomes of unconscious thought research, and highlights the current controversy in conscious versus unconscious psychology research, explaining why choice symposium peers found reluctance towards their ideas. Amongst these were Dijksterhuis et al. (2014). Specifically in response to Newell's study addressing the issue of experimenter versus participant attribute weights (Newell et al. 2009) they highlight other research that includes idiosyncratic weighting, from each individual participant, but finds unconscious thought to be superior. In Newell et al's (2009) study the participants were asked to give attributes importance weighting after the experiment, and the choices of the participants in the conscious and unconscious thought decisions were similarly accurate. However, by giving the attributes weight after the experiment, participants would naturally give weights that justify the decision they have already made, therefore their weighting is less valid. Usher et al. (2011) addressed the issue of participant versus experimenter attribute weighting, but in their study the participants gave the attributes a weighting before being shown the options and making their decision. Usher et al's study showed an advantage in the unconscious thought condition, in line with the expectations of the UTT model. By excluding this information from their review, Newell and Shanks (2014) potentially misinform the reader by not providing a full picture of research in the field.

Newell and Shanks vehemently defend the notion that consciousness guides all significant psychological processes, without offering any reasonable suggestion of where conscious thoughts come from if they are not guided by unconsciousness. Dijksterhuis et al. (2014) state that Newell and Shanks are making the same mistake that Descartes did in assuming everything that is begins in consciousness, meaning that the theoretical house that they are trying to build is standing on *"scientific quicksand"* (pg. 25). Disjksterhuis et al stand by their claim that the best way to understand conscious behaviour and decisions is to study the unconscious underlying processes which influence them. To try to understand consciousness without the unconscious precursors is a dead end. The field has matured, particularly with the advent of brain imaging and advances in computing, so that the theory of unconsciousness (UTT) is reliably established, and Newell and Shanks are forced to accept the current changes in the field. Many researchers now believe that quantitative biometrics can further the consciousness debate by giving improved insights into consumer behaviour, as will be discussed in Chapter three.

2.2.6 Summary

Consciousness is a complicated area, with varying definitions used within the literature. This section has introduced the concept of the non-conscious consumer, and provided insight into the relevant definitions or consciousness and awareness for clarity. The academic field of consumer behaviour research is predominantly in agreement with the Unconscious Thought Theory (UTT), although there are still some academics who are sceptical. The criticisms of the unconscious thought theory have also been presented in this section, for a comprehensive overview of the current research environment. However, there is substantial evidence in support of the UTT and this research will be based on the importance of consumers' subconscious responses.

2.3 Priming

2.3.1 Introduction

The previous section has outlined the burgeoning consensus within the literature that consumers often make decisions unconsciously. As discussed in section 1.3.3, two forms of human cognitive processes are given the labels System 1 and System 2, and can be roughly attributed to intuition and reasoning. System 1 can take over, process countless information and influence our judgements beyond our level of conscious awareness (Kahneman 2011). These judgements, decisions, and actions can be directly or indirectly influenced by features of the environment. Priming is the term for this type of unconscious influence; it is the way an aspect of an environment, whether it is words, images, colours, or even smells, can change responses, behaviours and choices. It happens subconsciously (we believe) because the System 1 mental processes automatically make the associative link between various ideas, with no mental effort requiring the conscious processes of System 2 to intervene. Priming was introduced as a concept in section 1.3.4. However, this section will look more deeply at how and why priming influences consumers' decisions, with examples of the influence of priming in consumer behaviour literature.

2.3.2 Consumer Priming

Priming is a phenomenon in which exposure to one idea can subconsciously evoke memories of related ideas; in the same manner exposure to an environmental stimulus can influence responses to other stimuli (Kahneman 2011; Murphy and Zajonc 1993). Our associative memory is vast, and every idea connects to countless other ideas. Therefore when an individual is primed towards a particular cue this can activate multiple ideas, which in turn activate many more. Priming can influence simple things like words and concepts, or more important things such as an individual's emotions and actions (Kahneman 2011).

Marketers regularly employ the use of priming techniques to influence consumers' purchasing decisions and brand associations (Minton et al. 2016). However, despite the abundant use of primes in marketing campaigns, Minton et al. (2016) argue that the research field has not yet developed a suitable framework for categorising priming techniques. Such a framework would need to acknowledge the challenges of measuring responses to primes, and provide insight about how to conduct research using priming techniques. When conducting priming research it is important to classify the type of priming technique which will be used, and the method by which the prime will be administered. The following subsections clarify the different priming techniques and priming methods which can be used.

Priming Techniques

Priming techniques can be categorised, based on the priming outcome that they produce, into three types; affective, behavioural and cognitive. These three types are in line with the ABC model of attitudes introduced by Breckler (1984), in which an attitudinal response to a stimuli can have affective, behavioural or cognitive observable response. Although priming has been proven to sometimes occur at a subconscious level (Chartrand et al. 2008), the responses to these primes still fall into these three categories.

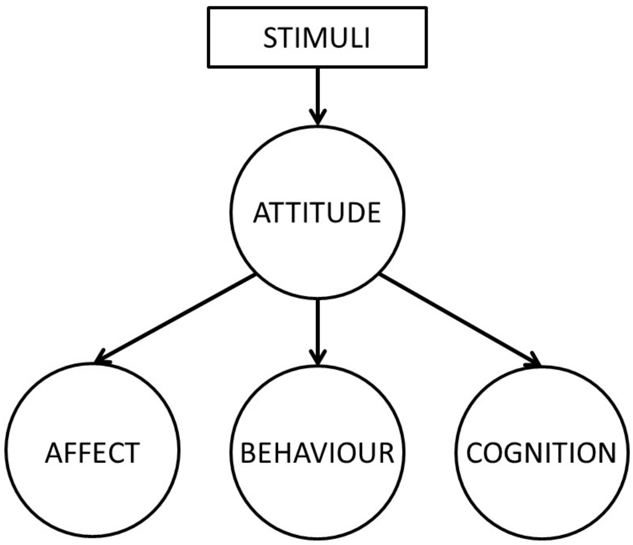

Figure 2.3: Breckler's ABC model of attitudes (Breckler 1984)

Affective priming influences an individual's feelings and emotional responses towards target stimuli. Affective priming can take the form of priming emotionally related words, or even emotional priming using pictures and colours. Raska and Nichols (2012) were able to conceptually prime their participants into healthier food choices with the use of love-related symbols. Behavioural priming, also sometimes known as social priming, relates to the actions and behavioural intentions caused by the prime. From a consumer behaviour perspective, behavioural priming involves looking at how marketers can use primes to influence and change the way the consumer behaves. A key example of this was when Fitzsimons et al. (2008) discovered that priming participants with the Apple logo leads to more creative behaviour than when primed with an IBM logo. Finally, cognitive priming relates to changes in an individual's thoughts because of a prime. The key examples of cognitive priming involve semantic priming, where one word can invoke changes in thoughts. Labroo et al. (2008) were able to semantically prime consumers to choose wines with images of frogs on them. Participants were either exposed to the prime word (e.g. “frog”), or a control word on a computer screen, and were asked to visualise the word in their minds. In the choice task that followed participants who were primed chose the target wine more often than the non-primed participants did. These studies show that consumers’ attitudes and responses can be altered with the use of different priming techniques, and can cause affective, cognitive or behavioural response changes. This research will apply these theories to investigate how colour priming influences consumers’ responses towards fashion products within a real-world retail environment.

Priming Methods

There are numerous methods by which an individual can be primed, for example primes can either be conceptual or perceptual. The difference between these two types of primes is that conceptual primes are related to the subjective meaning of the prime, whereas perceptual primes are focused on the form of the priming construct. Lee (2002) tested the effect of both conceptual and perceptual priming on her participants, demonstrating that a consumer’s brand choice is likely to be a result of conceptual priming if their decision is memory based, or a result of perceptual priming if the decision is stimulus based.

Repetition priming simply refers to the increasing amount of exposure to the prime that the participant receives. The more an individual is presented with a prime, the stronger the effect of the priming will be. Matthes and Naderer (2015) demonstrated this, by measuring the amount of snack food children ate, based on the number of product placement repetitions during a film. They found that the more a product appeared in the film, the more related snacks the children ate. Contrastingly, masked priming is a method in which the prime is only shown to the participant for a minimal amount of time, sometimes between 50 – 60 ms, usually immediately preceding the target stimuli (Minton et al. 2016). The prime is often shown for such a short amount of time that observer is often unaware of it.

Contextual priming is a subtle but potentially powerful form of priming, in which marketing or environmental cues surrounding a target stimulus influence an individual’s response (Minton et al. 2016). Berger and Fitzsimons (2008) demonstrated the influence of contextual cues on product evaluation with the use of trays in a cafeteria as the contextual prime. In the experiment, participants were exposed to two different slogans for a digital music player, either a slogan related to luggage or a slogan related to dining trays. Half of the participants of the study ate in the cafeteria with the dining trays. The participants who ate in the cafeteria with the trays *and* were exposed to the slogan with the tray connotations gave the digital music player the highest evaluations. This study, along with those previously mentioned, show that there is a burgeoning weight of evidence that priming can alter behaviour.

2.3.3 Priming and Mere-Exposure: Similarities and Differences

The mere-exposure effect is a phenomenon by which repeated exposure of previously unfamiliar stimuli causes an increase in the positive affective response towards said stimuli (Seamon et al. 1995). It became a highly investigated topic within mainstream psychology after Robert Zajonic published his monograph “Attitudinal Effects of Mere Exposure” in 1968 (Bornstein 1989). Zajonic defined mere-exposure as *“a condition, which just makes the given stimulus accessible to the individual’s perception”* (Zajonc 1968, pg. 1).

Despite the seeming similarities between the priming phenomenon and the mere-exposure effect, these areas of research have developed mostly independent of each other (Butler and Berry 2004). A key difference in existing priming and mere-exposure research is the reference to either implicit or explicit memory. Implicit memory is the non-conscious and unintentional retrieval of memories, whereas explicit memory involves conscious and deliberate recollection of stored information (Cooper and Schacter 1992). Priming research traditionally explores the way connections are made in the implicit memory, and how these can subconsciously influence human behaviour (Bargh et al. 1996; Johnston 2002). Priming studies most commonly involve non-affective judgments, after participants have had a single exposure to the priming stimuli (Butler and Berry 2004). On the other hand mere-exposure research focuses on affective responses towards stimuli that have been repeatedly exposed to a participant (Bornstein 1989; Seamon et al. 1995).

There is evidence to suggest that there is a common underlying mechanism governing both of these concepts (Butler and Berry 2004). Various studies have found evidence for the mere-exposure effect despite the participants lack of awareness of the influencing stimuli (Seamon et al. 1995). Kunst-Wilson and Zajonc (1980) exposed participants to 10 different irregular polygons for one millisecond, five times for each shape, then asked which shapes the participants recognised, and which shapes they liked. They found that the participants’ affective judgments had been influenced by the priming stimuli, although they did not recognise the stimuli that had primed their judgements. This suggests that the effects of mere-exposure can be based on information retrieved from implicit memory, essentially combining the theories of priming (subconscious recall of information) and mere-exposure effect (increased liking based on repeated exposure).

When discussing non-conscious influences of environmental stimuli on consumer decisions academics often discuss responses that may be caused by priming, the mere-exposure effect or a combination of both. As an example, if a particular type of product or brand has been recently primed, then these products or brands will be more readily accessible in the consumer memory, and are therefore more likely to be included in a consumer’s consideration set (Berger and Fitzsimons 2008; Nedungadi 1990). On the other hand, if an individual is repeatedly exposed to a particular product or brand, the mere-exposure effect is likely to cause increased positive affective responses towards that product or brand (Berger and Fitzsimons 2008; Janiszewski 1993).

2.3.4 Perceptual Fluency

A key explanation given for the mere-exposure effect is that it leads to perceptual or conceptual fluency, and it is the increased fluency that leads to the individual's favourable affective responses (Reber et al. 1998; Butler and Berry 2004; Lee and Labroo 2004). Perceptual fluency is defined as the ease with which an individual recognises the characteristics of a particular stimulus, whereas conceptual fluency is regarding the ease with which conceptually related items or ideas come to mind (Lee and Labroo 2004).

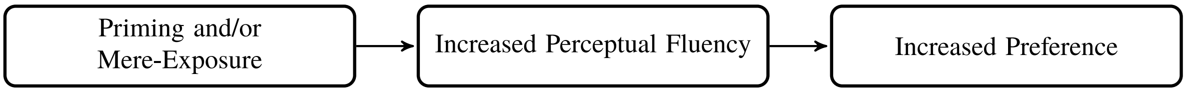

Figure 2.4: Flow of priming to increased preference, via increased perceptual fluency

Reber et al. (1998) determined that if perceptual fluency is the intrinsic cause of the mere-exposure effect, then it should be true that perceptual fluency manipulated by means other than repetition should also increase an individual's liking of a stimulus. To test this they conducted a number of experiments in which they used alternative methods to achieve a higher level of perceptual fluency. In one of these experiments participants were shown 20 target images of neutral objects, and asked to judge how pretty they thought the image was on a Likert-type scale. Each of the images was shown for two seconds, and was preceded by another image for just 25 milliseconds. The preceding image was either a contour that matched the target image, and therefore enhanced the participants' perceptual fluency, or a contour of a different image, consequently not enhancing the perceptual fluency. The preceding images were shown so quickly that many participants had not registered that they had been shown. It was found participants judged the target images that were joined with matching contour images as prettier than those with mismatching following images (Reber et al. 1998). Suggesting that the increased perceptual fluency, created by the matching contour, caused the participants to have a more favourable evaluation of the image. This also suggests that perceptual fluency can have an impact below the level of consciousness, as the participants were unaware of the preceding images.

In another experiment by Reber et al. (1998) perceptual fluency was manipulated by increasing the length of time that the participants were exposed to the stimuli for. They hypothesised that the longer the participants were exposed to the stimuli, the more information they would be able to extract from it (Mackworth 1963), and therefore their perceptual fluency would be increased. The stimuli, patterns made up of 32 white and 32 black squares, were shown to the participants for either 100, 200, 300 or 400 milliseconds, with a fixation point shown for 500 miliseconds between each. To test whether the effects of perceptual fluency were affectively positive or negative, participants were split into two condition groups. The positive condition group were asked to answer on a Likert-type scale whether they liked the patterns, and the negative group were asked if they disliked the pattern. The results showed that the liking judgments increased with the length of time the stimulus was shown for, and the disliking judgments decreased. This is consistent with the hypothesis that longer exposure time leads to increased perceptual fluency, and positively affects liking.

The findings of these experiments have been validated by numerous other perceptual fluency studies (Winkielman and Cacioppo 2001; Novemsky et al. 2007; Shapiro 1999). It is an accepted consensus amongst researchers that there are various factors that can increase the ease with which individuals process target stimuli, and more easily processed stimuli are liked more (Labroo et al. 2008; Reber et al. 2004). Increased mere-exposure and priming can cause increased perceptual and conceptual fluency, subsequently enhancing a consumer's affective response (Reber et al. 1998; Berger and Fitzsimons 2008; Janiszewski and Meyvis 2001).

2.3.5 The Psychology of Colour

It is well documented in literature that colour is one of the most dominant features that influences consumers' perceptions and behaviours (Kareklas et al. 2014; Aslam 2006; Bellizzi et al. 1983). Colour plays an integral role in retail features such as advertisements and store design (Bellizzi et al. 1983), and is also one of the key evaluative criteria for consumers when making a fashion purchase (Forney et al. 2005). Colour is an effective, yet inexpensive, tool that can be used to alter consumers' perspectives of a brand or product (Sliburyte and Skeryte 2014). The influence of colour is subtle, and can happen subconsciously, without the viewer being aware of the effect that the colour of a stimuli may being having on their behaviour or mood (Sliburyte and Skeryte 2014). There are two key schools of thought regarding how colours may impact human behaviour. The first of these, is that responses to certain colours are learnt over time Aslam 2006. Repeated exposure to colours with clear associated meanings, will eventually lead a colour to activate its paired association. For example, the colour red is used as a sign to stop in traffic lights, and is also used in stop signs. Over time, humans begin to associate the colour red with stopping, as this has been primed in their previous experiences. The second theory is that the response to some colour is based on biological predispositions (Elliot and Maier 2007). Some colour theorists posit that many colour associations developed from evolutionarily ingrained responses to different coloured stimuli (Elliot and Maier 2007; Mollon 1989). Elliot and Maier 2007 posit that colours that are considered positively cause approach responses, whereas colour that are considered negatively cause avoidance responses. In this way, colour can act as a positive or a negative prime on human behaviour.

Much of the theoretically based colour psychology research has been lightly guided Goldstein 1942 proposal about the colours red, yellow, blue, and green. Goldstein 1942 proposed that red and yellow are both stimulating, yet disagreeable colours, and that green and blue are calming and agreeable (Elliot and Maier 2007). More recently researchers have found a connection between Goldstein's proposal of the arousal a colour can cause, and the size of the colour's wavelength. For example, red, which is considered to be arousing, has a longer-wavelength. Whereas green, which is considered calming, has a shorter-wavelength (Stone and English 1998). Similarly, the colours red and blue have been posited as being associated with happiness and sadness, respectively. Soldat et al. 1997 proposed, therefore, that these colours can elicit behavioural responses and cognitive processes that correspond to these emotions.

Blue and red will both be used as prime condition colours during the experiments for this research. As both can elicit opposite emotional responses, it could be possible for either to skew the participants' emotional responses, particularly when considering the EEG data. However, due to the nature of the analysis this is not considered to be a problem in this research. Firstly, if the red prime skews the results in a positive approach direction, and the blue prime skews the results in a negative withdrawal direction, then when the data are analysed collectively these changes would theoretically balance each other out. Additionally, the analysis has considered a change in the emotional response towards target products, as opposed to an overall emotional valance during the task.

To test the influence of the colour red as a prime for avoidance behaviour in achievement context, Elliot et al. 2009 conducted an experiment in which participants were asked to conduct IQ tests. 30 participants, with an average age of 33.23 years old, took part in the study. None of whom had red-green colour blindness (Elliot et al. 2009). The participants were sat at a computer, on which they were told they would conduct an ID test. They were first instructed to concentrate on a fixation cross in the centre of the screen, after which the ID test cover page was shown for two seconds. Depending on the participants randomly selected condition group, they were either shown a red, green, or grey test cover page. To determine whether the colour of the test cover page caused an approach or withdrawal tendency, the distance that the participants moved themselves either towards or away from the screen was measured with an inclinometer sensor. The results found that the participants who were shown the red cover page moved further away from the screen than those in the green and grey conditions, as can be seen in the results presented in Figure 2.5.

Colour has been demonstrated to have a subtle, non-conscious influence on human behaviour and responses. However, there is limited existing literature demonstrating the influence of colour priming on consumers fashion choices and preferences. Colour is an integral and important aspect of fashion design, and also of retail design. This research

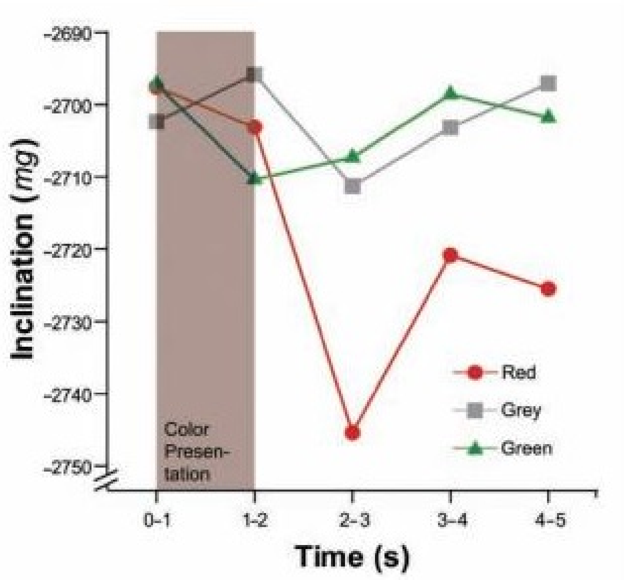

Figure 2.5: The distance of participants from the computer screen after been shown the test cover page for an IQ test, demonstrating the effect of red on avoidance behaviour in an achievement context (Elliot et al. 2009)

will study the influence of colour priming on consumers fashion choices, and whether colour priming can firstly, change the choices that the participants make and secondly, and more subtly, whether colour priming can influence the participants' physiological responses towards colour matching stimuli. The research will explore the link between colour priming, and the consumers' responses towards colour matching products.

2.3.6 Priming Influences in Consumer Behaviour

When NASA successfully landed the Mars Pathfinder in 1997, it was given a substantial amount of coverage by the world's media. In the same year, the confectionary company Mars Inc. experienced an increase in sales of their Mars Bars (White 1997). Although the chocolate treat has no relation to the Earth's neighbouring planet, the increased exposure of simply the concept 'mars' was enough to encourage consumers purchasing habits (Berger and Fitzsimons 2008). This is an example, albeit anecdotal, of increased exposure to stimuli priming consumers' behaviour.

Subliminal priming effects can also affect the quantity of a product that the consumer desires, or the amount that they are willing to pay for it. Winkielman and Cacioppo (2001) found that participants who were subconsciously primed with happy facial expressions, were willing to pay more for a drink than participants who were primed with angry faces. Thirsty participants who were subliminally primed with thirsty related words flashing on a computer screen, were found to consume more of a professed thirst-quenching drink than an alternative (Strahan et al. 2002). However, the same results in this experiment were not found in participants who were not already thirsty. In each of these drink related studies, none of the participants were aware of the influence of the primes on their behaviour (Tom et al. 2007).

Papies and Hamstra (2010) conducted an experiment in which they were able to manipulate the amount of food the participants ate by priming them with a dieting goal. In one condition, the door to a butcher's shop had a poster advertising a low calorie recipe, created to help people lose weight. In the control condition there was no poster on the door. Free tasters of food were available for all customers within the store, and the amount of food each customer ate was recorded by the investigator. The results showed that participants who considered themselves to be restrained eaters [1] were successfully primed to eat less food than those in the controlled condition. The activation of the diet goal had encouraged the participants to engage in goal-direct behaviour, by not overeating the available free snacks.

2.3.7 Colour Priming Influences in Consumer Behaviour

Many different types of priming techniques are used to influence consumer purchasing habits and brand evaluations. This research will specifically focus on perceptual influence of colour priming towards consumers' fashion product brand evaluations, measured by their affective and cognitive responses.

Semantic priming can be used to increase consumers' preference for a related product, as Galli and Gorn (2011) discovered when they primed participants with the words *black* and *white*. When participants were primed with the word black, then asked to indicate their reaction towards a black coloured product's brand name (for example, cola) they responded to the product more favourably than if they were primed with white. The same was true vice versa, when the participants were primed with white, and then asked to respond to a white related product (soymilk), they responded more favourably than those primed with black.

Based on the theoretical background of mere-exposure, priming effects, and perceptual fluency, Berger and Fitzsimons (2008) conducted a number of experiments to examine the effect of the everyday environment on consumers' product evaluation and choice. Having noted the lack of empirical evidence of priming in real-world settings, they conducted their first experiment in a natural environment. This initial field study was used to test whether certain products would be more accessible in consumers' memories following indirect priming links to those products.

In America, halloween is a popular and well-celebrated holiday, and fortunately for Berger and Fitzsimons this holiday brings with it many new environmental cues. Pumpkins can be seen on neighbours' front door steps and supermarkets decorate extravagantly with

[1] Participants filled in short questionnaires, including completing the Revised Restraint Scale (Herman and Polivy 1980), to indicate their eating behaviours.

predominantly orange displays. Then, by the time Halloween has passed, the orange environmental cues are conveniently taken away. Berger and Fitzsimons (2008) took advantage of this situation to test whether these environmental cues had an influence on the participants' recall of products associated with the colour orange. Participants were approached on a Saturday afternoon in the entrance of a local supermarket and asked to take part in a short questionnaire. The participants were asked to list the first products that came to their mind within different categories, such as candy, chocolate and soda (Berger and Fitzsimons 2008). The experiment was conducted twice, first during the week before Halloween, and repeated the week after, once the decorations had been taken down.

To measure the associability of the products to the consumers' memory Berger and Fitzsimmons used two methods; firstly they examined the percentage of consumers who mentioned each product, and they considered the order in which consumers mentioned the products in their lists. If a product was mentioned earlier in the list it was given a higher score to indicate that it came to memory with more ease than a product mentioned later in the list. Their results showed that for candy, chocolate, and soda, orange related products, such as Reece's chocolate and orange flavoured soda, were more accessible to consumers' memory when there was a higher concentration of orange environmental stimuli. This suggests that product accessibility can be primed by simple environmental cues such as colour.

The difficulty with conducting field studies in a natural environment is the inevitable influence of many other uncontrolled variables. To account for this, and to examine the influence of colour priming further, Berger and Fitzsimmons conducted another experiment in a laboratory setting (Berger and Fitzsimons 2008). In this subsequent study they investigated whether a colour prime can influence an individual's product choices, by asking participants to answer a survey making preference-based choices between consumer goods. The priming stimulus was the colour of the pen that the participants were given, which had either orange or green ink. To ensure that the participants had sufficient exposure to the prime colour they were asked to write a few sentences about something they had recently read before beginning the survey. The survey consisted of 20 choice sets, each with two product options, and they were asked to select the one they preferred. The products were everyday consumer products (drinks, detergents or confectionary) and pictures of all of the products were included in the survey. A number of the products were related to either green or orange, and some of the products were unrelated to these colours.

The results showed that participants who answered the survey using an orange pen were more inclined to choose the orange products, and similarly the participants who used a green pen were more likely to choose the green products. These findings are consistent with the mere-exposure effect theory; that increased exposure to environmental cues will increase an individual's liking of perceptually linked items and products.

2.3.8 Summary

This section has reviewed the priming phenomenon, compared the similarities and differences with the mere-exposure effect, and presented examples of the influence of priming in consumer behaviour. Limited literature exists regarding the influence of colour priming on consumers' responses towards prime matching products, however two studies by (Berger and Fitzsimons 2008) have been reviewed here. To exemplify the lack of existing literature regarding colour priming, a comprehensive review of colour priming related search terms is provided in Appendix A.

2.4 Emotions

2.4.1 Introduction

In addition to priming, emotions are central to consumer behaviour, and have a large influence on buying habits and purchase decisions (Bagozzi et al. 1999; Babin et al. 2004). This section will begin by introducing and defining some of the key terms surrounding emotional responses, and clarifying how these terms are being interpreted in this research in section 2.4.2. Following this, section 2.4.3 will demonstrate the role of emotions in decision making, and section 2.4.4 will describe the influence of retail environmental factors on consumers' emotional responses.

2.4.2 Definitions

There is sparse consistency in the terminology of emotions used in literature, often the terms 'affect', 'emotion', and 'mood' are used interchangeably, despite having different interpretations. Therefore Bagozzi et al. (1999) highlight the importance of individual authors' definitions of emotion related terms. In this research 'affect' and 'affective' are used as umbrella terms that include both state and trait emotional responses (Bagozzi et al. 1999; Coan et al. 2004). Bagozzi et al. (1999) consider 'affect' as a general term for mental feeling, as opposed to a specific psychological process. At a primitive level, emotions can be described as changes in mental states as a response to a reward or a punishment (Rolls 2006).

Emotions can be described either in terms of *state* or *trait*. A common definition of emotions is that they are a mental state that arises in response to events or thoughts, and often involving a psychophysiological process and psychical expression (Bagozzi et al. 1999). This definition of emotion matches a *state* type of affect, which is specifically responsive to an internal or external environmental change (Coan and Allen 2003). *Trait* affect on the other hand, refers to a mental state that is consistent and stable over time (Coan and Allen 2003). For example, trait can refer to a underlying sadness, or happiness, which is consistent over time. The key difference between emotion and a mood is that a mood has a much lower intensity than an emotion, and will last for a longer period of time (Bagozzi et al. 1999). In this research the term ”affective response” is used to convey emotional *state* changes as a response to environmental stimuli, and these are the specific emotional responses that are of interest.

2.4.3 The Role of Emotions in Decision Making

Until Simon (1955) introduced his theory of bounded rationality many choice researchers still believed that consumers were abundantly rational and capable of evaluating their choices to make the decision that would maximise their utility (Neumann and Morgenstern 1947). In the early 1960s critique of traditional consumer decision theories began to materialise, along with the emergence of behavioural decision research (Loewenstein and Lerner 2003). This new behavioural approach to decision research aimed to identify the key cognitive errors that consumers make when trying to judge outcomes, and how consumers simplify the decision process in order to cope with the overwhelming complexity of decisions (Loewenstein and Lerner 2003). However, until the early 2000s researchers still considered decision-making as a cognitive process, and largely ignored the role of emotions (Loewenstein and Lerner 2003).

The increased acceptance of the importance of emotions in decision-making can be attributed to some major discoveries in the field, such as the discovery that emotional defects will have a negative impact on the ability to make sensible or rational decisions (Damasio 1994; Wilson et al. 1993). It has also been found that decisions can be influenced by affective states, even if the effect is unrelated to the decisions at hand (Lerner and Ketler, 2000), and incorporating affect can increase the explanatory power of decision making models (Loewenstein and Lerner 2003; Mellers et al. 1997).

The retail market is becoming increasingly saturated with countless alternatives for all products, meaning consumers continually need ways to simplify their decision-making. This leads to consumers basing their decisions more on emotional judgements of how a product will make them feel, as opposed to the complicated cognitive evaluation of the numerous potential outcomes associated with each product (Koo et al. 2014; Pham et al. 2001).

There is empirical evidence that shows the various ways that emotions will affect consumer behaviour, such as amount of time and money spent in store (Babin and Darden 1995), customer satisfaction (Dawson et al. 1990) and the perception of rewards from the customer-retailer interaction (Babin et al. 2004).

The retail environment can stimulate a consumer's perceptual and psychological thoughts and feelings, causing a change in their cognitive and emotional state (Bagozzi 1986; Sherman et al. 1997). These thoughts and feelings are the internal processes intervening between the consumer's environment and their behavioural responses towards said environment (Koo and Lee 2011). Several researchers have demonstrated the effect of a retail atmosphere on consumer behaviour, and argued that the physical store environment is central in forming a retailer's image (Kotler 1973) and it produces affective and cognitive evaluations that lead to behavioural responses (Bitner 1992; Kumar and Kim 2014). The Mehrabian and Russell (1974) Stimulus-Organism-Response (S-O-R) framework was developed to evaluate these internal cognitive and affect processes, from how they are influenced by environmental cues, and how they in turn affect behavioural responses (Kumar and Kim 2014). The S-O-R framework is discussed in more detail in section 4.3, as it forms the overarching theoretical framework for the current research.

2.4.4 Consumers' Emotional Responses

To investigate the relationship between retail store environment and consumer emotions Sherman et al. (1997) conducted a large-scale field study, using genuine shopping behaviour as an example. As consumers left fashion stores in shopping centres they were approached and asked to complete a self-administered questionnaire, which would measure the consumers' perceptions of the retail environment, and measure their emotional state. Of the 1480 shoppers who were approached, 61.4% agreed to take part, leaving them with 909 respondents. Sherman et al. (1997) argue that measuring emotional state outside of the store, after the shopping experience, was the most reliable method as it does not intrude or interrupt the consumers' shopping experience, which could cause the consumer to become angry or irritated, distorting the results. Sherman et al. (1997) suggest that this could be the reason for the inconsistent results found by researchers attempting to measure emotion whilst in-store (Donovan et al. 1994).

The results showed that elements of a retail environment will positively influence a consumer's mood, specifically enhancing their in-store pleasure and arousal, which will in turn influence their response towards the environment such as the amount of money they spend in store, or number of items they purchase. The findings confirm that consumers' emotions are significant factors in buyer behaviour (Sherman et al. 1997). Whilst these are positive results, there are some limitations of this study. Individuals are more likely to participate in the study if they are in a positive mood (Isen et al. 1982), therefore the results may be distorted by not including the responses from the 38.6% who did not wish to participate. This limitation is extended by additional potential bias in that all participants asked have chosen to visit the store that they have just exited, which is likely to cause a positive bias towards the store. Additionally, by conducting the experiments after the participants had finished shopping, they were unlikely to be able to accurately recall their thoughts and feelings, due to imperfect memory. This is one of the flaws of self reported feedback from participants in consumer based studies, that the methods proposed in this thesis aim to overcome. By using eye-tracking and EEG, data can be collected during the real-time of the experiment, without interrupting the participant's natural behaviour.

More recently, Koo and Lee (2011) investigated the relationship between three key emotional responses to online and offline retail environments, and their influence on purchase intention. The three variables of emotion that they chose to explore were dominance, arousal, and pleasure (Mehrabian and Russell 1974). Dominance refers to a consumer's feeling of control or influence towards their surroundings (Lunardo and Mbengue 2009). Arousal was separated into energetic arousal and tense arousal. Energetic arousal is defined as feeling stimulated, vigorous or excited by the shopping experience, whereas tense arousal is defined as feeling anxious or nervous (Matthews et al. 1990). Pleasure was used to determine how joyful or satisfied a consumer feels regarding their online or offline retail environment (Ward and Barnes 2001).

As consumers had finished their shopping and were preparing to leave the shopping center interviewers approached them, and asked whether they had experienced traditional in-store shopping, as well as online shopping, in the past three months. If they had, they were asked to answer the questionnaire, which included questions related to the emotion variable (dominance, tense arousal, energetic arousal and pleasure) and intent (Koo and Lee 2011). The answers were given on a five-point Likert-type scale, varying from "did not feel at all" to "felt very much" (Koo and Lee 2011, pg. 1744). The results regarding the traditional offline in-store retail environments showed that the positive emotions (energetic arousal and pleasure) both had a positive influence on intention. In the online retail environment it was also found that energetic arousal and pleasure had a positive impact on intention. These results provide further evidence that retail environments cause emotional responses in consumers, and that these emotional responses subsequently influence consumer behaviour.

Kumar and Kim (2014) investigated the impact of store atmosphere, specifically social cues, design cues, and ambient cues, on a consumer's cognitive and affective evaluations, and how these lead to either approach or avoidance behaviours. Thirteen fashion retail stores that sold both male and female apparel were selected, including Hollister, Gap, and American Apparel. Their research model was modelled on Mehrabian and Russell's (1974) Stimulus-Organism-Response (S-O-R) framework for analysing environment psychology. The participants were asked whether they strongly agreed or strongly disagreed with statements regarding social, design and ambient cues within store, and had their cognitive and affective evaluations towards the store and merchandise, and monitored their perceived approach-avoidance behaviour (Kumar and Kim 2014).

The results found that there was a positive correlation between consumers' cognitive evaluations of the store and their approach behaviours, and the affective evaluations of the merchandise had a direct positive impact on the consumers' approach-avoidance behaviours. One of the key limitations of their study that Kumar and Kim (2014) identified with their study was that the self reported method relied on participants recalling their thoughts and feelings from memory. This reduces the reliability of the information, as the answers may not have been accurate due to potential memory loss.

2.4.5 Summary

Researchers now better understand the crucial role that emotions play in decision making. Consumers have to make countless decisions due to the plethora of available products, meaning they will often simplify the process by relying on their *gut instinct*, or essentially relying on their emotions. This section reviewed several experiments which were able to provide empirical evidence of a retail environment influencing the consumers' emotions. However, many of these experiments were conducted based on surveys and self-reported verbal responses, which can be compromised by participant bias or memory loss. This research proposes a methodology which aims to overcome this issue by recording the participants' physiological and neural responses using mobile eye-tracking and EEG devices. The methodology for the experimental set-up in a real-world simulated retail environment will be discussed in Chapter four.

2.5 Chapter Summary

Several empirical studies based on insights from consumer decision-making and environmental psychology theories have identified that store atmosphere will evoke emotional responses within consumers (Groeppel-Klein 2005). However, these studies have predominantly replied on self-reported methods, with participants answering questions using Likert-type scales to document their thoughts, feelings and responses (Sherman et al. 1997; Koo and Lee 2011; Kumar and Kim 2014). In experiments investigating priming and the mere-exposure effect, results often also rely largely on Likert-type scale rating and forced preference judgements (Butler and Berry 2004). The validity of these responses is questionable, because they happen after the participant has left the store, and it is unlikely they are able to accurately recall their cognitive and affective processes (Groeppel-Klein 2005). Several academics have noted the problems with trying to measure emotions using self-reported responses, due to the complexity of emotions (Davidson 2004; Ohme et al. 2011; Poels and Dewitte 2006). Additionally there is often a non-conscious element of the internal affective and cognitive evaluations that the consumer is not aware of to report, even if they could remember it (Berridge and Winkielman 2003). The retail environment can invoke emotional responses, however these responses have typically been analysed after the event (Sherman et al. 1997; Kumar and Kim 2014; Koo and Lee 2011). This delay between the shopping experience, and answering the survey questions, can mean the participants forget the emotions they experienced, or their mood may have changed by the time they answer the questions, meaning they answer more positively or negatively based on their mood.

This chapter has provided a comprehensive overview of subconscious influences that the retail environment can have on consumers, and how these interplay with the consumers' behaviour. It is clear that due to the subconscious nature of the influence of retail environments on consumers, it is necessary to adopt techniques which can evaluate responses at a subconscious level. Chapter three will review methods and theories for achieving reliable information about consumers' subconscious responses towards a retail environment, by using biometric measures such as eye-tracking and EEG.

Chapter 3

Physiological Measurement for Understanding Consumer Behaviour

3.1 Introduction

As discussed in Chapter two, consumers' responses towards environmental stimuli often occur below their level of conscious awareness, and therefore self reported research methods can lack reliability. In this chapter eye-tracking and Electroencephalogram (EEG) technologies will be reviewed as methods for measuring consumers' underlying cognitive and affective (emotional) responses. These quantitative methods can also provide information during the real-time of the experiment.

Section 3.2 begins by introducing *Neuromarketing*, the broad term used for measuring consumers' biometric and physiological responses to stimuli that are hoped to promote purchase and consummatory behaviour. Following this sections 3.3 and 3.4 introduce the two key technologies which will be used in this research, eye-tracking and EEG (respectively). Relevant theories for interpreting and analysing data obtained by both methods will be reviewed. Finally, section 3.5 demonstrates previous studies which have applied these methods to consumer behaviour research.

3.2 Neuromarketing

Neuromarketing is a subset of the general field of neuroeconomics, which is an interdisciplinary field of research that combines theories from economics, neuroscience, and psychology to understand the brain during decision-making (Kenning and Plassmann 2005). The term *neuromarketing* was first coined by Professor Ale Smidts in 2002 (Lewis and Phil 2004), and the first formal neuromarketing conference took place in 2004. Neuromarketing techniques involve measuring consumers' biometric or physiological responses to marketing stimuli, using technologies such as eye-tracking for measuring eye movements, Galvanic Skin Response (GSR) for measuring stress response, Electrocardiogram (ECG) for measuring the heart, or Electroencephalogram (EEG), functional

Magnetic Resonance Imaging (fMRI), or Positron Emission Tomography (PET) for measuring the brain.

A key advantage of neuromarketing methods over traditional market research techniques is that they do not rely on the participants to self report, as it is unlikely that any participant would be able to perfectly describe their subconscious motives or internal neural processes (Britt 2004; Fugate 2007). Custdio (2010) also reports that most factors that have an influence on a consumer's decision making and influence the consumer's behaviour are not consciously perceived and are therefore not possible to report. Another benefit is that when conducting a neuromarketing study using EEG or other brain imaging techniques, the participants are less able to bias or influence the results, because the changes in brain are activity caused by subconsciously responding to environmental cues cannot be overtly controlled by the participants (Camerer et al. 2005; Custdio 2010). Eye-tracking technologies allow researcher's to monitor the subtle eye-movements of participants, which are believed to relate to underlying cognitive mechanisms. Neuroscience techniques are able to delve into the fundamental biological processes beyond the scope of traditional marketing techniques, and with the correct methodology and analysis techniques can provide a richer perspective of the psychological and behavioural processes in decision making (Hubert and Kenning 2008).

However, neuromarketing, as a discipline, is not without criticism. Some previous neuromarketing studies have been chronically underpowered, which has led to numerous failures to replicate reported findings. This is a general issue in brain imaging literature, where low powered studies have failed to replicate when reinvestigated (Boekel et al. 2015) . Furthermore, many neuroimaging and psychology journals do not accept replication studies, only publishing original research, which propagates the reliance on false positives. In fact, recent research Martin and Clarke (2017) highlighted that only 3% of psychology journals welcome replication papers.

Another issue with neuromarketing studies is that they cannot always provide a convincing representative environment for the participant due to technical restrictions, which could influence the consumers' behaviour and therefore taint the results (Custdio 2010). For example fMRI technology can investigate subcortical brain activity, however participants are restricted to lying still within the large machine. Mobile eye-tracking and EEG studies require the participant to wear the devices on their head, which may have an impact on how naturally they behave during the experiment. It could make them feel embarrassed or cause minor discomfort.

Conducting neuromarketing style studies can also be problematic due to the complexity of the interaction between consumer and product, as well as requiring a high level of skill and expertise to conduct the experiments and interpret the results. It is important to set-up the experiment carefully to ensure the data obtained is reliable, repeatable and robust.

Specifically with regard to this research, this requires the integration of EEG and eye-tracking data acquisition tools with a real world shopping environment. For example when using an eye-tracker it is essential to ensure the distance from the pupil to the tracking cameras will not shift throughout the experiment, and that the gaze position is accurately calibrated before recording. Moreover, in order to obtain clean signals in EEG data, this requires accurate positioning of the electrodes, removing hair away from the scalp, and keeping the skin clean underneath the electrode. A saline solution is used to improve the conductivity signal between the skin and electrode. These measures are all undertaken in order to improve data acquisition before preprocessing or data optimisation methods (smoothing, motion correction, band pass filtering etc.) can be implemented.

Interpretation of results requires numerous stages of analysis to be performed before we can understand and have confidence in the outcome. For example, an EEG device does not directly demonstrate human behaviour; the outputs are discrete electrical signals that are aligned with neuronal firing in different areas of the brain. These electrical signals need layers of processing before they can be transformed into frequency bands, which can then begin to be correlated with human behaviour. Although informed by decades of research theories, there is still no definitive and straightforward approach to deciphering the complex relationship between brain activity and human behaviour.

3.3 Eye-Tracking

3.3.1 Introduction

It has been found in numerous studies that there is a clear link between our eye movements and our cognitive processes. It was Alfred Yarbus' work that *"most clearly called attention to the intrinsically cognitive nature of eye-movement"*, over 50 years ago (Hayhoe and Ballard 2005, pg. 188), and he was described by Pannasch et al. (2008) as the pioneer in the field. In his book "Eye Movements and Vision", Yarbus et al. (1967) presented the detailed findings of his studies on the eye's saccades and fixations, sparking great interest into further research of the neurological relationship of these movements. Glaholt and Reingold (2011, pg. 2011) stated that monitoring eye-movements is a valuable tool for tracking a decision maker's search behaviour.

Humans take in millions of bits of information via the visual system, most of which never gets consciously processed, though it does have a subconscious impact on behaviour and preferences. Mere-exposure to an environment or stimuli, can lead to increased perceptual fluency, leading to increased preference (as described in section 2.3.3). This can all happen subconsciously, meaning a participant would not be able to verbally report everything they have taken in. However an eye-tracking device can monitor these movements to gain a more accurate representation of what the participant looked at, for how long, and the sequence of those eye-movements. From a consumer's eye movements, according to the Gaze Cascade Effect (Shimojo et al. 2003; Simion and Shimojo 2006, 2007), we can infer the consumer's preferences, as the Gaze Cascade Theory states that the areas of interest which receive the most attention are the preferred items. The Gaze Cascade Theory is discussed in detail in section 3.3.5.

Eye-tracking devices track the fixations, saccades, and scanpaths made by the consumer. Pavlas et al. (2012) describe a fixation as a relatively stable eye-in-head position that lasts for a minimum of 100-200ms. A saccade is described as the rapid movement of the eye between fixations, and a scanpath is a combination of the fixations and saccades in their chronological order. When analysing eye-tracking data it is most common to focus on the fixations; either the number of fixations on a particular area of interest, or the duration of the fixations in that area. Figure 3.1 shows a gaze plot, which is a visual representation of a scanpath. The data in this example is from a short segment of one participant's data. In the gaze plot fixations are represented by circles, and the larger the circle is, the longer the fixation it represents was. The lines in between the fixations represent the saccades. The number within each circle demonstrates the order in which the fixations occurred.

Figure 3.1: Fixations and saccades represented by a short gaze plot.

3.3.2 Eye-Tracking Devices

Eye-tracking is used by a wide variety of scientific research domains, such as experimental psychology, neuroscience, and computer science, to investigate visual processes (Mele and Federici 2012). Such varied applications of eye-tracking technology have required different varieties of eye-trackers to be developed. The two key types of eye-trackers available are desk-mounted screen-based stationary eye-trackers and head-mounted mobile eye-trackers (Mele and Federici 2012).

One thing that all eye-trackers have in common is that there needs to be a camera facing the participant's eye, which will trace the movements of the participant's pupil. Eye-trackers illuminate the eye with infrared light to distinguish between the pupil and the iris, helping to determine the exact position of the pupil (Pavlas et al. 2012). Infrared light has a lower frequency on the electromagnetic spectrum compared to visible light and so cannot be detected by the human eye, whilst reflecting from the iris (Sousa 2010). A screen-based eye-tracker will position the eye-facing camera below the screen that the participant is looking at. In a mobile eye-tracker the eye-facing camera will be positioned close to the participant's eye, but without obstructing their view.

As well as the eye-facing camera, all eye-trackers need a method of recording what the participant is looking at. For a screen-based eye-tracking device this varies according to whether the screen in question is a computer desktop, a tablet, or mobile phone device. When using an eye-tracker with a computer desktop the two are connected, therefore the eye-tracking software can do the recording of the screen internally. For a tablet that cannot be connected with the eye-tracker, the participant's frame of vision will have to be recorded by a second camera. For a mobile eye-tracker an additional camera will also be used to record the participant's view. This camera will be mounted onto the headset or glasses, facing the direction of the wearer's gaze.

One of the key advantages of using an integrated desktop eye-tracking device is that the participant's fixations can be automatically mapped onto the image that they are looking at. Whereas, when using a mobile eye-tracker, the positions of the participant's fixations have to be manually mapped onto a two dimensional image after the experiment. This can cause a lengthy analysis process, and allows room for human error when mapping the fixations. To mitigate the potential human error when mapping the fixations for this study, the investigator went through each recording twice. The first time was to initially map the fixations, the second was to ensure that the fixations were in the correct place.

3.3.3 Mobile Eye-Tracking Devices

A key aim of this research is to investigate consumers responses is a real-world retail environment, therefore a mobile eye-tracking device needs to be used. Eye-tracking technology has evolved to a high standard recently, and as such there are a number of mobile eye-tracking glasses available for researchers with a reasonable budget.

A mobile eye-tracker that would appeal to a research with the most modest of budgets would be the Pupil Labs wearable eye-tracker, which can be used alongside open source software for recording and analysis (Kassner et al. 2014). The device is supposedly capable of device accuracy up to 0.6 degree of a visual angle, with a processing latency of only 0.045 seconds. The device is incredibly light, at only 9g, and includes two cameras; one facing the wearer's right eye pupil, and the other facing outwards to record the world view. In theory, an eye-tracker which enables researchers to analyse data in free to use open source software is a great idea. However, in practice the Pupil Labs eye-tracker does not perform well enough to compete with the more state of the art eye-trackers available today. The Pupil Labs eye-tracker was first considered for this research and was used during the pilot investigations, however it was deemed unsuitable for this research. A key problem was with the pupil detection software; dark coloured irises or thick eye-lashes would be detected by the software as the wearer's pupil, therefore providing inaccurate information of where the user was looking. Also, the device is also not entirely mobile, as the glasses require being connected to the recording device (either a laptop or computer) via the USB port.

Two more advanced, mobile eye-tracking devices available are the Tobii Pro Glasses 2 and the SMI glasses 2. Both devices are completely mobile, as the glasses are connected to small recording units which can be kept in the wearers pocket or attached to a belt. Both eye-trackers are capable of gaze accuracy of 0.5 degrees per visual angle, however the Tobii device is able to automatically compensate for slippage, caused by possible movement of the glasses on the wearer's face. The Tobii software makes this possible with it's unique *3D eye* model, which maintains knowledge of exactly where the wearer's whole eye is in the 3D space. This means that the Tobii device will maintain the ability to record at a high gaze accuracy even if the wearing is moving erratically.

3.3.4 Subconscious Nature of Eye Movements

Eye-movements can either be conscious or subconscious, they are either controlled by covert attention, or they are attracted by the saliency of items in the environment. Understanding exactly what the participant sees is not the same as understanding what they are consciously aware of.

The visual system can process 10,000,000 bits of information per second, vastly out performing the conscious ability to process between 10 to 60 bits per second (Dijksterhuis and Nordgren 2006; Zimmermann 1989). A consumer will take in informational cues from the environment that they are not even aware of, but will influence their behaviour. For this reason it is better to use eye-tracking technology than self reported measures, because eye-tracking can highlight the subconscious influences that the participant might not even be aware of themselves.

3.3.5 Gaze Cascade Effect

Consumer preferences are not always consistent, they develop with the use of information processing strategies, and can be influenced by a number of environmental factors (Bettman 1979; Shams 2013). Depending on the complexity or familiarity of the decision task, a consumer's preference may be based on retrieval of existing knowledge (Smith 1989) or constructed based on available information (Gregory et al. 1993).

Previous research has provided empirical evidence of the relationship between visual attention and preference formation (Shams 2013). The mere-exposure effect demonstrates that increased or repeated exposure to a stimulus, increases processing fluency, which in turn increases preference (Reber et al. 1998).

Another concept in visual attention research is *"preferential looking"*, this refers to an individual spending more time looking at the stimuli that they like the most (Shams 2013). Shimojo et al. (2003) proposed that preferential looking and the mere-exposure effect interact during a decision making task, forming a positive feedback loop. The more a consumer likes a product, the more they will look at it (preferential looking), and the more they look at it, the more they will like it (mere-exposure effect). Shimojo et al. (2003) classified this as the *Gaze Cascade Effect*. The Gaze Cascade Effect (Shimojo et al. 2003; Simion and Shimojo 2007, 2006) predicts that in a preference-based decision eye-tracking experiment the areas of interest that receive the most visual attention are those most preferable to the participant. This will form the theoretical basis for this research's eye-tracking hypothesis. This theory will be used as a tool to indicate the participants' subconscious preference for particular stimuli.

3.3.6 Top-Down versus Bottom-Up

Eye-movements can be described as either being *top-down* or *bottom-up* processes. Top-down eye-movements are focused on task relevant stimuli, and are consciously controlled (Theeuwes 2010; Orquin et al. 2013). Where-as bottom-up search is less controlled, and largely determined by the features of the environment (Theeuwes 2010). When searching in a supermarket for a box of cereal, for example, a consumer will often first engage in a bottom-up search, taking in information of all of the available cereal boxes to inform their decision. However, if the consumer goes into the supermarket knowing that they want to buy a box of, for example, Coco Pops™, they will perform a predominantly top-down controlled visual search in the cereal aisle, hunting for the yellow box with a monkey on it.

Search tasks are a combination of both bottom-up and top-down processes. A decision-maker is likely to combine a voluntarily search the environment (top-down control) with involuntarily becoming aware of elements of the environment, due to their enhanced saliency (bottom-up influence) (Shams 2013; Bettman et al. 1998). There is evidence to suggest that top-down processing is the most influential on visual attention (Desimone and Duncan 1995; van der Lans et al. 2008), whereas other evidence suggests bottom-up search is the most influential (Theeuwes 2010; Shams 2013). Orquin et al. (2013) suggest that decision-makers learn over time, and are therefore able to increase in the level of top-down eye-movement control, subsequently causing a decrease in the amount of bottom-up eye-movement control needed in their search task.

3.3.7 Saliency and Bottom-Up Control

The visual system will often use saliency to guide eye-movements rapidly around a scene to gain an overview and to minimise the complexity of the scene analysis (Itti et al. 1998). The saliency of a stimulus within an environment will have an impact on the attention it receives. This was demonstrated by the attention on the models' faces, which are highly salient. Other than the models' faces, judging by the heat-map of the collective participants' fixations on the retail environment, there appear to be no other salient distractions within the scene. Although the participants' eye-movements appear to be initially drawn to the faces of the models in the images, their attention then shifts to the dresses. This is in line with the view that bottom-up control operates immediately when eyes meet a new visual scene, whilst top-down control take a little longer to operate (Orquin and Lagerkvist 2015; Theeuwes 2010; Vries et al. 2011). Some researchers believe that saliency in fact has no impact on human visual attention outside of laboratory experiments (Tatler et al. 2011). Others do believe saliency has an effect on eye-movements, however they argue that it only has an effect when there are not strong task demands on attention (Orquin and Loose 2013). Saliency, and the consequent bottom-up eye-movements, have minimal or no influence on the results that affect the tested hypotheses of this chapter. The saliency of the models' faces is short lived, as the task demands on attention shift the eye-movement control.

3.3.8 Task Orientation and Top-Down Control

Top-down control is often defined as goal-driven attention (Orquin and Loose 2013). The goal that the participants were presented with for this experiment was to search for their favourite three dresses. It is evident from the heat maps, and the lack of attention received by the non-task relevant stimuli such as the handbags, that this had an influence on the participants' eye movements. The similarity found within the gaze-plots shows that the participants followed a particular pattern due to the task they were undertaking.

This also indicates that their eye-movements were largely consciously top-down controlled.

Top-down control is highly cognitive and conscious. The hypothesis being tested in the previous section (the eye-tracking priming sub-hypothesis, H2a) refers to the subtle influence of priming stimuli within an environment. The strong nature of the task control over the eye-movements could explain why the priming effect was not significant. High levels of cognitive control over eye-movements, over an extended decision time, will cause participants to make a deliberate well thought out choice, less likely to be influence by subconscious effects such as priming. This means that even if the priming effect may have influenced their response towards the products, the longer they had to make a choice the less chance there was of being influenced by priming.

3.3.9 Analysis Methods

Pavlas et al. (2012) describe a fixation as a relatively stable eye-in-head position that lasts for a minimum of 100-200ms. A saccade is described as the rapid movement of the eye between fixations, and a scanpath is a combination of the fixations and saccades in chronological order. Eye-tracking devices are able to track the fixations, saccades and scanpaths made by the wearer. When analysing eye-tracking data it is most common to focus on the fixations, either the number of fixations on a particular area of interest, or the duration of the fixations.

Fixations are mapped onto the visual stimuli that the participant viewed during the experiment, and these fixations are then grouped into the specific Areas Of Interest (AOI) that the investigator is interested in. The fixation metrics, for example, the number of fixations on one AOI, can then be compared against the number of fixations on a different AOI. These groups of data can be compared for differences, typically with a significance level of $p<0.05$. The statistical test that should be used depends on the frequency distribution of the data. If the data are normally distributed parametric statistics such as t-test or analysis of variance measures are employed, however if the data are not normally distributed a non-parametric measure such as a Mann Whitney U-test may be suitable. Normality can be determined using a Shapirio Wilks or a Kolomgorov Smirnov test.

3.3.10 Summary

Eye-movements are intrinsically linked to our cognitive behaviour, whether it is consciously controlled (top-down) or subconsciously influenced (bottom-up) (Orquin et al. 2013). The visual system can capture so much information that it is likely most of it will not reach an individual’s conscious awareness, making them unable to comprehensively report their experience (Dijksterhuis and Nordgren 2006). There is also a strong link between visual stimuli and its influence on consumer preference and increased liking. The mere-exposure effect and the Gaze Cascade Effect provide evidence of this, and both often occur without the consumers' awareness (Shimojo et al. 2003).

Due to the subconscious nature of the influence of visual stimuli on consumer behaviour, eye-tracking offers a reliable insight into the consumer cognitive processes and product preferences, much more so than self-reported measures are able to provide, as the consumer is unlikely to be aware of the impact that the environmental cues have had on their choices (Dijksterhuis and Nordgren 2006). The Gaze Cascade Effect, stating that participants increased gaze bias is indicative of preference, provides the theoretical underpinning for analysing the eye-tracking data in the current research. The participants' gaze bias has been quantified by the calculation of fixations in relevant AOIs. Specifically the total dwell time and the fixation count within each AOI.

3.4 EEG

3.4.1 Introduction

Arguably the best way to explore consumer behaviour, including peoples' emotions, attention, and memory, is by directly assessing brain responses (Ohme et al. 2010; Zaltman 2003; Damasio 1994). The relatively recent advent of computerised analysis tools and systems capable of handling large quantities of data has opened up neuroimaging to standardised research. One of the most well established techniques is electroencephalogram (EEG) recording. The first use of EEG in psychological studies was in 1979 (Morin 2011). An EEG device uses multiple electrodes placed on the wearer's head to measure changes in electrical potential in the brain. Electrical activity in different areas of the brain, at different frequency levels, can be indicative of behavioural responses. EEG has high temporal resolution and low spatial resolution, limiting the area of interest in the brain to cortical regions, although deeper lying brain structures have become more accessible with advanced computer and correction methods.

Khushaba et al. (2012) noted that as peoples' choices are affected by subconscious processes, it is important to examine the changes in the well established EEG frequency bands (alpha, beta, theta, delta and gamma) in relation to the changes of preference during decision-making. It is the activity in the prefrontal cortex (PFC) that is of most interest when using EEG data to assess emotion. It has been recognised by many researchers that there is a notable asymmetry between the EEG detected in the left and right hemispheres of the PFC, that can be linked to emotional responses (Davidson et al. 1979; Ohme et al. 2010; Khushaba et al. 2012). Morin (2011) specified that alpha frequencies in the left PFC are related to positive emotional responses, and in the right PFC they are related to negative emotional responses.

3.4.2 EEG devices

Electroencephalography (EEG) is a technique that is able to read cortical level electrical brain activity (Teplan 2002). Brain imaging analysis is a well established method for the measurement of human cognitive and affective responses that is both valid and reliable (Custdio 2010). An EEG device uses electrodes placed on the participant's scalp and measures the change in electrical potential around the outer layer of the brain. The change in electrical potential is caused when one brain cell sends a message to another, along the synapse, which causes a small amount of electrical potential. When multiple neurons become active at the same time, enough electrical potential can be caused to create a powerful enough electrical charge to travel through brain tissue and skin, where it can be recorded by the EEG electrodes placed on the scalp (Cohen 2014).

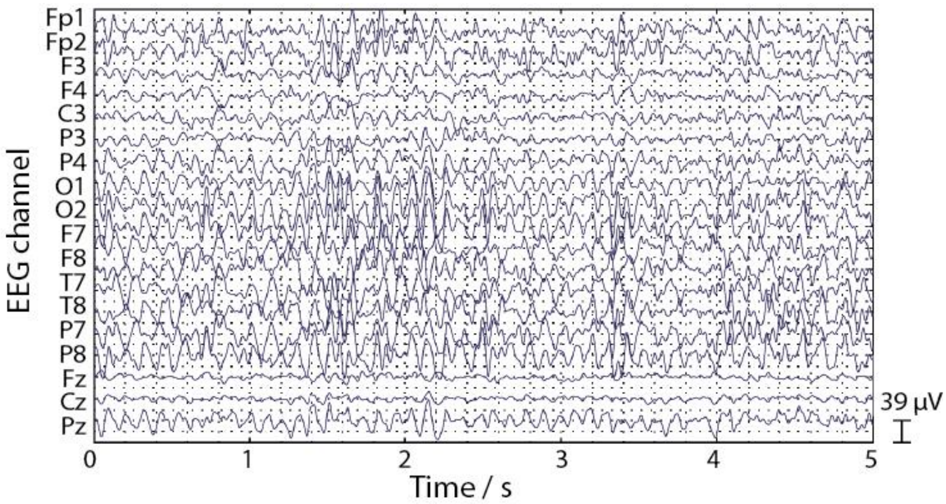

Figure 3.2: An example of standard EEG signals (Casson et al. 2017)

The output of an EEG device is electrical signals, that typically look like those shown in Figure 3.2. To the untrained eye EEG signals look messy and are difficult to interpret without significant experience (Casson et al. 2017). The signals in Figure 3.2 are shown in the time domain, however for analysis of human behaviour it is typical to transform the signals into the frequency domain. The Fourier Transform is the most commonly used to transform frequencies from the time domain into the frequency domain. The Fourier transform works by decomposing the signal into its sinusoidal components (sine wave graphs of the different frequencies) breaking the time signals down into frequency subspectral components (Akin 2002). There are six frequency bands that the signals are commonly grouped into, which are; delta (2-4 Hz); theta (4-8 Hz); alpha (8-12 Hz); beta (15-30 Hz); lower gamma (30-80 Hz); and upper gamma (80-150 Hz).

The 10-20 electrode system is used to ensure that when replicating studies, electrodes are universally used in the same locations. The electrode system is named the 10-20 system because the electrodes are positioned 10% of the scalp size away from each other. The electrode positions of the international 10-20 system can be seen in Figure 3.3. The head is separated into five sections, from the front to the back of the head, and labelled with a letter accordingly. The letters are FP, F, C, P and O, which relate to the fronto polar, fontal, central, parietal and occipital areas (Klem et al. 1999). Within the five areas, each electrode position is also given a number to identify its loction. Electrodes on the left hemisphere are represented by odd numbers, and electrodes on the right hemisphere represented by even numbers (Casson et al. 2017).

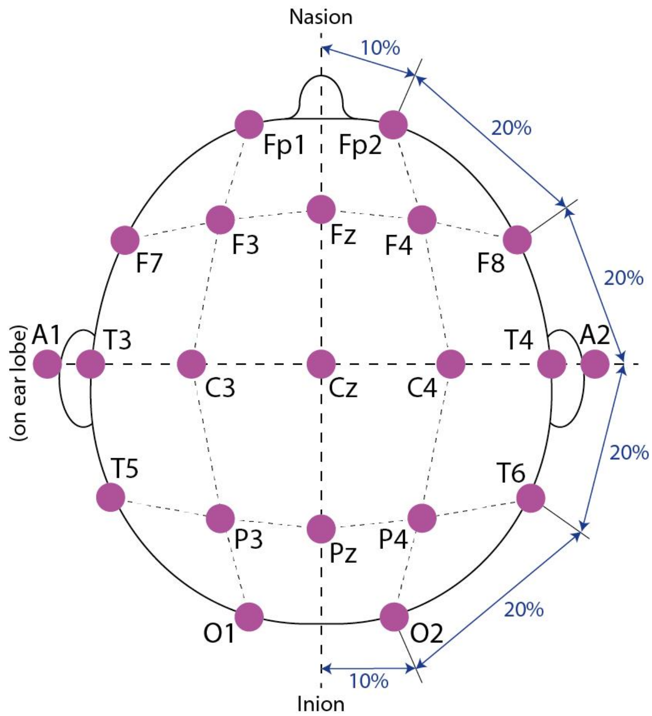

Figure 3.3: The standard 10-20 electrode location system (Casson et al. 2017)

There are various methods of ensuring electrodes stay in the correct position on the wearers head. One of these is to use an electrode cap. An electrode cap on a wearer's head can be seen in Figure 3.4.c. The electrode cap can be used to ensure electrodes are in the correct 10-20 international EEG position locations, and they ensure they stay in relatively the same place throughout the experiment. Two electrodes can be seen in Figure 3.4.a, and Figure 3.4.b shows how the electrodes are secured into the cap. Here a conductive gel has also been used to improved the conductivity between the wearer's scalp and the electrodes. Alternatively electrodes can be affixed to the participants head using a sticky conductive gel, which is thicker than the gel used for conductivity with the electrode cap. The sticky gel holds the electrode in place securely; however it is messy and leaves the participant with the sticky gel in their hair, which is not desirable. The electrodes are connected to a recording device, which restrict the wearer's movement to within the length of the electrode wires. These are typically short, and therefore the wearer will remain seated during an experiment.

Fixed EEG devices, like the ones shown in Figure 3.4 do not allow the participant to move freely when wearing them. However, a number of mobile devices are available that are not constrained by electrode wires. Three examples of these can be seen in Fig-

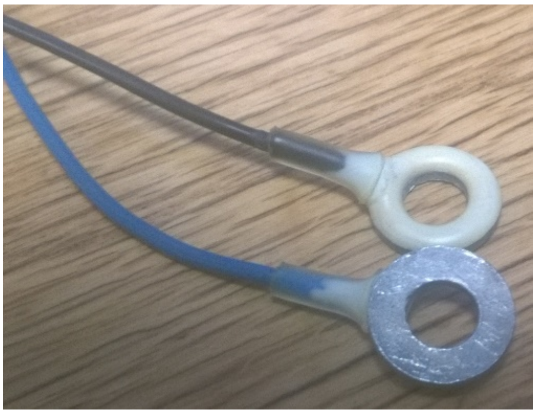

Figure 3.4.a: Electrodes

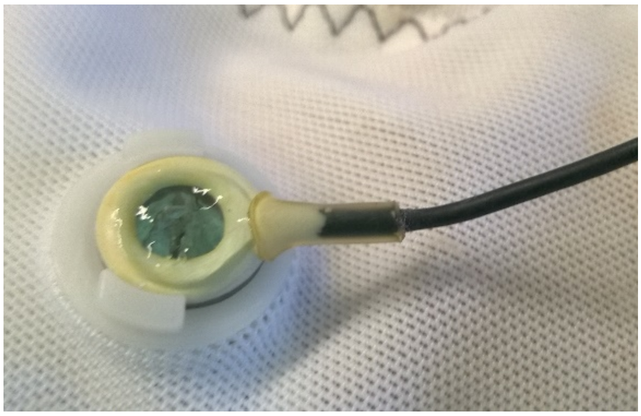

Figure 3.4.b: Electrodes fixed into cap, with conductive gel

Figure 3.4.c: Electrode cap on wearer

Figure 3.4: Electrodes are connected to the electrode cap, which is then worn by the participant. A gel is used to improve conductivity between electrode and scalp (Casson et al. 2017).

ure 3.5. The aim of mobile EEG devices is to enable real-world neuroimaging in situation which conventional EEG would not be suitable for (Casson et al. 2017). Mobile EEG devices typically have fewer electrodes than a standard fixed EEG device does, and record data at a lower sampling frequency.

The devices that can be seen in Figure 3.5 are the Muse, the Emotiv EPOC and the Enobio. The Muse EEG device contains seven electrodes; two of which are reference electrodes positioned behind the ear, and the other five are positioned on the band that sits across the wearer's forehead. It is able to record at a sampling frequency of 256Hz. The Emotiv EPOC headset records at a lower sampling frequency than the Muse, at 128Hz, however it contains more electrodes and therefore can obtain data from more areas of the brain. The Emotiv EPOC contains 16 electrodes in total; 14 for recording the wearer's brain activity, and two as reference electrodes. Of the three mobile devices discussed here, the Enobio has the highest sampling frequency, at 500Hz. The Enobio is also available with different numbers of electrodes, either 8, 20, or 32. The number of electrodes required entirely depends on the stages of analysis required for the specific EEG experiment. In this research, the key electrode positions of interest are F3 and F4, located in the frontal area of the brain. Therefore, it would not be necessary to use a 32 electrode EEG device, for example.

Figure 3.5.a: Muse

Figure 3.5.b: Emotiv EPOC

Figure 3.5.c: Enobio

Figure 3.5: Mobile EEG Devices

3.4.3 The Brain

The brain is made up of roughly one hundred billion neurons, each of which are extensively interconnected and constantly receiving input from hundreds of other neurons, whilst also creating connections from their own nerve endings to hundreds more neurons (Glimcher and Fehr 2013). Neurons create both electrical and chemical reactions, the first of which is the electrical reaction which propagates within a nerve cell. This then triggers a cascading chemical process that transfers chemical substances, known as neurotransmitters, across the synaptic cleft from axon to dendrite, into another nerve cell. The brain is often divided into multiple regions and subdivisions for ease of understanding and classification. The whole of the brain is made up of three divisions, which are the telencephalon, the mesencephalon and the brainstem, however it is only the telencephalon, also referred to as the forebrain, which is typically analysed in neuromarketing research (Glimcher and Fehr 2013). The telencephalon itself can be divided further into three regions, the cerebral cortex, the basal ganglia and the thalamus. The basal ganglia is located in the centre of the brain, beneath the cerebral cortex, and is also made up of many subdivisions. Activity in the basal ganglia can only be monitored using imaging techniques that have high spatial resolution like fMRI, or PET but these tools have very high cost, infrastructure and are relatively poor at detecting rapid changes in brain signals (low temporal resolution). In addition they cannot be adapted for real world scenarios or reflect normal everyday behaviour because of the scanner environment and limitations of the technology being accessible or mobile. Therefore, for the purposes of this research, scope will be limited to technology that permits a more representative environment to real consumer shopping habits. However areas of the basal ganglia output information, via the thalamus, to the frontal cortex, which can be monitored with the use of EEG. The amaydala is one of these areas of the basal ganglia, and is discussed in more detail in section 3.4.4, because it is frequently identified as being important in emotional responses and processing.

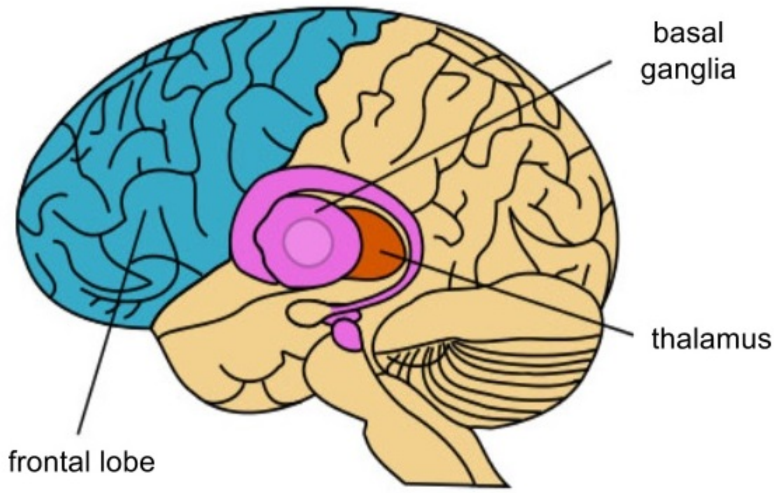

Figure 3.6: The frontal cortex, the thalamus and the basal ganglia within the human brain

The cerebral cortex lies underneath the surface of the scalp, a thick sheet of grey matter crumpled and folded to fit within the skull (Glimcher and Fehr 2013). Due to its proximity to the surface of the scalp, it is possible to measure electrical activity in the cerebral cortex using EEG. It was once believed to be largely homogenous in function, however this began to be disproved when scientists discovered that different areas have different, and often quite discrete, roles. This encouraged Brodmann to analyse the cerebral cortex in great detail post-mortum, (Brodmann 1909; Garey 1994), and he discovered 52 anatomically different areas, which he then numbered. His system for cytoarchitectonic brain regions is still widely used today (Glimcher and Fehr 2013).

The brain has a clear central divide and can be simple separated into two hemispheres, the left and the right. These hemispheres communicate via the large arch shaped areas of white matter which connects them, called the corpus callosum. There have been many different ideas as to how the different hemispheres are responsible for different actions of the brain, and this is still debated today. However, in terms of emotional analysis existing literature provides empirical evidence to suggest that asymmetrical differences are indicative of differential responses. This literature will be discussed more in the following sections 3.4.6 and 3.4.7.

3.4.4 The Amygdala

There is an almond shaped mass of cells, situated deep within the centre of the brain, which is appropriately called the amygdala (the Latin term for almond) (Davis and Whalen 2001). The amygdala is part of the brain that is associated with emotional processing (Davis and Whalen 2001; Davidson 2002). It is reported that the amygdala that will detect and recognise affective stimuli (Anderson and Phelps 2001), research suggests it then generates appropriate physiological and behavioural responses to the affective stimuli (especially fear) (LeDoux 2000; Bechara et al. 1999) and finally may be responsible for storing the stimuli in declarative memory (Hamann et al. 1999). It is reported that the instinctive feeling of fear originates in the amygdala, and in studies investigating the amygdala response to facial expressions; expressions of fear have always activated a greater response than other emotions. It is widely reported that the amygdala is important for responding to negative events and unpleasant emotions, and this idea of the amygdala predominantly responding to fear and negative emotion has led to theories treating the amygdala as a 'protection device' (Murray 2007).

However, there is also significant evidence that the amygdala processes positive emotions, such as those important to stimulus-reward learning (Murray 2007). In an experiment in which participants were shown photos of unfamiliar faces and given a positive, neutral, or negative piece of information with each face, Somerville and Whalen (2006) found that the amygdala reacted more sensitively to faces associated with positive or negative emotions than to faces associated with neutral emotions. When Johnsrude et al. (1999) tested participants' responses to images of food that were paired with either a low, medium, or high probability of a food reward they found that participants displayed a preference for the high reward images, despite being unaware of the link between the image and the probability of reward. Whereas participants with impaired amygdalae were unable to express such a preference. The results from both of these studies support the theory that the amygdala associates sensory inputs and their affective valence, and has an equally important role in processing positive emotions as well as negative ones (Murray 2007).

3.4.5 The Prefrontal Cortex

Unfortunately due to the amygdala being positioned deep within the human temporal cortex it is only possible to study its responses using Magnetic Resonance Imaging (fMRI) or Positron Emission Tomography (PET) systems. MRI and PET scanners are extremely expensive, specialized equipment and are not suitable for mobile or naturalistic studies. However, there is a significant connection between the amygdala and the prefrontal cortex (PFC), a region of the frontal lobe of the brain, positioned closer to the surface of the scalp. The amygdala and areas of the prefrontal cortex project responses back and forth between each other during emotional processing. The prefrontal cortex (PFC) is responsible for representing whether the stimuli detected by the amygdala holds a positive or negative valence (Oschner et al 2002). Collectively the amygdala and PFC detect, encode and determine the affective value of stimuli (Bechara et al 1999, Rolls, 1999). The positioning of the prefrontal cortex makes it possible to be measured using electroencephalography (EEG), therefore it is possible to measure human emotional responses to stimuli without requiring access to a MRI or PET scanner.

Phineas Gage

The brain's prefrontal cortex (PFC) is responsible for multiple complex functions, however its role in the processing of emotions is widely recognised (Vecchiato et al, 2011, Davidson, 2002). The first notable revelation of a connection between the PFC and impaired rationality and emotional function was discovered in 1848 with the fascinating case of Phineas Gage (Damasio 1994). Whilst working on expanding the railroad across Vermont, Phineas Gage suffered a terrible head injury. To make way for the new railroad, Gage and his colleagues were blasting stone out of the way to create a straight and at path for the tracks. Unfortunately, as Gage was momentarily distracted, an explosion went off prematurely. Instead of blasting away the stone it fired an iron rod upwards, straight through Gage's left cheek, piercing through his skull and front of his brain, exiting through the top of his head. Gage did not lose consciousness however, and he was able to command that his colleagues carry him to the ox cart, which he rode to the hospital. Despite the severity and size of the injury, Gage was proclaimed cured within two months. However, this speedy recovery was barely noteworthy in comparison to the astonishing change of character that was about to happen. Before the accident Gage had been considered highly efficient and capable by his employers, and largely liked amongst many friends. However, after the accident he was so deeply changed that old friends could hardly recognise him.

Dr Harlow (1868, pg 278) recounted twenty years after the accident that *"the equilibrium or balance, so to speak between his intellectual faculties and animal propensities, seems to have been destroyed.* What Gage had lost was his ability to make rational decisions. Since the case of Phineas Gage cognitive neuroscientists have continued to study the effect of prefrontal damage on patients ability to make decisions. Antonio Damasio and his colleagues introduced "The Somatic Marker Hypothesis", as a neural explanation for the inability of patients with PFC damage to make real-life decisions (Damasio et al. 1996). The hypothesis is based on the fact that emotions are essential for decision-making, and they have uncovered the strong link between the patient's malformations in emotional processing, and their weakened ability to make real-life decisions (Bechara et al. 2000). This link provides evidence that the PFC has a highly important role in regulating emotional responses, and therefore it is possible to study peoples' emotional responses to stimuli by examining the activity in the PFC during a given task or experiment.

3.4.6 Davidson's Model of Emotion

It has been demonstrated in the literature that it is the prefrontal cortex (PFC) that controls responses to emotional stimuli that originate in the amygdala, and processes the positive or negative valence of these emotional responses. In 1979, Davidson and his colleagues were the first cognitive scientists to link the electrical activity in the brain, which can be measured using EEG, and affective responses (Morin 2011). They introduced Davidson's model of emotion that highlights the asymmetry in the prefrontal cortex, and how it can be used to indicate a positive or negative response to negative stimuli (Davidson et al. 1979). The model does not assume that emotional valence processing is lateralised in the PFC, however it assumes that it is possible to detect emotion-related lateralisation due to the fact that emotions comprise of approach and/or withdrawal components (Ohme et al. 2010). Following this original hypothesis that emotion is differentially lateralised in the PFC, Davidson and colleagues (Davidson et al. 2000) identified that the approach and withdrawal responses are linked to pre-goal achievement emotions, so the responses should be understood to be in the context of trying to achieve a goal. Specifically, it is the left side of the PFC that mediates positive approach tendencies whilst the right side of the PFC that instantiates negative withdrawal tendencies (Vecchiato et al. 2011).

In 1990, to test their hypothesis, Davidson and his colleagues conducted an experiment in which they showed participants film clips designed to induce either approach or withdrawal emotional responses. Happiness was the approach-related positive emotion, whilst the negative withdrawal-related emotion was disgust (Davidson and Hugdahl 1996). The participants were right handed women between the ages of 17 and 41. It was important that only right handed participants were used as left-handed people often have different hemispheric specialisation (Davidson et al. 1990). The first clip they were shown was neutral to allow the participants to acclimatise to the procedure, then they were shown two positive film clips, followed by two negative film clips. The films clips were in colour, silent, and lasted for 60 seconds. The participants were left in a dimly lit room, with no intercom between them and the room the experimenters were in, to limit the extent to which the participants felt like they were being watched and analysed. A video camera recorded the participants' facial expressions as they were watching the film clips, which would be used during the analysis to determine when the participants experienced happiness or disgust.

To analyse their results Davidson et al. (1990) coded the video clips of the participants' expressions using the Facial Action Coding System (FACS) (Ekman and Friesen 1977). Using this coding system they were able to determine the times at which participants felt happiness or disgust, and then use this to delineate the EEG data and only analyse these segments of data (also known as an epoch of data). The EEG data had to be removed of muscle and movement artefacts, then each of the epochs was transformed into the frequency domain using Fast Fourier Transform (FFT). It has been found that the alpha power frequency is the most demonstrative of task performance (Davidson et al. 1990), so the level of alpha power is the best indicator for the approach-withdrawal responses. Their results showed that there was a high level of alpha activation in the right side of the pre frontal cortex.

Their results in the right hemisphere supported their hypothesis, however the findings in the left hemisphere were less conclusive. This is possibly due to an error in experimental design, as the video clips may have induced an amusement emotional response, as opposed to an approach emotional response. It is important at this point to be clear about the distinction between positive and negative emotions and approach and withdrawal tendencies (Davidson et al. 1990) The current research is focused on the participants' approach and withdrawal responses towards the dresses in the simulated real-world retail environment. Therefore Davidson's model of emotional will provide the theoretical framework for the EEG analysis.

Environmental psychologists have posited that there are two general and opposite forms of behaviour found when individuals react to an environment, which are categorised as approach and avoidance (Bitner 1992; Mehrabian and Russell 1974). These approach and avoidance behaviours are found in consumers' reactions to retail environments (Bitner 1992). Robert and John (1982) suggested that the retail environment can elicit approach and avoidance emotional responses even outside the levels of conscious awareness. EEG can measure participants' responses even if they are not consciously aware of them, making it the perfect tool for this research's investigation. Touchette and Lee (2017) applied the use of EEG recording and Davidson's model of emotion to measure consumers' responses to attractive or unattractive apparel products. The garments were categorised into attractive and unattractive groups based on the results of Likert-type survey. The study included 17 male and 17 female right handed participants, between the ages of 19 and 21 years old. Alpha power recorded in the F3 and F4 locations was used to calculate an asymmetry index score in the prefrontal cortex, in accordance with Davidson's model of emotion (Davidson et al. 1990). Their results were significantly different between when the participants were looking at the attractive clothes and when they were looking at the unattractive clothes. Positive frontal asymmetry scores were found when looking at the attractive clothes, indicating an increase in left frontal cortical activity. Whereas negative frontal asymmetry scores correlated with the participant viewing the unattractive clothes, indicating an increase in right frontal cortical activity. These results support the use of Davidson's model of emotion in the analysis of consumers responses to garments.

3.4.7 EEG Emotion Analysis

The most commonly reported equation employed to calculate the frontal asymmetry index is log of right alpha – log of left alpha (Coan et al. 2004; Miller and Tomarken 2001). The natural log of the alpha value is used to overcome the risk of the results being positively skewed, which is a potential risk with untransformed power values (Coan et al. 2004).

$$10\log_{10}\sqrt{(RightAlpha)} - 10\log_{10}\sqrt{(LeftAlpha)}$$

There is an inverse relationship between alpha power (between 8-12 Hz) and underlying cortical activity, as decreases in alpha power have been observed during an increase in cortical activity (Coan et al. 2004). A positive output to the asymmetry equation shown above would therefore indicate a higher level of alpha activity in the right hemisphere, which is equivalent to a lower level of cortical activity in the right hemisphere, or a higher level of cortical activity in the left hemisphere (Miller and Tomarken 2001). According to Davidson's model (Davidson et al. 1979) an increase in cortical activity in the left hemisphere of the pre-frontal cortex is indicative of a positive approach emotional response.

The most common electrode positions used for measuring emotional response are the F3 and F4 locations (Miller and Tomarken 2001; Goodman et al. 2013; Allen et al. 2001; Davidson and Fox 1982). Alpha power is most often acquired by using a Fast Fourier Transform (Allen et al. 2001; Kop et al. 2011), however other methods for obtaining the alpha power over time are available, such as Gabor transform or the Welch method (Goodman et al. 2013).

The underlying emotional processes that can be measured by EEG are either classed as *"trait"* or *"state"* (Bagozzi et al. 1999). A *trait* affect is a consistent mental state, and is typically much lower in intensity than a *state* change in emotion, and will last for a longer period of time (Coan and Allen 2003; Bagozzi et al. 1999). *Trait* affect is measured as the consistent alpha asymmetry during resting EEG (Goodman et al. 2013). A *state* affect is a mental state that has been changed due to an individual's internal thoughts or external environment (Pentus et al. 2014). A state emotion is a specific response, therefore through EEG it is measured as the change in alpha asymmetry. In this research the consumers' response towards elements of the environment is of interest, so it will be the change in the alpha asymmetry score, in response to the stimuli that will be of particular interest.

3.4.8 Summary

EEG devices are used to measure electrical activity in the wearer's brain, which through multiple stages of analysis can be used to measure emotional responses. This section has introduced EEG devices, and how they are typically used to measure brain activity. Following this an overview of the human brain has been presented, focussing on areas in the brain which have been reportedly linked with emotional responses, such as the amygdala and the prefrontal cortex (PFC).

Davidson's model of emotion is a widely used theory for measuring emotional responses, relating to approach and withdrawal behaviours. The model uses alpha asymmetry in the prefrontal cortex as an indicator of approach or withdrawal emotional responses. The F3 and F4 electrode positions, as identified in the 10-20 international electrode system, will be used in the analysis for this research to infer activity in the pre-frontal cortex.

3.5 Application of Methods in Consumer Behaviour Research

3.5.1 Introduction

Many studies have used eye-tracking to analyse consumer behaviour. Often specifically looking at the relationship between the saliency of a product or item, and the visual attention it receives, coupled with the causal or effect link between increased visual attention and increased preference. A significant proportion of this research is in accordance with the Gaze Cascade Theory. EEG can be used as a measure of emotional response, with differential hemispheric increases in cortical activity indicating an approach or withdrawal tendency. Therefore EEG can be used to assess consumers' emotional responses towards marketing stimuli or products. A limited number of studies have combined eye-tracking with EEG in a consumer preference style experiment, and the most pertinent of these are discussed in this section. Gaps in the literature that have been identified will also be discussed in the summary to this section.

3.5.2 Eye-Tracking

The first known study to use eye movements to analyse advertisements was conducted by Nixon (1924), who hid behind a curtain to observe consumers eye-movements whilst they were flicking through a magazine (Wedel and Pieters 2008). It was sometime after that that Karslake (1940) also looked at eye-movements on advertisements, however he used a Purdue Eye Camera to collect more specific data of where exactly the participant's eyes were focussed. A major reinforcement for the use of eye-tracking in marketing research came from Russo (1978) paper, entitled "Eye-Fixations Can Save The World", in which he reviewed five cognitive process tracing methods and argued that studying eye-movements is highly effective and offers advantages over other methods (Wedel and Pieters 2008). Despite the advantages of eye-fixation methodologies over simple observation and report, Russo noted that verbal protocols are complementary with eye-movements and consequently recommended that multiple process tracing methods should be used simultaneously (Wedel and Pieters 2008).

Janiszewski (1998) conducted four experiments measuring participants' eye-movements in order to investigate exploratory search behaviour and the influence of bottom-up processing mechanisms on visual attention. In goal-directed search behaviour, visual attention is predicted to be top-down process controlled by the individual, and the time spent browsing specific stimuli is determined by the stimuli's relevance to the current goal (Janiszewski 1998). Whereas with exploratory search behaviour, an individual's visual attention is created and diverted by the stimuli competing for attention, controlled largely by bottom-up processes. The experiments tested the visual search patterns and amount of time spent focussing on a focal stimulus, dependent on the attention demanded by the surrounding stimuli. In one of the experiments a retail catalogue was used as a proxy for a shopping environment. The study demonstrated the influence of display layout, stimuli size and contrast on bottom-up mechanisms of eye-movements. Highly salient items will attract more attention from the viewer, and are therefore more likely to be looked at for longer (Janiszewski 1998).

Consumers often make irrational decisions, departing from optimal methods of decision making, due to limited capacity to process relevant information (Mormann et al. 2012). Evidence from visual and decision neuroscience research has shown that the methods the human brain uses for processing visual information can cause decision making biases (Krajbich et al. 2010; Shimojo et al. 2003). The formation of these decision biases is formed by two stages; firstly it has been shown that attributes of visual saliency, such as brightness and colour, can influence the amount of time an individual will spend looking at a stimulus when they are making a decision (Itti et al. 1998). Secondly, the more attention a stimulus receives, the higher the liking ratings are likely to be, and the stimulus is more likely to be chosen (Mormann et al. 2012; Shimojo et al. 2003). To test this theory, Mormann et al. (2012) conducted food choice experiments in which they manipulated this visual saliency of different items throughout the different trials.

Figure 3.7: The layout used by Mormann et al. (2012) to show the choice items to the participants. Images of all products except one (central right) have been edited to 65% brightness, to make the central right product stand out.

Seven participants took part in the experiment, in which they made forced choices between pairs of food. Before the choice task the participants were asked to rank 15 snack food items in order of preference. This was used to determine the impact of existing preference on the choices. Images of the two food items that they were required to choose from were shown on a computer monitor, whilst they rested their chin in a chin rest and a desktop eye-tracker recorded their eye-movements. To mimic the overcrowded display that would be found on a supermarket shelf or in a vending machine, the two items the participants could choose from were surrounded by eight other products. An example of how the products were shown to the participants can be seen in Figure 3.7. The brightness of the food items in each display was manipulated so that one item was more salient then the others. This was achieved by decreasing the brightness of all items to only 65%, except for one of the choice options which remained at 100% brightness. This made one of the choice items stand out amongst the other products.

The results demonstrated the impact of visual saliency bias in choices. In the shortest exposure times the more visually saliency (brightness) of a product was 200% more likely to influence the participant's than a 1-point increase in the product ranking (as determined by the initial product rankins provided by each participant)(Mormann et al. 2012). During longer exposures, the visual saliency was 25% more likely to influence the decision. The impact of the visual saliency of the item was found to be stronger when the relative preference ranking between the two choice items was lower.

Chandon et al. (2009) conducted an eye-tracking study to investigate the influence of in-store factors on consumers' attention and evaluation of brands. The specific in-store factors that were examined were the number of shelf facings that a product has, and its positioning in the display, both vertically and horizontally. Previous studies have shown that increasing the amount of shelf space a product has can increase the product's sales, even if the product's location and price remain the same (Inman et al. 2009; Chevalier 1975; Wilkinson et al. 1982). Dreze et al. (1994) found that increasing the display size area for a product had a positive effect on sales. These findings are also in line with the Gaze Cascade Theory. Based on this previous research, Chandon et al. (2009) hypothesised that increasing the number of product facings will have a positive but marginally diminishing impact on the attention and evaluation. Eye-tracking research has shown that different shelf locations received different amounts of attention. Chandon et al. (2009) hypothesised that products positioned in the centre of the shelf will gain more visual attention than products in less central locations.

Planograms replicating supermarket shelves were created for the experiment, twelve containing brands of soap and twelve containing pain relievers. Participants were randomly shown one planogram of each product type. The planogram of pain medication can be seen in Figure 3.8. The participants' eye-movements were monitored throughout the task, and afterwards they were asked questions regarding their preferred choices. The key finding of the experiments was that the number of product facings had a strong influence on the visual attention to that product, and subsequently had a strong influence on the brand evaluation (Chandon et al. 2009). This is consistent with other literature and the Gaze Cascade Effect that suggests increased saliency, causes increased visual atten-

Figure 3.8: The planogram of pain medication used for eye-tracking analysis by Chandon et al. (2009)

tion, and increased visual attention leads to increased liking and preference (Shimojo et al. 2003; Zajonc 1968).

The results also showed that those products positioned in the centre of the diagram received the most attention (Chandon et al. 2009). This experimental set up was designed to look like a real supermarket shelf, however the study was still conducted on a computer screen and therefore may not be representative of how consumers would act in a natural retail environment, although may be indicative of internet or online purchasing behaviour.

The Gaze Cascade Effect suggests that visual attention plays a large role in the consumer decision making process (Gidlöf et al. 2017; Shimojo et al. 2003). Many previous studies have demonstrated this effect in lab based studies (Glaholt and Reingold 2009; Chandon et al. 2009; Armel et al. 2008; Pärnamets et al. 2016), and recently Gidlöf et al. (2017) investigated the theory by conducting a study in two real-world supermarkets. A total of 74 participants took part in the study, which was conducted in two separate supermarkets belonging to the same chain. Participants wore a mobile eye-tracking device, and were ask to conduct their normal shopping, however they were asked to include the purchase of cereal, pasta and yoghurt. Participants were given a 100 SEK (Swedish Krona) voucher to spend during their shopping task, which is enough to purchase the required products for the study, including the high end products.

Gidlöf et al. (2017) note that it is not uncommon to have substantial amounts of invalid data or data loss in mobile eye-tracking studies. This is because it is easy for a mobile eye-tracking glasses to fall out of place during the experiment and nullify the calibration. Data can also be invalidated by uneven lighting within the supermarket, as the eye-tracker is sensitive to differences in lighting conditions. Unfortunately, they were unable to obtain valid data for all participants in each of the supermarkets (Gidlöf et al. 2017).

Despite the challenges of conducting real-world eye-tracking experiments, Gidlöf et al. (2017) found that there was still evidence in support of the Gaze Cascade Theory. The amount of time spent looking at the products, and the number of fixations on each other, was highly predicative of whether a product would be purchased by the participant. Figure 3.9 demonstrates the probability that the participant would buy a product, against the amount of time they spent looking at it.

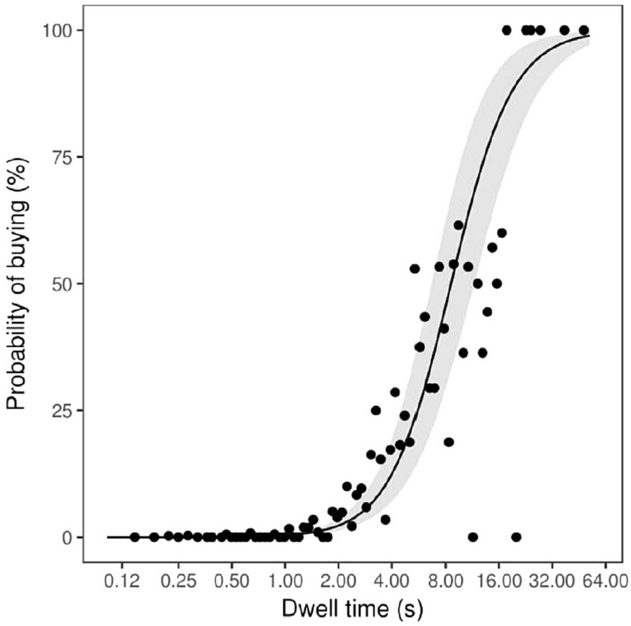

Figure 3.9: Increase in dwell time correlating to an increase in probability of purchasing an item (Gidlöf et al. 2017)

Many eye-tracking studies have focussed on food decisions in a supermarket, and there is limited literature investigating the influence of visual attention on preference of fashion products. Menon et al. (2016) conducted an eye-tracking based experiment to examine the relationship between the price of a fashion product, and the amount of time spent looking at the products. The participants were asked to go through 25 pictures of products on the Facebook page of the company being studied. The prices of the products were varied randomly. The results found a u-shaped interaction between the price and amount of time spent looking at the product. As the price increased between ISK (Icelandic Króna) 5900 and ISK 11900 the amount of time spend looking at the product decreased, then as the price increased again up to ISK 15900 the amount of time spent looking at the products increased again. Although this study does not relate to consumer preference, as the current research does, it is presented here as an example of eye-tracking beginning to be used to analyse consumer responses in a fashion product related context. However the literature relating eye-tracking and fashion purchasing remains limited.

3.5.3 EEG

Ohme et al. (2010) identified that due to the complex and internal nature of consumers' experience of advertising, it cannot be accurately measured by self-reported measures. Marketers are becoming less confident in the use of verbal feedback to advertisements due to the limitations of being able to provide an accurate and valid measure of the internal reaction to an external stimulus. To overcome this, Ohme et al. (2010) measured consumers' responses to video adverts using electroencephalogram (EEG). Using Davidson's model of emotion as a theoretical framework (as discussed in section 3.4.6), they measured brain wave activity in the frontal cortex, and expected a left hemispheric dominance of cortical activity as an indication of a positive approach reaction towards the adverts. The specific adverts that they tested were three well-known Sony Bravia™ TV adverts, including "Paints", "Play-Doh", and "Balls". All three adverts were highly appreciated by marketing experts and consumers, receiving praise and industry awards.

The experiment involved right-handed participants who were planning on buying a new television within the next three months. The experiment included 30 additional distractor adverts, so the participants sat still and watched a total of 33 adverts, with a 20 second black screen between each. The participants wore a 16-channel EEG device, with the electrodes positioned according to the 10-20 International Electrode Placement System, and the reference electrode positioned behind the right ear. To analyse the results, Fast Fourier Transform, using a Hanning window, was applied to the frontal Electrodes (Fp1, Fp2, F3, F4, F7 and F8) to calculate the alpha power (between 8- 12 Hz). The alpha power of the left frontal electrodes was averaged, and compared to the average alpha power of the right frontal electrodes. A positive approach response is indicated by increased hemispheric activation in the left frontal region, whilst a negative withdrawal response is indicated by increased hemispheric activation in the right frontal region, in accordance with Davidson's model of emotion. ANOVA and post hoc tests were used for statistical comparison of hemispheric activation during the emotional and informational stages of the adverts and during the baseline.

The results found dominant left hemispheric activation during the "Balls" advert, however there was no significant response during the "Paints" and "Play-Doh" adverts. Ohme et al. (2010) state that their results show that brain waves are a suitable measure of consumers' subtle physiological reactions towards marketing stimuli. Ohme et al. (2010) predicted that the use of EEG can significantly enrich marketing solutions, and suggest that the use of additional biometric measures (such as Electromyography (EMG) and Galvanic Skin Response (GSR)) could enhance the findings.

These suggestions were most likely based on the findings of their previous study in which they measured consumers' reaction to advertising stimuli using a combination of EEG and GSR (Ohme et al. 2009). To ensure the participants were not aware of which advert was being tested, they were shown a television show, and the adverts were shown in between. There were three conditional groups, the first was shown version one of the target advert, the second was shown version two of the target advert and the third group was used as a control, and was not shown the target advert at all. There was only a very subtle difference between version one and version two of the advert, which was a change in which the female model was presented between the 21st and 25th seconds of the advert. Ohme et al. (2009) hypothesised that by using biometric measurements a different response to the different versions of the adverts can be identified, that would not be identified by self-reported measures.

The EEG data were analysed in accordance with Davidson's model of emotion, calculating an asymmetry index to show the difference in frontal left and right hemispheric activation by measuring the level of alpha power. The results found a statistically significant difference between the asymmetry index values for the different versions of the advert at the 22nd second, just after the model appeared on screen. The skin conductance reinforced these findings, as the average level of arousal whilst the model was on screen was significantly higher in the second version of the advert than during the first. These results demonstrate that a consumer's brain will react differently to subtle changed in marketing stimuli, even if the difference is not highly recognisable at a conscious level.

Ravaja et al. (2013) investigated the predictive capability of asymmetry in the prefrontal cortex when consumers are presented with various brands, at differing prices. Their hypothesis was based on the mounting evidence demonstrating the crucial role that emotional responses play in consumers' decision making (Bernheim and Rangel 2004; Kahneman et al. 1999; Loewenstein and Lerner 2003; Shiv and Fedorikhin 1999; Slovic et al. 2004). Ravaja et al. (2013) hypothesised that a strong positive emotional response during the pre-decision period, demonstrated by increased left frontal activation, indicates that the product will be chosen by the participant.

Thirty three right-handed participants, between the ages of 20 and 44, who are responsible for their household's grocery shopping took part in the study. The EEG device used the following electrode positions; F3, F4, C3, C4, T7, T8, P3, P4, O1 and O2. The electrodes were mounted into a Lycra cap, and were referenced behind the ears, and the ground electrode was positioned on the collarbone. The experiment consisted of seven different product categories (chocolate, crisps, toothpaste, orange juice, detergent, biscuits and coffee), two products for each product category (national brand and private label brand) and 16 different price points. The participants were shown a total of 224 trials on a computer screen in a random order. The image of the product and a price were shown for six seconds, the pre-decision period, then the participants were prompted to select whether they would or would not buy this product.

A frontal asymmetry index was calculated by taking the natural log of alpha power in the left away from the natural log of alpha power in the right, using the data from the mid frontal electrode positions F3 and F4. Due to the inverse nature of alpha power and cortical activity, a positive asymmetry score indicates higher cortical activity in the left hemisphere. The results showed that participants had significantly higher left frontal activity in the pre-decision period before products that they would choose to purchase, validating frontal EEG responses as an indicator of consumer preference.

3.5.4 Eye-Tracking and EEG Combined

Eye-tracking alone cannot identify the affective (emotional) responses of the wearer towards the stimuli (Ohme et al. 2011). Eye-movement data provides valuable information regarding the wearer's visual attention, which can be indicative of preference according to the Gaze Cascade Theory (Shimojo et al. 2003), however this is not necessarily an indication of positive emotional response. Pupil dilation has been shown to be related with emotional engagement, however pupil dilation can also change based on the participant's cognitive workload (Tversky and Kahneman 1973), the brightness of light surrounding the pupil (Beatty and Lucero-Wagoner 2000), or the angle and direction of the participant's gaze. For this reason, pupil dilation alone is not a reliable measure of consumers' emotional responses (Ohme et al. 2011).

Based on the limitations of eye-tracking alone, Ohme et al. (2011) conducted an experiment to determine the emotional responses of consumers looking at different DVD covers, using a combination of EEG and eye-tracking. The only difference between the two DVD covers was that the first version was the original cover, and the second version included logos highlighting the awards that the film had won. The eye-tracking results of their experiment showed that respondents engaged in visual exploration, and looked at all of the key elements of each, in both versions of the DVD cover (Ohme et al. 2011). Interestingly, in the second version the awards logos were found to be detrimental to the legibility of the DVD cover. The additional cognitive processing required for these extra elements distracted the participants' visual attention, whereas on the original version of the DVD cover they had more time and effort to browse the movie images. If Ohme et al. (2011) had made a recommendation based purely on the results of the eye-tracking, they would have recommended the first version of the DVD cover (original, no awards logos).

The emotional responses were determined by calculating a frontal asymmetry paradigm, using the EEG data. When comparing the overall emotional response to each of the DVD covers, there was no significant difference found. It would seem that the additional information about the awards the film had won had no influence on the consumers' perception of the DVD cover. Making a recommendation solely on the EEG findings,Ohme et al. (2011) would no have suggested a difference between either cover.

However, Ohme et al. (2011) were able to make more reliable recommendations when they combined the data from the eye-tracker and the EEG. They used the eye-tracking data to identify different elements of the DVD covers, then cross referenced this with the emotional responses found in the EEG data at that time. When the participants' looking at the second version of the DVD cover were looking at the award information on the cover, they found emotional preference towards this element. This suggests that they should recommend the use of award logos, as it is more effective in creating an emotional response. Based on their findings, Ohme et al. (2011) believe that an integrated analysis approach offers a more reliable perspective. The combined use of EEG and eye-tracking enriches the understanding of consumer responses, by being able to clearly identify which elements of product packaging causes different emotional responses. These combined methods could also be used to help make practicable recommendations for other visual stimuli, such as adverts, websites and digital media (Ohme et al. 2011).

Khushaba et al. (2013) conducted a combined eye-tracking and EEG experiment to investigate product preferences, with the aim of guiding manufacturers to create products as compatible with consumer preferences as possible. Specifically they were interested in their participants' preferred types of crackers, dependent on different shapes, flavours and toppings. The participants wore a wireless EEG headset, whilst different choice sets were shown to them on a computer that was fitted with a desktop Tobii-Studio eye-tracker (Khushaba et al. 2013). Eighteen participants were shown a total of 57 different choice sets, which included three different cracker options. The participants were asked to select their favourite and least favourite crackers out of the options in their choice set, and were given as much time as they liked to do this.

One of the key objectives of this research was to observe the changes in cortical activities, based on the preference of the crackers that the participants were looking at. Khushaba et al. (2013) analysed the EEG data in all frequency bands, across different brain regions, and found clear inter-hemispheric phase synchronisation in the frontal and occipital regions, which indicates communication between the left and ride sides of the brain during the tasks.

Despite using the Tobii-Studio eye-tracker, it is not clear what use the eye-tracking data were to Khushaba et al's experiment. They appear to have not managed to use the data in a clear and combined manner. There is no discussion in their paper of how the eye-tracking data correlates with the findings from the EEG data. This highlights the difficulty of using a combination of EEG and eye-tracking in a single experiment.

3.5.5 Discussion

This section has presented examples of experiments using eye-tracking, EEG, or a combination of the two to investigate consumers' emotional responses towards marketing stimuli or products. Janiszewski's (1998) experiments highlighted the influence of product size and contrast on consumers' eye-movments, noting that the more salient an item is, the more visual attention it will receive. Mormann et al. (2012) found also found that saliency can influence consumers' choices, especially when their pre-existing perception of two products is evenly matched. Chandon et al. (2009) findings supported this, demonstrating that an increase in product facings caused an increase in visual attention, and in line with the mere-exposure effect, this caused an increase in positive brand evaluation. Gidlöf et al. (2017) conducted an eye-tracking experiment in a real-world supermarket, and despite some challenges of conducting mobile experiments and consequent loss of data, their results provided further confirmation of the Gaze Cascade Theory.

Ohme et al. (2011) and Ohme et al. (2009) conducted experiments using EEG to measure consumers' emotional responses to various marketing stimuli. Using Davidson's model of emotion, and calculating a frontal asymmetry index, Ohme et al. (2011) demonstrated how an increase in alpha activity indicates a positive emotional response. They also demonstrated how subtle changes in human gestures can be picked up by the consumer's subconscious, and can be identified in EEG data Ohme et al. (2009). Ravaja et al. (2013) also used Davidson's model of emotion, and were able to demonstrate the ability of frontal EEG asymmetry as an indicator of consumer choice.

Ohme et al. (2011) recognised the potential to improve consumer responses validity by combining data from both an eye-tracker and an EEG device. They tested their theory using two slightly different versions of DVD covers, and were able to give a more valid and reliable recommendation of which version the consumers preferred based on a combination of the timings of the eye-movement fixations, and the EEG emotional responses.

These studies have demonstrated the reliability and validity of using eye-tracking and EEG to measure consumer responses. Eye-tracking indicates visual attention, and increased visual attention can be a cause of consumer preference of a product. EEG can be used to monitor consumers' emotional approach or withdrawal tendencies towards marketing stimuli, when analysed in accordance with Davidson's model of emotion. Combining the two methods increased the reliability and validity of the findings, taking advantage of the temporal nature of EEG by aligning it with the timing provided by the statistical fixation data from the eye-tracking.

A limitation of the discussed studies, is that with the exception of Gidlöf et al. (2017), the experiments are all laboratory based, in which participants view products or choice items on a computer screen. This is unrealistic, and cannot confirm whether the findings would be replicated in a more realistic, natural shopping environment.

Brunswik (1943) was one of the first psychologists to raise the issue of ecological validity, expressing concern that by focussing predominately on artificial experiments the findings would not be truly representative of human cognition. Neisser (1976) also argued that unrealistic experiments would only enhance understanding in those specific experimental conditions, and that findings would not necessarily be applicable to real-world experiences. More recently Ladouce et al. (2017) also noted the limitation of laboratory based experiments, and presented an alternative approach for investigating human cognition in the real world. Their approach capitalised on recent technological advances for recording brain activity (using EEG) and eye-movements (using eye-tracking). They posit that there is significant value in investigating human responses in mobile environments, particularly the value of transforming theoretical knowledge into impact (Ladouce et al. 2017).

However, conducting mobile eye-tracking and EEG experiments requires overcoming substantial technical challenges. Ladouce et al. (2017) comment that to study human responses in complex mobile environments, will require innovations of experimental designs, data processing, and analytical methods. The research presented in this thesis aims to overcome these technical challenges and conduct consumer experiments in a real-world realistic simulated environment, allowing participants to move freely during stages of the shopping task. A novel methodology is proposed which uses the fixation times, identified by the eye-tracker, to select the epochs of EEG data that are of interest for statistical analysis. The experimental design will be described in chapter four, and the methods for conducting the highly time localised EEG analysis will be detailed in chapter six.

3.6 Chapter Summary

This chapter has demonstrated the usefulness of eye-tracking and EEG as a measure of consumer cognitive and affective (emotional) responses to environmental stimuli. In the field of eye-movement research many findings and theories have enabled marketers to understand what consumers' visual attention on their products means. Eye movements can either be top-down or bottom-up controlled. Dependant on the task, tracking visual attention either determines conscious cognitive or subconscious cognitive and affect responses. A combination of the mere-exposure effect and preferential looking, the Gaze Cascade Effect (Shimojo et al. 2003) is a feedback-loop cause and effect relationship between visual attention and preference. The Gaze Cascade Effect will be used as the theoretical basis for analysing the eye-tracking data in this research.

In brain research, understanding emotional responses either requires looking at the sub-cortical central areas of the brain including the amygdala, or measuring responses in the pre-frontal cortex. Davidson's model of emotion, measured using an asymmetry index, can indicate whether someone has an approach or withdrawal response towards stimuli. This asymmetry index is calculated using alpha activity, measured by an EEG device, in the prefrontal cortex. Davison's model of emotion will be used as the theoretical basis for analysing the EEG data obtained in this research.

Both eye-tracking and EEG are useful tools for analysing consumers' responses to environmental stimuli, as demonstrated by many of the experiments discussed in this literature review. Combined information from the two can enhance the validity and reliability of consumer study results (Ohme et al. 2011). (Russo 1978) advocated that whilst eye-tracking was a useful tool for measuring consumers' responses, and was able to obtain information that traditional methods could not, it could be used more effectively by combining it with other consumer data collection methods.

This summary of the eye-tracking and EEG literature has highlighted the validity and reliability of these methods for analysing consumer responses to environmental stimuli. It has also identified various gaps in the literature, such as the lack of using eye-tracking or EEG to measure the effects of visual priming, the lack of combined eye-tracking and EEG studies for consumer research and the lack of realistic environmental studies, outside of the lab, not based on a computer screen. Ecological validity is important to ensure that the responses recorded during the experiment are reflective of real-world responses.

Chapter 4

Hypotheses and Experimental Design

4.1 Introduction

This research investigated whether consumers' physiological responses whilst shopping can be influenced by environmental stimuli. The first key aim of the study was to prime consumers' behaviour towards particular products based on the stimuli in the retail environment. The second aim was to measure consumers' internal physiological processes related to their cognitive and affective decision making processed, in a natural, real world setting.

It is important to understand that consumers are not entirely rational, they do not make consistent decisions that can be predicted accurately by using economic models and theories. It has been widely recognised that to understand consumers' behaviour it is necessary to investigate the psychological factors affecting consumers' behaviour, as discussed in chapter two. Combining economics and consumer behaviour research with psychological and neuroscientific understanding of human behaviour is essential to improving understanding of how consumers operate.

As discussed in the chapter two, the priming paradigm demonstrates how easily humans are influenced by their surroundings. In a similar manner, the retail environment heavily influences consumers' emotional state and subsequent behavioural responses. To understand how heavily consumers are influenced by their environment this study has employed priming effect techniques aiming to influence consumers' behaviour. Specifically it tested the influence of colour priming on consumers' fashion choices for the first time.

Consumers are often unable to accurately recall and recount clear descriptions of the thoughts and feelings they experienced throughout a shopping task (Calvert and Brammer 2012). One reason for this is that they may simply forget the thoughts and feelings they experienced whilst they were shopping. Another reason is that the environmental cues affect them subconsciously, so they are not aware of the effect that the environment is having on their internal emotional state, and subsequently on their choices. This study has attempted to overcome these issues by measuring consumers' subconscious responses directly during the shopping task using biometric measures.

This research followed a positivist research philosophy: only information derived through direct observation and measurement, and logically represented, results in authoritative knowledge. The research design was quantitative, applying statistical analysis to electroencephalogram (EEG) and eye-tracking data to quantify the cognitive and affective responses of the participants during the shopping task. The Stimulus-Organism-Response (S-O-R) framework (Mehrabian and Russell 1974) has been used as a basis for the theoretical underpinnings of this study. The S-O-R framework was developed for studying environmental psychology, and it is commonly applied to a retail context (Kumar and Kim 2014). The framework will be discussed in more detail in section 4.3.

The equipment used for this study was a mobile EEG headset and mobile eye-tracking glasses. The use of EEG and eye-tracking is justified by extensive research in consumer behaviour and decision making research, as discussed in chapter three. Predominantly EEG and eye-tracking studies have been conducted on participants who are sitting still, completing a task on a computer screen in a laboratory setting. However, this study is interested in how consumers behave in the real world, and how they would likely behave in an actual retail store environment, with genuine environmental cues influencing their behaviour. For this reason a mobile EEG device and eye-tracker was used, and the participant had a realistic store to undertake the task in. Combining mobile EEG and eye-tracking is one of the technical innovations that this research seeks to develop, as previous research combining the two technologies, whilst allowing the participant to move freely, is limited. In order to set up an environment that could be controlled by the investigator, and changed accordingly for the different priming effects, a simulated retail environment was built for the experiments to take place in.

This chapter will being by outlining the two hypotheses, and the subsequent sub-hypotheses of this research in section 4.2. Then the overarching theoretical framework for this research will be discussed in section 4.3, and the research tools will be reviewed in section 4.4, giving justification for their use. Finally, the full description of the procedure will be documented in section 4.5.

4.2 Hypotheses

There are two hypotheses being tested in this research, which are related to using physiological measures to identify the participants' preferences, and their response towards the priming. The findings of the first hypothesis validated the use of the chosen methods for analysing consumers' responses during a mobile shopping task, and was measured as the difference between the responses towards the garments that they choose (their preferred items) and the items that they did not choose. The second hypothesis, testing the influence of the priming effects within the simulated retail environment, was measured as the difference between their response towards the target stimuli (prime matching coloured dresses), and the non-target stimuli.

Hypothesis 1: ***Preference Hypothesis.*** *There will be a measurable difference in the participants' physiological responses towards the products that they choose and the products that they do not choose.*

Hypothesis 2: ***Priming Hypothesis.*** *There will be a measurable difference in the participants' physiological responses towards products that were prime coloured and those that were not prime coloured.*

The preference hypothesis (H1), which could validate the application of the methods into a mobile environment, is based on the literature that was introduced in chapter three. Sections 3.3 and 3.4 introduced the theory and analysis methods for using eye-tracking and EEG to investigate human behaviour. Section 3.5 then highlighted the gap in the literature when using eye-tracking and EEG in consumer based studies. The studies are traditionally carried out in laboratory settings, with participants completing tasks which simulate shopping environments on a computer screen. In response to the previous literature, this research aims to improve on the ecological validity of previous studies in the field, by proposing a methodology which allows participants to move freely in a semi-realistic environment. This is formalised by investigating the first hypothesis (H1).

Chapter two highlighted the importance of understanding participants' subconscious responses, and demonstrated how priming and emotions can influence consumers' behaviour. Examples were provided of studies which investigated consumer priming in a retail environment, and emotional responses during shopping tasks. However, these studies relied on self reporting from the participants, which could be unreliable due to participants not being aware of the subconscious influences on their behaviour. The second hypothesis (H2) of this research proposes using eye-tracking and EEG to investigate the consumers' subconscious responses to priming.

Hypothesis 1a: ***Eye-tracking.*** *There will be a statistically significant difference in the dwell time and fixation count between the dresses which the participants choose, and the dresses they do not choose.*

Hypothesis 1b: ***EEG.*** *There will be a statistically significant difference in the asymmetry index scores between when the participants are looking at the dresses that they choose, and the dresses that they do not choose.*

Hypothesis 2a: ***Eye-tracking.*** *There will be a statistically significant difference in the dwell time and fixation count between the prime coloured dresses, and the dresses that are not prime coloured.*

Hypothesis 2b: ***EEG.*** *There will be a statistically significant difference in the asymmetry index scores between when the participants are looking at the prime coloured dresses, and the dresses that are not prime coloured.*

Within each hypothesis, there are two different measures because of the two different technologies used to record the participants' subconscious responses. These formed two separate sub-hypotheses within each hypothesis. The first of these is eye-tracking, and the second is EEG. The eye-tracking data was analysed using the Gaze Cascade Theory, and the participants' gaze bias will be quantified as the dwell time and the fixation counts on the different stimuli. Therefore the eye-tracking sub-hypotheses are that there is a measurable difference in the participants' dwell time and fixation count between the chosen and not chosen dresses (H1a) and between the prime matching and not prime matching dresses (H2a). The EEG data was analysed in line with Davidson's model of emotion, using an asymmetry index to indicate approach or withdrawal tendencies towards different stimuli. The EEG sub-hypotheses are that there will be a statistically significant asymmetry score between the chosen and not chosen dresses (H1b), and between the prime matching and not prime matching dresses (H2b).

4.3 Theoretical Framework

4.3.1 Introduction

Mehrabian and Russell (1974) introduced the Stimulus-Organism-Response (S-O-R) model as a paradigm for studying the effect of environmental stimuli on an individual. They posited that environmental stimuli (S) cause internal reactions (O) that heavily influence one's behavioural responses (R) (Jang and Namkung 2009). The model was originally presented as a framework for environmental psychology research, and it has since been broadly applied to a retail context (Mummalaneni 2005; Kumar and Kim 2014; Platania et al. 2016). When this model is applied to a retail context, the stimulus (S) is the shop environment including all stimuli within it, which affects the consumers' internal evaluation (O), which determines the subsequent approach or withdrawal response (R) to the products (Kumar and Kim 2014).

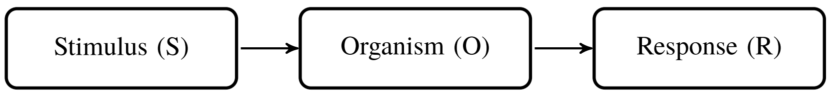

Figure 4.1: Mehrabian and Russell (1974)'s Stimulus-Organism-Response model for Environmental Psychology

4.3.2 Stimulus

The first frame of the model is the stimulus (S); these are the environmental cues that elicit various responses. In 1973 Philip Kotler coined the term *atmospherics* to describe all aspects of a retail setting and demonstrated the importance of their impact. Since then there has been widespread acknowledgement of the influence of the environment on consumers' behaviour. Kotler (1973, pg. 50) described atmospherics as "the conscious designing of a space to create certain effects in buyers". There are numerous elements of a retail store that can influence a shopper, such as the number of employees, the background music, the temperature, the store layout and the general aesthetic or colour scheme (Kumar and Kim 2014).

This study used priming as a method to influence consumers' behaviour. Priming is a phenomenon in which exposure to a particular stimulus influences an individual's actions. Priming is discussed in more detail in section 2.3. In a priming experiment there are two groups of stimuli of interest; the priming stimuli, that should influence the consumers' behaviour, and the target stimuli, to which the consumers' behaviour has been influenced. The target stimuli of this study was the garments that the participants chose from. The priming stimuli will be the colour scheme of the in-store merchandising, specifically the colour of the clothes worn by the mannequins and the colour of the dress in the visual display images. As there are many other elements of the atmospherics of a store, these had to remain neutral and be controlled between participants.

4.3.3 Organism

Whilst the stimuli are always external to the individual, the organism (O) stage of the model is concerned with the internal evaluations. These are the internal processes that occur after the exposure to the external stimuli, and before the subsequent external responses and reactions (Bagozzi 1986). They consist of physiological changes related to feeling and thinking activities (Kumar and Kim 2014, pg. 686).

The internal processing states can be categorised as two different types of evaluation; either cognitive or affective (Bellizzi and Hite 1992; Kumar and Kim 2014). Cognitive evaluations relate to a consumer's thoughts about their shopping experience, whereas affective evaluations relate to the emotions and feelings that they experienced. Internal evaluations are physiological processes in which environmental cues are transformed into meaningful information (Kumar and Kim 2014; Bettman 1979).

Eye-tracking is a popular tool for monitoring a participant's cognitive processes (Salvucci and Goldberg 2000). It can glean information about consumers' non-conscious responses that they may be unaware of. This study used eye-tracking as a method to determine the influence of the priming stimuli (i.e. the colour of the visual merchandising) on the participants' preferences, in accordance with the Gaze Cascade Theory (Shimojo et al. 2003). More details of the Gaze Cascade Theory can be found in the literature review in section 3.3.5.

A consumer's affective evaluations can either drive approach or avoidance tendencies (Platania et al. 2016). As with the cognitive evaluations, consumers are often unable to accurately recall their affective evaluations of products, and do not realise how their emotions may have been influenced by the environment around them. In this study the participants' approach or avoidance affective responses were recorded using an EEG device, and results were analysed in accordance with Davidson's model of emotion (Davidson et al. 1979). By using EEG, recording directly during the experiment, a more valid response will be possible. More details of Davidson's model of emotion can be found in the literature review, in section 3.4.6.

4.3.4 Response

Mehrabian and Russell (1974) advocated the principle that people respond with two opposing forms of behaviour, approach and avoidance (Bitner 1992). Approach behaviour is a reflection of a positive response to the stimuli, and contrastingly avoidance behaviour is reflective of a negative response to the stimuli. Avoidance behaviour is another commonly used termed for withdrawal behaviour; both terms are used interchangeably within literature. According to Mehrabian and Russell (1974) there are three intervening emotional states that cause approach or avoidance behaviour within any environment; pleasure (or displeasure), arousal (or non-arousal) and dominance (or submissiveness) (Donovan et al. 1994; Stylios and Chen 2016).

Many studies have applied Mehrabian and Russell's S-O-R framework to retail environmental research and measured their participants' responses by asking them to answer questions in a survey, to which the answers were given typically using a Likert-type scale (Foxall 1997; Jang and Namkung 2009; Kumar and Kim 2014; Platania et al. 2016; Lee and Yun 2015). The benefit of this approach is that it allows for a more detailed taxonomy of emotions to be tested, because emotional states can be broken down into more detail than simply negative or positive at a semantic level (Kumar and Kim 2014). The use of a Likert-type scale answering system also identifies the varying degrees to which the emotional responses were felt.

However, there are also some problems with the reliability of consumers' responses to a survey. Kumar and Kim (2014) noted that their respondents had to recall information from memory, which makes it possible that the accuracy of the self reported responses might have been jeopardised by memory loss. To overcome this issue, in this study more accurate real time measures were taken. The consumers' internal physiological processes were measured using eye-tracking and EEG.

4.3.5 Store Atmospherics

Philip Kotler (1973) is widely credited as the founder of researching atmospheric effects on consumer behaviour (Turley and Milliman 2000). Whilst he was the first to coin the term *atmospherics*, several other researchers had begun to test the effects of manipulating the environment, years before Kotler's article (Cox 1964, 1970; Smith and Curnow 1966; Kotzan and Evanson 1969; Frank and Massy 1970; Curhan 1972). These preceding studies predominantly focused on the effect of the allocation of shelf space on the subsequent sales of the product, whereas Kotler (1973) expanded on these theories and considered the effect of the whole retail atmosphere.

Kotler (1973) recognised that when making a purchase decision, peoples' responses are based on more than just the tangible product that they are deliberating on purchasing. Decisions are based on the total scenario, of which one of the most important features is the shop where the product is purchased. In some circumstances the atmosphere of the retail environment can be more influential on the purchase decision than the product itself (Kotler 1973). Kotler uses the term atmospherics to describe the method of designing a space purposely to manipulate buyers' behaviour. He identified that humans are affected by all of their senses, and he segmented influential atmospherics into the following four dimensions; visual, aural, olfactory, and tactile.

There is a consensus in the literature that the retail environment has an effect on a consumer's behaviour (Kotler 1973; Robert and John 1982; Bitner 1992; Turley and Milliman 2000; Jang and Namkung 2009; Platania et al. 2016), although the extent to which academics believe it influences decisions may vary.

The environmental stimuli are pivotal to this experiment because they can all affect the behavioural responses of the participants. In this study there were target stimuli, which were the garments that the participants can choose from, and the response to which is measured. There will also priming stimuli, which were the colour of the visual merchandising in the store, which set the prime effect to influence the participants' behaviour. The second hypothesis of this research (H2) is that the colour of the visual merchandising (the priming stimuli) will have an impact on the participants' subconscious responses towards the dresses which match the priming colour. A key aim of this study is to measure the influence of the priming effect using eye-tracking and EEG.

4.3.6 Summary

The S-O-R model forms the framework for the theoretical underpinnings of this study. The framework is a highly regarded model for researching environmental psychology, and is regularly applied in the context of consumer behaviour. A key novelty of this research is the focus on measuring the internal responses, essentially the *Organism* stage of the theoretical framework, which is not easily measurable in a mobile setting. This has been achieved by using biometric methods to measure consumers' subconscious responses to a simulated retail environment, specifically eye-tracking and EEG.

4.4 Apparatus and Materials

4.4.1 Introduction

The S-O-R model has been identified as a suitable theoretical framework for this study. The apparatus and materials used in the experiment need to be able to reliably set the stimulus of the experiment, and accurately measure the participants' responses.

The environment needed to be as realistic as possible, to ensure that the participants acted as similarly to how they would in a real-store as possible. Also it is essential that the investigator could control the environment. For this reason a simulated retail environment was built in which to conduct the experiments, which is described in section 4.4.2. The retail environment in this framework is considered to be the stimulus (S).

The tools for measuring the consumers' internal processes (O) and responses (R) were an eye-tracker and a portable EEG headset. These technologies, and how the data were analysed, are discussed in sections 4.4.3 and 4.4.4. Results from the EEG and eye-tracker cannot be biased or influenced by the participants, as people have little to no control over their subconscious brain activity (Hubert and Kenning 2008). The anticipated challenges of synchronously combining mobile eye-tracking and EEG data, and why they have not been widely used together, are discussed in section 4.4.5.

4.4.2 Simulated Retail Environment

The aim for this study was to obtain as natural a response as possible from a participant, in order to establish ecological validity the store needs to be a realistic as possible. However, the decision was made not to conduct the experiments in a commercial retail store. The reasoning was twofold; firstly, it is essential for the investigator to have complete control over all environmental stimuli, because the environmental stimuli are pivotal to the experiment. There are many control variables in the store that need to remain the same for all participants, such as the general layout, the visual merchandising (except for the colour, which is an independent variable of this study), the noise and the number of other customers present. The independent variables also needed to be set and changed by the investigator when necessary, such as the colour of the mannequins' clothing, and the colour of the dresses in the images. In a real store there would be no control over these aspects, the stock would change regularly, the visual displays could be changed, and the amount of people present would always differ.

Secondly, the participants need to wear an EEG headset and eye-tracking glasses throughout the experiment. Whilst the devices chosen are reasonably comfortable and user friendly, it can take participants some time to adjust to wearing them. In the presence of other shoppers, there would be risk of embarrassment by looking different which would most likely cause the participants to act unnaturally and be a significant distraction. In the simulated retail environment the introduction and set-up time before the task began gave the participant some time to adjust to wearing the devices. Seeing photos of the investigator (the only other person present) wearing the devices also aided the participants' comfort.

A simulated retail environment was created for the experiments to take place in. The investigator had full control over all variables within the store, and no other people were present. The simulated retail environment can be seen in Figure 4.2.

Figure 4.2: Simulated retail environment in which the experiments took place

Retail Environment Atmospheric Variables

There are numerous aspects of a retail environment that impact buyer behaviour. Five of the most influential atmospheric variables for the consumer are the colour scheme, the music, the store layout, the temperature and the number of employees (Kumar and Kim 2014).

Colour is a useful tool for influencing human behaviour and decision-making at a non-conscious level (Jalil et al. 2012). Colour impacts humans' cognitive interpretations as well as their affective evaluations (Babin et al. 2003), subsequently influencing their behaviour. Berger and Fitzsimons (2008) found that using colour had a priming effect on consumers' purchasing decisions, as discussed in section 2.3.7. The current research will investigate the effect of the colour of the visual merchandising in the store on the participants' responses towards garments of the same colour.

Music is reported to have an influence on consumer behaviour because it can alter peoples' mood and emotions (Cheng et al. 2009). Researchers have found that happy or sad music can cause physiological changes in the listener (Schmidt and Trainor 2001). Schmidt and Hanslmayr (2009) used EEG to measure brain behaviour when listening to either happy or sad music, and found that different types of music elicit distinct frontal asymmetry. However, the object of interest in this study is specifically the consumers' responses to the colour of the visual merchandising, and EEG will be used as one of the physiological measurements of this. To ensure that the response of interest is not influenced by other environmental factors the decision has been made to not play any music in the store. The retail environment will remain silent to minimise confounding factors that could impact on the participants' responses.

Turley and Milliman (2000) list many other general interior variables, all of which are important to be aware of and minimise their influence for this experiment. Their list includes flooring, lighting, paint and wallpaper, temperature and cleanliness. Berman and Evans Berman and Evans (2013) include the store exterior and the point-of-purchase area in their categorisation of retail stores' atmospheric variables. However, due to space limitations, these were unable to be fully incorporated into the design for this study.

Pilot Room Layout

A number of pilot investigations were conducted before the set-up for the final experiment was decided upon. The aim of the initial pilot investigations was to test run the equipment, and to observe the participants' movements within the simulated retail environment. The pilot layout was not realistic enough to convince participants that they were in a real shopping environment, however it served a purpose to inform the final room layout, technology choices, and study design.

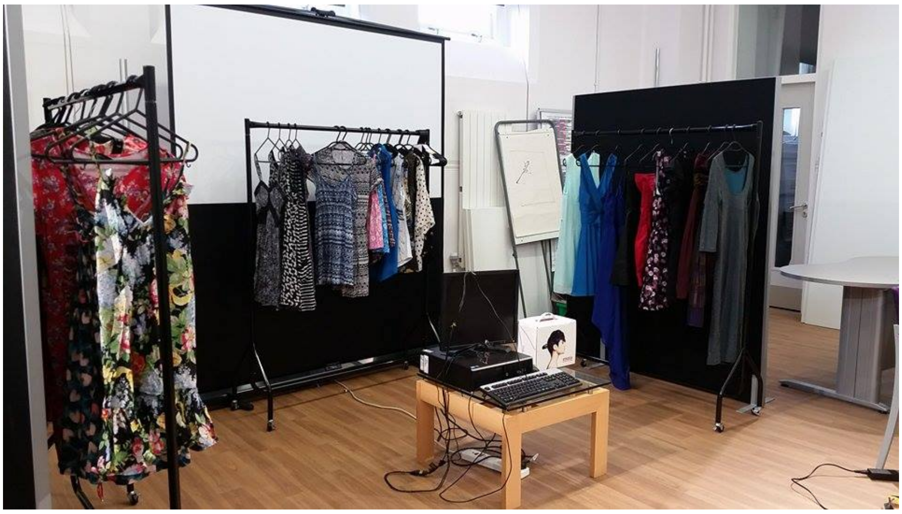

Figure 4.3: Layout of the Pilot Retail Environment

The room layout during the pilot investigations can be seen in Figure 4.3. The available room to conduct the pilot investigations was too large to fill with clothes, so a smaller area of the room was cornered off with the use of free-standing display panels. The clothes were donated to the research by friends of the researcher, and were displayed on three rails lining the edges of the retail environment. The initial eye-tracker that was used for the pilot investigations needed to be connected to a computer via a USB cable during recording. For this reason, a computer had to be located on a small table in the middle of the room, so the participants could walk around the computer and the eye-tracker could still be connected. No colour priming techniques were applied during the pilot studies, as the available clothes did not meet the necessary criteria for the study.

Room Layout

Due to the nature of the experiment, it was important that the participants did not see anything in the retail environment before the task began. For this reason a temporary wall partition was used to block the retail environment from their view whilst the task was being explained and the headsets were being set-up and calibrated.

The simulated retail environment for the final experiments was built into an old storage room on the basement floor in the University's Sackville Street Building. The first stage for developing the space was to complete clear out all of the older shelving, the files, empty cardboard boxes and general rubbish. Once the space was clean it required a fresh coat of paint and something to cover the dirty old carpet. The walls were painted neutral colours; grey on the main wall as a feature wall and white on the side walls. The floor was covered with a smooth laminate flooring, similar to those found in large high street fashion stores. The straight arms, glass shelves, wall fixings, and the full and half size mannequins were purchased from ebay™. The plinths which the full sized mannequins stood on were built by a family friend. The frames for the visual images were borrowed from the Warehouse™ clothing store in Manchester, and the picture within them were printed in the University's graphic support workshop. The colours of the models' dresses in the visual display images were edited by the school of materials CAD (Computer Aided Design) technician.

Once the retail environment was set up there were two walls that had rails of clothing of them; these were named *Wall 1* and *Wall 2*. They can be seen in Figure 4.4.a and Figure 4.4.b respectively. The design of the straight arms, glass shelves, pictures display was based on typical retail store design. Care was taken to ensure there was an adequate amount of space between products, so the store did not look overcrowded or cramped.

Choosing The Products

Dresses were chosen as the product that would be available in the store. This is because a dress is a one-garment-outfit, which minimised the need for participants to consider

Figure 4.4.a: Wall 1

Figure 4.4.b: Wall 2

Figure 4.4: Wall 1 and Wall 2 within the Simulated Retail Environment

other garments that they would need to wear or style with the garment they are choosing. The dresses chosen were all single-colour dresses, with no pattern or multi-coloured design. It was also important to have some dresses in the same style, but different colours. This would make it possible to know whether the participant was influenced by the style or the colour. A total of 23 dresses were present in the two walls. Of the 23 dresses, three were pink, nine were blue and six were red. As well as the different prime matching (dependent on the condition group the participant was in) dresses, there were also two white dresses, two green dresses and one taupe dress. The imbalance in the number of dresses in each of the priming colour conditions was due to availability of suitable dresses in high street stores at the time of conducting the experiments.

Setting the Prime

The prime in this experiment was the colour of the visual merchandising displays, which included two images in metal frames, and three mannequins. The images that were chosen can be seen in Figure 4.5. The mannequins and images remained the same, and the style of clothing on the mannequins remained as similar as possible; only the colour was changed. So that the colour of the visual merchandising had the largest impact possible, all other colours in the store design remained neutral. The walls were painted white and grey, the mannequins' bodies were white, and the plinths that the mannequins stood on were also white. The rails are silver metal, and there were see through glass shelves, which added an element of style, but not colour, to the room. The mannequins can be seen in Figure 4.6, dressed in blue for the blue prime condition.

4.4.3 Eye-Tracking

The two key types of eye-trackers available are desk-mounted screen-based stationary eye-trackers and head-mounted mobile eye-trackers (Mele and Federici 2012). Desktop

Figure 4.5.a: Image on Wall 1 during pink prime

Figure 4.5.b: Image on Wall 2 during pink prime

Figure 4.5.c: Image on Wall 1 during blue prime

Figure 4.5.d: Image on Wall 2 during blue prime

Figure 4.5.e: Image on Wall 1 during red prime

Figure 4.5.f: Image on Wall 2 during red prime

Figure 4.5: Advertising images used on Wall 1 and Wall 2 within the Simulated Retail Environment during the three different prime conditions

eye-trackers are limited by the lack of movement for the participant. During the experiment participants need to remain within a specific distance from the eye-tracker and screen (varying with model of eye-tracker), and too much participant movement is detrimental to the results. Natural behaviour requires an individual to be unconstrained in their movements (Duchowski 2002). Mobile eye-tracking allows participants complete freedom of movement in natural settings, either indoor or outdoor (Mele and Federici 2012).

One of the key contributions of this research is to investigate consumers' responses in a more realistic retail environment than in studies, which have conducted eye-tracking experiments with tasks on a computer screen. A novel methodology is proposed which allows participants to move freely during stages of the experiment, allowing a more natural shopping behaviour to be observed and examined. For this reason it was essential to use a mobile eye-tracker.

Figure 4.6: Mannequins dressed in blue during the blue prime condition

Eye-Tracking Device Selection

The first eye-tracker that was used in this study was the Pupil Labs mobile eye-tracker, which has been briefly discussed in section 3.3.3, and can be seen in Figure 4.7. This eye-tracker was used in the pilot investigations, and can be seen worn alongside the mobile EEG device, in Figure 4.8. Pupil Labs have developed their eye-tracker since the early stages of this research, and their mobile eye-tracker is now available to purchase pre-assembled. However, at the time of using the Pupil Labs eye-tracker in this research, Pupil Labs provided a recommended list of cameras and necessary equipment to purchase, sold their 3D printed glasses frames, and provided a list of instructions for users to follow to build their own eye-tracking device. This mean that the eye-tracker was affordable on a low research budget (<£200), however building the device was time consuming and the resulting eye-tracker was relatively basic. At the time of use, the software was unfortunately in its primitive stages, and had a number of difficulties. The software had issues picking up the correct pupil location of many wearers, especially if they had thick eye-lashes. Additionally, the software could not provide any statistical output for the data, as there was no way to map fixations onto Areas Of Interest (AOIs). After the pilot investigations, the self-built Pupil Labs mobile eye-tracker was deemed unsuitable for the purposes of the current research.

Due to the unsuitability of the Pupil Labs eye-tracker, a more state-of-the-art eye-tracker

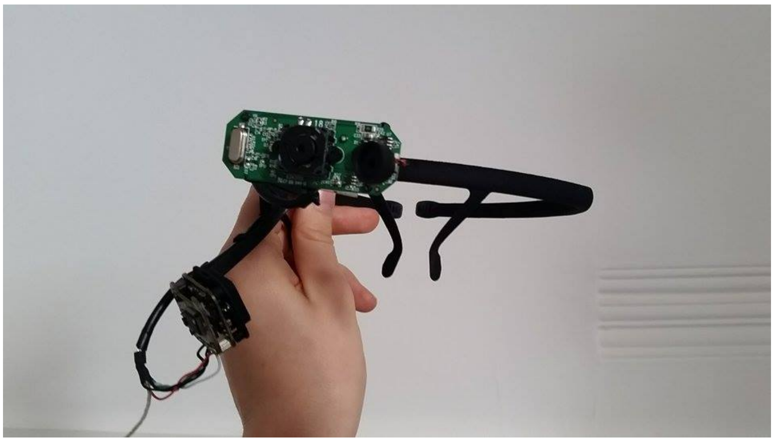

Figure 4.7: The Pupil Labs Mobile Eye-Tracker

was chosen for use in the final experiments. The specific model of eye-tracker that was chosen was the Tobii Pro Glasses 2, which can be seen in Figure 4.9. The device is made up of the head unit, and the recording unit. The head unit is the glasses that the participant wears, it includes one forward facing scene camera, four eye-facing cameras, a gyroscope and an accelerometer, and only weighs 45 grams. The head unit can be seen in 4.9.a. The glasses are connected to the recording unit which contains a Secure Disk (SD) card where the eye-tracking data are stored. The recording unit can connect via wi-fi to a tablet or computer with the Tobii controller software, to calibrate the eye-tracker and then begin the recording. The recording unit can be seen in Figure 4.9.b. The calibration uses a bullseye style image, which the participant stares at during the calibration, to ensure that the eye-tracking is positioning the wearer's gaze point in the correct location. The bullseye used for calibration can be seen in Figure 4.10.

Eye-Tracking Analysis

Mobile eye-trackers output data as fixation coordinates on a video, which are difficult to map onto two dimensional images (Kiefer et al. 2014). Fixations need to be manually mapped onto images that represent the three-dimensional environment that the experiment took place in. When analysing eye-tracking data an investigator needs to specify the environmental stimuli that are of interest, marking them as areas of interest (AOIs). Once fixations have been mapped and the AOIs have been identified, metrics can be calculated such as the number of fixations on an AOI, or the total duration of the fixations on an AOI. Figure 4.11 shows the AOIs drawn onto the first wall of the simulated retail environment. Each AOI was drawn manually as an outline of the stimuli of interest that it is identifying, and the shape has been filled in with a matching colour. For instance the AOIs on the pink dresses can be seen in Figure 4.11 highlighted as pink shapes, and the blue dresses are highlighted as blue shapes.

Fixation metrics relating to different AOIs can then be statistically analysed to provide quantitative analysis of the participants' gaze data. Depending on the normality of the

Figure 4.8: The Pupil Labs mobile eye-tracker worn alongside the Emotiv EPOC EEG headset by a participants for the pilot investigations

Figure 4.9.a: Head unit

Figure 4.9.b: Recording unit

Figure 4.9: The headset and recording unit of the Tobii Pro Glasses 2

frequency distribution of the data, different statistical comparisons could be used. If the data are normally distributed, a parametric test such as an ANOVA could be used (Duchowski 2007). Whereas if the data are not normally distributed, a non-parametric test, such as the Mann Whitney U-test could be used.

Eye-tracking results can also be presented in useful visualisation forms, either a heat-map or a gaze-plot. The heat map works in a traffic light fashion, displaying red over the

Figure 4.10: Eye-tracking calibration tool

Figure 4.11: Areas of Interest (AOIs) drawn onto the image of Wall 1

position where the gaze was most prominent, down to green where it was less prominent. The colour scale used for the heat map can be seen in Figure 4.12. When the *Tobii Analyzer Pro* software calculates a heat map, these can either be based on raw gaze data, or recognised fixation data. Within this thesis, all heat maps are generated from true fixation data, not raw gaze data. Heat maps can also be built based on the fixation count on an area, or the total dwell time on an area. In this thesis all heatmaps are generated based on the fixation count.

When generating a heat map, a scale max value can be set to determine the quantity of fixations that will warrant showing as red on the heatmap, down to green. If the scale max value is set to 40, then the heatmap will show as red in areas which received 40 fixations. Areas which received 20 fixations ($\frac{40}{2}$) will be shown as yellow, and this will blend out to green where there were few fixations. The size of the heatmap image is based on the number of pixels, so data may be generated slightly differently dependant on the screen.

A heat map of a single participant's fixation data on wall one of the retail environment, with a scale max value of 3 counts, can be seen in Figure 4.14. This means that in the areas which display red, there were three or more fixations.

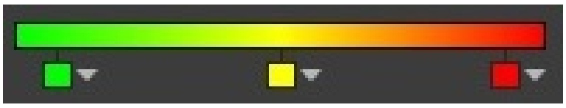

Figure 4.12: Heat map colour scale

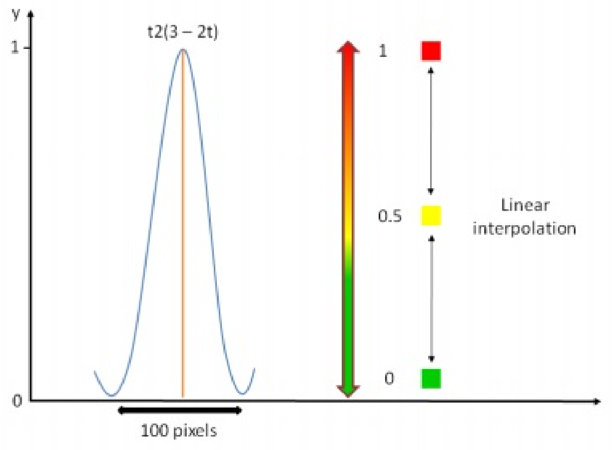

Figure 4.13: Heatmap colour distribution, relative to the scale max value set for each heat-map

A gaze plot shows the whole scan path of the participant. The fixations are represented by circles, which vary in size depending on the length of the fixation; the longer the fixation, the larger the circle. The saccades are represented by the lines between the circles. The path that this creates is also numbered, so that the chronological order of the fixations can be observed. An individual participant's gaze plot can be seen in Figure 4.15. Whilst visual representations are useful to indicate the overall trend of the participants' eye-movements, they are strengthened when supported by quantitative analysis of the fixation metrics, such as dwell time and fixation count. For this reason, the eye-tracking related sub-hypotheses (H1a and H2a) will be tested by a quantitative comparison of the dwell time and fixation count between the chosen and not chosen dresses (H1a), and between the prime matching and not prime matching dresses (H2a). This is based on the Gaze Cascade Theory, as discussed in section 3.3.5.

4.4.4 EEG

To allow the participant to have full freedom of movement it was essential for the EEG device used in this experiment to be mobile. Mobile EEG devices typically have fewer electrodes than a stationary EEG device would have, and may have increased noise issues due to the sending of the data wirelessly (via Bluetooth) from the device to the recording unit. However mobile EEG devices are typically much more user friendly, and allow freedom of movement.

Figure 4.14: Heat map of a single participant's fixation data on wall one of the retail environment. Scale max value = 3 fixation counts

Figure 4.15: Gaze plot of a single participant's fixation data on wall one of the retail environment

This research used the Emotiv EPOC™ EEG headset which has 14 recording electrodes positioned in the 10-20 system positions around the edge of the head and two reference points, which are placed behind the ears. The Emotiv EPOC™ was used during the pilot investigations, and found to be suitable for use in the final experiments. It is completely mobile, sending data to the computer via a Bluetooth USB connector, and it only requires saline solution to wet the sponges that cover the electrodes to create a good enough conductivity between the electrodes and the participant's scalp. A significant limitation of the Emotiv system is the relatively low sampling frequency (128Hz) making it more difficult to filter out noise artefacts from the data compared to fixed EEG systems. The Emotiv epoch EEG headset was chosen because it is light, portable and uses saline soaked sponges, making it comfortable and natural for subjects to wear and still retain free movement. It can be seen in Figure 4.16. It also contains a gyroscope, which mea-

Figure 4.16: The Emotiv EPOC EEG headset

sures the rotary motion of the wearer's head.

Frequency Representation

EEG data are represented as oscillations, which can be described by their frequency, power and phase. Frequency is measured in hertz (Hz), representing the speed of the oscillations, specifically how many cycles it goes through in one second (Cohen 2014). The power of an oscillation is its squared amplitude, and the phase is the oscillation's position along the sine wave, measured in either degrees or radians (Cohen 2014).

Frequency representation is the most powerful and standard method of representing time signals. It gives a clear visualisation of the periodicities of the signal, which can help in understanding the underlying physical phenomena that the results indicate (Quiroga 1998). The different frequency bands are most commonly grouped as; delta (2-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (15-30 Hz), lower gamma (30-80 Hz) and upper gamma (80-150 Hz) (Cohen 2014).

EEG analysis

For this research the EEG data was analysed in accordance with Davidson's model of emotion (Davidson et al. 1979). More details regarding Davison's model of emotion can be found in section 3.4.6. The model posits that an increase in cortical activity in the left hemisphere of the pre-frontal cortex is indicative of positive approach tendencies, whilst an increase in activity in the right is indicative of negative withdrawal tendencies. This activity is best measured by the level of alpha power at the F3 and F4 electrode locations (Miller and Tomarken 2001; Goodman et al. 2013; Allen et al. 2001; Davidson and Fox 1982). Due to the inverse nature of alpha power and cortical activity, an increase in alpha power is equal to a decrease in cortical activity, and vice versa. Therefore a decrease in alpha power in the left frontal hemisphere is indicative of a positive response.

Further details of the stages of analysis required for the EEG data are discussed in chapter six, and provide a technical contribution of this research. This includes how the data were prepared (section 6.2), how the two devices were tightly aligned so that highly time localised analysis could be conducted (section 6.3), and how the relevant epochs of EEG were identified (section 6.4.

4.4.5 Combining Mobile Eye-Tracking and EEG

It is challenging to combine mobile eye-tracking and mobile EEG data. Methods for measuring eye-movements and brain responses are even more challenging when the wearer is mobile: however, this mobility gives an experiment higher validity based on the participants' more natural behaviour.

Mobile Eye-Tracking

Mobile eye-trackers can facilitate eye-movement recording in natural settings, enabling a much greater variety of natural behaviours to be studied than can be achieved with screen based eye-trackers (Hayhoe and Ballard 2005). However, whilst screen-based eye-trackers can determine the location of a fixation as a coordinate of the image on the screen, mobile eye-trackers can only return the fixation information as a coordinate on a video, which is then difficult to map onto a real world object (Kiefer et al. 2014). To conduct statistical analysis with eye-tracking data it is fundamental for the fixations to be mapped onto the Areas of Interest (AOI), found in a two-dimensional snapshot image. Mapping every single fixation, for all participants, is a very time consuming process.

Mobile EEG

Mobility of the wearer creates issues for EEG that could be detrimental to the quality of the data. EEG signals are commonly contaminated with artefacts caused by the wearer's movements (Murugappan et al. 2010). Movement artefacts are problematic for EEG data, and efforts should be made to reduce the number of artefacts and to minimise their effect on the quality of the data (AlZoubi et al. 2009).

One solution for reducing the number of movement artefacts that are found in the EEG data is to ask the participant to reduce their movement as much as possible. It is common practice in fixed EEG experiments to request that participants refrain from overt movement as much as possible throughout the task (Suleiman and Fatehi 2011; Zheng et al. 2014). For this experiment the task was adapted to include periods of time in which the participant was standing still: more details of the task can be found in section 4.5.5. It is during the standing still phases that cleaner EEG data will be able to be recorded, ensuring that the experiment produces some usable epochs of clean EEG data.

Even when participants stand as still as possible it is still likely there will be some movement artefacts in the data. Unfortunately complete removal of these movement artefacts could also remove valuable EEG signal information (Murugappan et al. 2010). Instead of removing whole epochs of EEG data, filters can be applied to remove high-frequency artefacts, whilst keeping the underlying EEG signal (Cohen 2014).

The novel solution proposed by this research is to conduct highly time localised analysis. The timings of the fixations recorded by the eye-tracker can be used to indicate which epoch of EEG data are necessary for analysis in line with the research hypotheses. By focussing on such specific segments of EEG data it, there are naturally some segments in which the participants are moving (and causing noise in the data) and segments in which they are more still. After removing the epochs which contain motion artefacts, there are still motion free epochs valid for analysis. This method requires highly accurately aligned timing between the two devices, which is made possible due to both the Tobii eye-tracking glasses and the Emotiv EEG device containing gyroscopes. The method for syncronising the devices in time is discussed in section 6.3.

Synchronisation Difficulties

Another difficulty of using mobile eye-tracking and EEG together is to ensure highly accurate temporal synchronisation of the devices' recordings. The synchronisation is important because the timings of the fixations in the eye-tracker recording will be used to inform which epochs of EEG data need to be analysed. Fixations by nature are very short (approx 100ms - 200ms), so if the recorded timings are out of sync by more than half a second the whole segment of interest in the EEG data could be lost. One way to ensure that the devices are well synchronised is to use an additional software to force the devices to start at the same time (Khushaba 2013). In this experiment this was done using a graphical user interface (GUI) created in MATLAB coding software to control autohot keys, which would start the eye-tracker recording then immediately send a marker into the EEG data. More details of this can be found in 4.5.5.

Despite ensuring that the recordings begin instantaneously with each other, the two devices can still drift apart from each other over time. As they are mobile, both of the devices are battery powered. This means that even small changes in temperature and battery voltage can cause clock drift. Therefore, the reported sampling frequency of the device will not remain constant throughout the experiment. The proposed method of highly time localised analysis relies on the timings in one device (the eye-tracker) to inform the correct segments of data to analyse from the second device (the EEG headset).

This means that highly accurate alignment of the data is imperative for this research. Section 6.3 explains in detail how the devices were re-aligned.

4.4.6 Summary

To allow the investigator to have full control over the research environment a simulated retail space was built in which to conduct the experiments. All atmospheric elements within the retail environment were controlled for, except for the colour of the visual merchandising (prime). This was the independent variable of the study, and used as the priming effect. The eye-tracker that was used was the Tobii^{TM} Pro Glasses 2, and the EEG device chosen was the Emotiv EPOC headset. There were some anticipated difficulties with combining EEG and eye-tracking in a mobile setting. These technical challenges include the lengthy fixation mapping stage for the eye-tracking analysis, detrimental movement artefacts in the EEG data, and ensuring highly accurate synchronisation between the two devices.

4.5 Data Collection Methods

4.5.1 Introduction

In this section the methods used to collect data will be discussed. This includes the choice of participants, the pre-experiment preparation that was undertaken, the details of the task that the participants undertook, and the ethical issues that have been considered and approved for this experiment.

4.5.2 Participants

The object of the study was to measure consumers' responses to the products available to them. The products that were chosen were simple dresses from high street retailers. The participants therefore needed to be likely to purchase from this category of products. Due to the targeted gender of most clothes, it is most sensible to recruit participants of a single gender. For this reasons females between the age of 18-25 were chosen.Barnes and Lea-Greenwood (2006) identified that it is young female consumers who are most likely to be enticed into shopping in high-street fashion stores.

It was important for participants to be right handed, as previous research has found evidence to suggest that the underlying neural networks differ between left and right handed persons (Kelly et al. 2015). Recruiting both left and right handers is possible but requires insight into the hemispheric specialization of each left hander and is only feasible in large neuroimaging cohorts with specific brain lateralisation tasks. If participants would usually wear glasses whilst they are shopping, their vision should be corrected to normal by wearing contact lenses on the day of the experiment.

Participants were recruited using an event organising website. Emails and posters were used to attract the attention of potential participants, which included a link to the event website. The website also included information on what the study was about, what would be required of the participant, and how they could win a dress for their participation. If they were interested they could choose and book in for a time slot that suited them. The website informed the investigator when a participant signed up, including the participants' contact details, including their email addresses. The investigator would then email the participant, welcoming them to the study and sending them the relevant paperwork for them to have a read through beforehand if they were interested. The paperwork included the participant information sheet, the consent form and the detailed experiment plan.

The participants were aged between 18 and 27, with a mean age of 22.31 years old. All participants were right handed, with normal or corrected to normal (with contact lenses) vision. Almost all participants were students studying courses within the School of Materials at the University of Manchester. The participants who were not students also had materials related jobs, including a lecturer in the design, fashion, and business department, and a fabric technologist.

4.5.3 Pre-Task Participant Preparation

Before the experiment takes place, it was important for the investigator to ensure everything is in order, ready for the experiment to run smoothly. These checks included ensuring that both the EEG headset and the eye-tracker have a suitable level of battery life, all software is open and ready to record, and that the retail environment is clean and the clothes are neat and tidy. The investigator also needed to ensure that the required paperwork was available to give to the participant.

The instructions that the participants had to follow during the shopping task were very specific, so it was important that the participants fully understood exactly what they were being asked to do. For this purpose, a detailed experimental plan document was created. It was sent to the participants to familiarise themselves with when they first signed up to take part in the experiment and the researcher went through this very thoroughly with the participant prior to commencing the experiment. The detailed experiment plan can be found in appendix B.1, which include two pages of details that were used to explain the experiment to the participant. The investigator went through the experiment plan with the participant, to ensure they were comfortable with having the EEG and eye-tracker placed on their heads. Regarding the EEG device being put on their head, it was important to ensure that participants would be happy with the small amount of saline which would be used, to help the electrode conductivity. The saline would not leave any large residue on their hair, but could make it feel temporarily damp where it was applied. No participants reported any issue with this.

As an incentive to encourage people to take part in the experiment, a prize draw was advertised. The prize that participants could win would be one of the dresses from the simulated retail environment. This not only acted as an enticement for people to sign up, but also as an incentive for participant to really care about the dress that they chose during the shopping task.

4.5.4 Equipment Set-Up

After participants had been fully briefed the equipment was set up and calibrated. The participant put on the Tobii Pro Glasses 2 eye-tracker first, as putting it on after the EEG headset can nudge the EEG electrodes out of position. Once the glasses were on, and in a comfortable position, the eye-tracker was ready to be calibrated. This is a relatively simple process: the participant is required to look at the centre of a bullseye dot whilst the researcher uses the Tobii controller software to calibrate the system on this fixation point. On the computer display used for calibrating the system a small red circle indicating where the Tobii glasses wearer is looking, should be in the central circle of the bullseye. If the red circle is not in the right place, the eye-tracker can be re-calibrated, repeating this process until the red circle and the bullseye target appear perfectly aligned.

Once the eye tracker was calibrated the EEG headset was put in place. On the Emotiv EPOC headset the electrodes are already positioned in the 10-20 electrode position, which made it easier for the investigator to be confident that the electrodes are in the correct position. However, it is still important to be careful when positioning the headset. The reference electrodes used were positioned at P3 and P4, which are underneath the ears. The other electrode locations used were AF3, F3, F7, FC5, T7, P7, O1, O2, P8, T8, FC6, F8, F4 and AF4. The positions of the electrodes can be seen in Figure 4.17.

Once the electrodes were in the correct position, it was important to ensure that each electrode had a strong and clear signal. One method of doing this is to create a parting in the hair underneath the electrode using a tail-end comb. If the hair was particularly thick, hair clips would be used to hold the hair out of the way. In addition to moving the hair out of the way, a conductive gel was applied to the scalp using a flat-head cotton bud at the place where the electrode would meet it. The Emotiv software uses a traffic lights system to indicate whether an electrode is connected, and whether it has a good signal. Once there is a good signal at all electrodes, indicated by a green light in the software, then the participant is ready to take part in the experiment. Figure 4.18 shows what both of the devices look like when worn together.

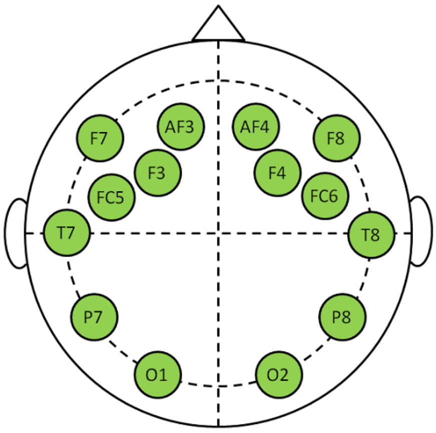

Figure 4.17: Emotiv EPOC headset electrode positions, demonstrated on the 10-20 electrode system

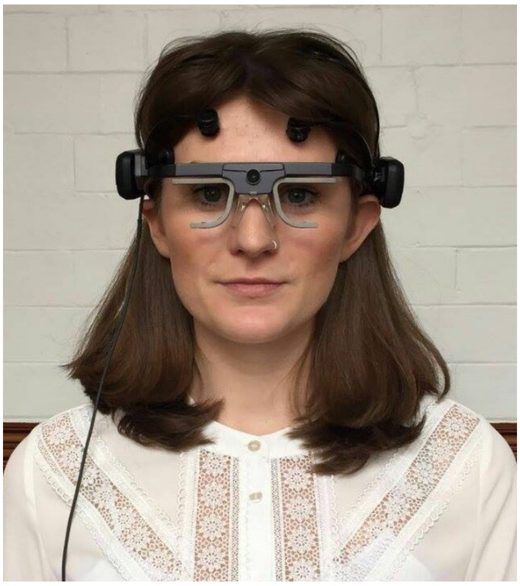

Figure 4.18.a: front view

Figure 4.18.b: side view

Figure 4.18: Both the eye-tracker and EEG device being worn at the same time. This was the set up for the participants during the experiment

4.5.5 Task

The first part of the experiment required recording one minute of baseline data, to be used for comparison to the active components of the experiment. The participant was asked to sit quietly, and as still as possible, whilst staring at a blank white wall. The researcher told the participant when the minute began, and when enough time had elapsed. Once the baseline data had been recorded, the participant was asked whether they had any outstanding questions before they entered the retail environment to begin the main part of the experiment. Until now the retail environment had been out of sight to the participant, hidden behind a wall partition. The priming stimuli were all positioned inside the retail environment, so the participants were first exposed to the priming when they entered the retail environment to begin the experiment. The visual merchandising which were used as the priming stimuli are visible at multiple angles to ensure the participants are full immersed with the prime colour. There was a prime coloured image on each wall, and mannequins wearing the prime coloured clothing opposite next to the main wall (Wall 1).

To start the experiment the participant stood facing the partition wall. The researcher then began the recording from the eye-tracking device, using a simple GUI to send a marker to the EEG data to indicate when the eye-tracking recording began, then moved the partition out of the way, so the participant could enter the retail environment and begin the main task. The marker sent by the GUI (Figure 4.19) to the EEG data was essential to allow synchronisation of the timings from the EEG and the eye-tracking devices.

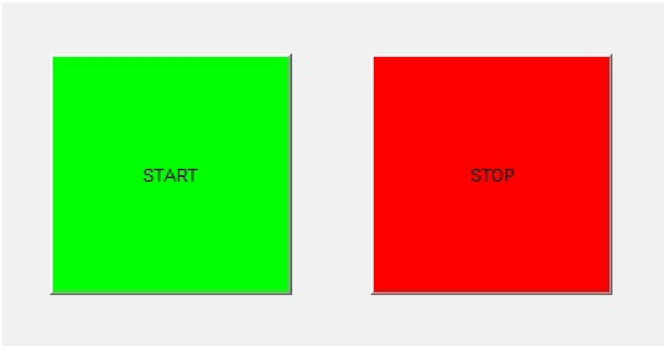

Figure 4.19: The Graphical User Interface (GUI) used to synchronise the beginning and ending of the eye-tracking recording with sending a marker to the EEG data

Russo and Leclerc (1994) identified three key stages of the decision making process that can be traced using eye-tracking, which are orientation, evaluation, and validation. During the current experiment, the participants were instructed to view each of the walls of clothing in three stages. These stages are demonstrated in Figure 4.20. The stages included periods of time in which the participants stood still, and times during which they moved freely and browsed the clothes at their leisure. The reasons for this set-up were twofold: firstly the standing still stages allowed a time in which EEG data could be recorded with minimal noise and motion interference and, secondly, the aim was to replicate the three stages identified by Russo and LeClerc (1994).

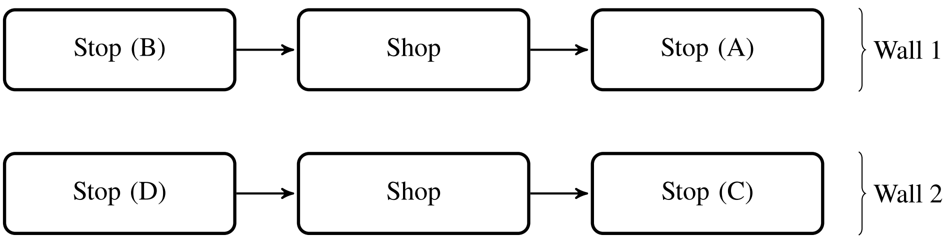

Figure 4.20: The stages of the experiment process. The participants were asked to follow *Stop-Shop-Stop* procedure for each wall of clothing

The participants were instructed to focus on Wall 1 when they first entered the simulated retail environment, followed by Wall 2. Their first instruction was to walk into the shop, and stand completely still, facing the largest wall of clothing (Wall 1). Whilst they are stood still they were told to think about their first impression of the clothes they could see. The participants were asked to think about which things they liked, which items stood out to them, and which items they were not interested in. This first stage of the process, designed to imitate the orientation stage of the decision-making process, as identified by (Russo and Leclerc 1994). This stage is indicated by the *Stop (A)* stage, seen in Figure 4.20.

Once participants had gathered enough information to get a reliable first impression of the clothes, they were told to move forward and browse through the clothes as naturally as they would in any shop. This moved participants into the second stage of the process, the *Shop* stage in the diagram 4.20. During this phase they were told they could look at all of the clothes on this first wall, have a feel of the fabrics, or even hold the items up to see how they looked against themselves in the mirror. They were encouraged to use this phase to have a closer inspection of the clothes, to help inform their decision of which they would like to choose. This stage was intended to imitate the evaluation stage of Russo and Leclerc (1994)'s three stages.

Finally, when the participant feels like she has had enough time to browse the clothes, she was instructed to return to the first spot where she stood to look at the clothes, and look at all of the clothes again from this short distance. This was the second stop (*Stop B*) stage of the process. It was during this third phase that the participant was asked to think about their decision, and decide which of the clothes on that wall they would be interested in choosing. This stage was intended to reproduce the third stage of Russo and Leclerc (1994)'s three stages, the validation stage.

After completing this full *Stop-Shop-Stop* procedure for Wall 1, the participant was asked to turn Wall 2, and repeat the same three-stage process. The participant was told that once they had completed all of the stop-shop-stop stages for each of the walls of clothing, then enough EEG and eye-tracking data would have been gathered for the experiment. At this point the participant picked out her three favourite dresses and return to the set-up area with the dresses.

After the eye-tracking glasses and EEG headset had been removed the investigator asked the participant some questions in a semi-structured interview. During these questions the participant identified the preference order of her three chosen dresses.

4.5.6 Ethical Approval

Research Ethics approval was sought for the study from the University of Manchester Research Ethics committee, an independent ethical review board staffed by academics, clinicians and ethicists.

The key issues that the ethics committee seek to safeguard include personal and contact details of the participants, the method of obtaining consent, potential risks of the experiment and safeguards in place, medical intervention, and data protection and confidentiality. It was important to clarify that the participants were healthy adult volunteers over 18 years of age, capable of giving their own informed consent for participation in the study. Participants were given a consent form to sign if they wished to continue, after the details of the experiment had been explained, before the equipment was set up. There were no risks to the participants that could cause any pain or discomfort; in addition there were no discussions between the researchers and participant that share sensitive information that could be embarrassing. There was no need for medical intervention or supervision for this experiment; participants did not need to notify their GP that they were taking part in the study. Each participant's data were saved with a unique four digit anonymised ID code to protect their identity, and any results would be published or presented anonymously. All data were fully anonymised, there is no information to connect the participant numbers to the participants' personal information.

4.5.7 Summary

This study has used quantitative methods, obtaining data in a one to one situation between the investigator and the participant. The participants chosen were right handed females between the ages of 18-25, with normal or corrected to normal vision. The participants were given clear details of what was expected of them during the shopping task before the equipment was set up. Once the participant was prepared and the equipment was calibrated the shopping task was able to begin. Ethical considerations were taken when designing the data collection method, and approved by the University of Manchester Ethics Committee.

4.6 Chapter Summary

This chapter began by outlining the hypotheses that have been tested in this research. The two hypotheses are related to measuring the participants' preferences (H1) and the influence of the priming (H2). Within each hypothesis there are two sub-hypotheses, relating to the techniques that were used to evaluate the hypotheses; either with the eye-tracking data (H1a and H2a) or with the EEG data (H1b and H2b).

The overarching theoretical framework that will be used in this research is Mehrabian and Russels' (1974)'s S-O-R model. The model was developed as a general tool for environmental psychology research, and therefore provides a suitable framework for investigating consumers' responses to priming cues in a retail environment.

A real-world simulated retail environment was built within a University building for the experiment to be conducted in. The details of how this was designed and created are provided in section 4.4. To allow the participants to move freely throughout the experiment it was imperative to use mobile eye-tracking and EEG equipment. The Tobii Pro Glasses 2 have been chosen to use to measure the participants' eye-movements, and the Emotiv EPOC EEG head set has been chosen to measure their brain activity. The anticipated technical challenges of combining eye-tracking and EEG data in a mobile setting have been discussed.

Finally, section 4.5 outlined the data collection methods in detail, including the preparation of the participant to ensure they understood what was required of them during the shopping task, the setting up of the equipment, and the stages of the experimental task itself. Ethical approval has been awarded for this research.

Chapter 5

Eye-Tracking Methods and Results

5.1 Introduction

Chapter three highlighted the close link between our cognitive processes and eye-movements. Chapter four then described a methodology for measuring this in a realistic shopping environment. In this chapter eye-tracking is used to measure and quantify this link, in the context of colour priming towards dresses. The colour of the visual merchandising displays has been used to prime the participants' responses towards different coloured garments within the simulated retail environment. Depending on the condition group the participant was in, they were primed with either pink, blue or red visual displays.

This chapter begins by presenting the dress choices that the participants' made, and commenting on interesting features of these choices in section 5.2. The colour of the dresses that the participants chose, and the relative popularity of each coloured dress during the different prime conditions, give and initial indication of whether the priming techniques had an impact on the participants' responses and preferences. Once the data have been prepared, quantitative statistical comparisons are made between the duration and number of fixations on different stimuli within the retail environment. The stimuli of interest for the analysis are the 23 dresses which the participants were able to choose from during the experiment. Each of the dresses is highlighted as an Area Of Interest (AOI), and fixation metrics regarding each AOI are exported from the *Tobii Analyzer Pro* software for analysis.

This chapter begins with section 5.3 detailing the processes for preparing the eye-tracking data for analysis. Section 5.4 investigates the first hypothesis, as discussed in section 4.2, that there will be a difference in the participants' gaze bias towards the three dresses that they chose over the dresses that they did not choose. The null hypothesis will be rejected based on a statistically significant difference ($p<0.05$) of the dwell time and fixation count between the chosen and not chosen dresses. This hypothesis is based on the Gaze Cascade Theory (Shimojo et al. 2003) which states that there is a positive feedback loop formed between participants looking at products that they like, whilst gaining positive preference towards products that they look at the most. The findings of this hypothesis replicate well known eye-tracking results from non-mobile, non-realistic environments and so justify the method of using eye-tracking in more natural, ecologically valid environments, demonstrating that it can replicate those previous findings.

Section 5.5 then investigates the second hypothesis, which proposes that there will be a difference in gaze bias towards the garments that the participants are primed towards, compared to the other garments, as discussed in section 4.2. This hypothesis is based on the priming phenomenon, in which individuals' responses to target stimuli (prime coloured dresses) can be influenced by priming stimuli (visual merchandising colour). This hypothesis is also dependent on positive findings from the first hypothesis, to ensure that the methods used in this experiment to indicate preference towards a product is reliable and valid. Following this, section 5.7 explores the nature of the participants' eye-movements using qualitative evaluation of eye-tracking visualisations. This is used to evaluate the level of cognitive control, particularly bottom-up versus top-down, participants had over their eye-movements during the experiment.

Finally, section 5.8 combines and discusses all of the results, highlighting the impact of cognitive control on the participants' eye-movements as an explanation for the findings of the hypothesis investigations.

Full scripts and all eye-tracking fixation data are available at the following link: https://github.com/C
LAB/Eleanor-PhD-Eye-tracking

5.2 Participant Dress Choices

At the end of the shopping task the participants were required to choose their three favourite dresses from the retail environment. The choices that they made give an indication of the influence that priming may have had on their behaviour. The full list of choices, during the three different prime conditions, can be seen in Table 5.1.

Of the dresses available for the participants to choose, there were three pink dresses, nine blue dresses, and six red dresses. There were also dresses available in non-primed colours; green, taupe, and white. Due to the imbalanced number of the prime-coloured dresses, a scaling factor will be applied so that the choices can be compared evenly. For this the number of pink choices will be divided by one (3 pink dresses; $\frac{3}{1} = 3$), the blue choices will be divided by three (9 blue dresses; $\frac{9}{3} = 3$), and the red choices will be divided by 2 (6 red dresses; $\frac{6}{2} = 3$).

So that the popularity of each coloured dress can be compared evenly between the different conditions, the number of times the dress was chosen will also be divided by the number of choices that were made during that condition. All participants make three choices, the pink prime condition had ten participants, and the blue and red prime conditions had eight participants. Therefore 30 choices were made during the pink condi-

Table 5.1: The participants' dress choices

Participant Number	Dress Choice 1	Dress Choice 2	Dress choice 3	Prime Condition
2751	Green Suede	Taupe Skater	Burgundy Skater	Pink
1994	Navy Suede	Navy Shirt	Navy Tee	Pink
6789	Navy Shirt	Green Shirt	Navy chiffon	Pink
1906	White Ribbed	Pink Ribbed	Pink rollneck	Pink
1408	Green Shirt	Pink Suede	Navy Shirt	Pink
2511	Navy Rollneck	Navy Chiffon	Green Shirt	Pink
1824	Burgundy Skater	Red Belted	White Skater	Pink
1996	Navy Shirt	Pink Ribbed	White Ribbed	Pink
2406	Navy tee	Navy Suede	Pink suede	Pink
1901	Red Ribbed	Navy Suede	Navy Shirt	Pink
9532	Green Shirt	Navy Shirt	Green Suede	Blue
1992	Green Suede	Navy Suede	Green Shirt	Blue
2304	Navy Shirt	Red Chiffon	Green Suede	Blue
0212	Navy Suede	Red Ribbed	Navy Rollneck	Blue
2604	Navy Suede	Green Shirt	Green Suede	Blue
8000	Navy Suede	Green Suede	Navy Shirt	Blue
9382	Red Belted	White Ribbed	Green Shirt	Blue
3537	White Ribbed	Red Skater	Navy Suede	Blue
0927	Green Shirt	Navy Shirt	Navy Suede	Red
2413	Red Ribbed	Pink Ribbed	White Ribbed	Red
0810	White Ribbed	Taupe Skater	Navy Tee	Red
9421	Pink Ribbed	Navy Shirt	Taupe Skater	Red
7927	Red Belted	Green Shirt	Navy Skater	Red
2021	White Ribbed	Red Skater	Pink suede	Red
1637	Green Shirt	Blue Belted	White Ribbed	Red
2911	Pink Suede	Navy Tee	Red Ribbed	Red

tion, and 24 choices were made during the blue and red prime conditions. The number of dresses chosen, and the standardised relative popularity of each dress during each condition can be seen in Table 5.2.

Table 5.2: Relative popularity of different coloured dresses

Prime Condition	Colour of dress	Number of dresses chosen	Standardised relative popularity
Pink Prime	Pink Dresses	5	0.17
Pink Prime	Blue Dresses	13	0.14
Pink Prime	Red Dresses	4	0.07
Pink Prime	Green Dresses	4	0.20
Blue Prime	Pink Dresses	0	0.00
Blue Prime	Blue Dresses	9	0.13
Blue Prime	Red Dresses	4	0.08
Blue Prime	Green Dresses	9	0.56
Red Prime	Pink Dresses	4	0.17
Red Prime	Blue Dresses	7	0.10
Red Prime	Red Dresses	4	0.08
Red Prime	Green Dresses	3	0.19

The pink dress was chosen five times during the pink condition. There were 30 choices made during the pink condition, and as there were three pink dresses to choices from the scaling value is simply to divide by one. Therefore, the calculation to determine the relative popularity of the pink dresses during the pink prime condition was $\frac{5}{30} \div 1$. There were 13 blue dresses chosen during the pink condition, however as there were three times more blue dresses than pink dresses, the popularity of the blue dresses will be divided by three, to produce a standardised relative popularity. The calculation for the blue dresses relative popularity during the pink prime was $\frac{13}{30} \div 3$.

A key point of interest from these results is the difference in popularity of the pink dresses during the different conditions. As can be seen in Figures 5.1.b and 5.1.c the popularity of the blue and red dresses remained relatively stable throughout the three colour conditions. However, the pink dress was proportionally the most popular dress during the pink and red prime conditions, yet was not chosen by a single participant during the blue condition. As can be seen in Figure 5.1.a. This suggests that pink and red priming conditions had an influence on the popularity of the pink dress, as without the prime of these matching and similar colours, the pink dress was not popular at all.

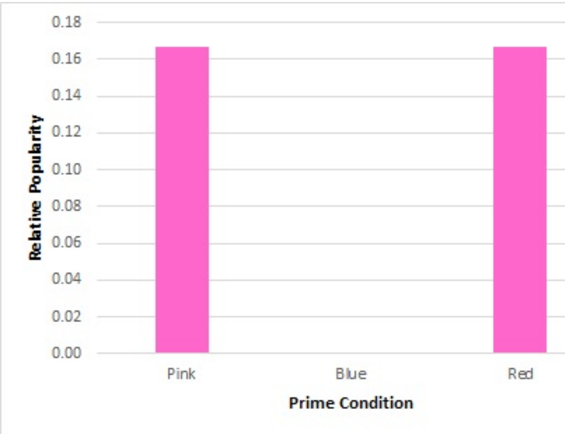

Figure 5.1.a: Pink dresses popularity

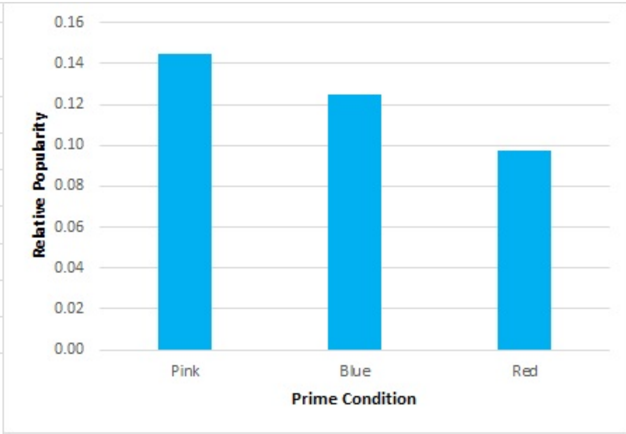

Figure 5.1.b: Blue dresses popularity

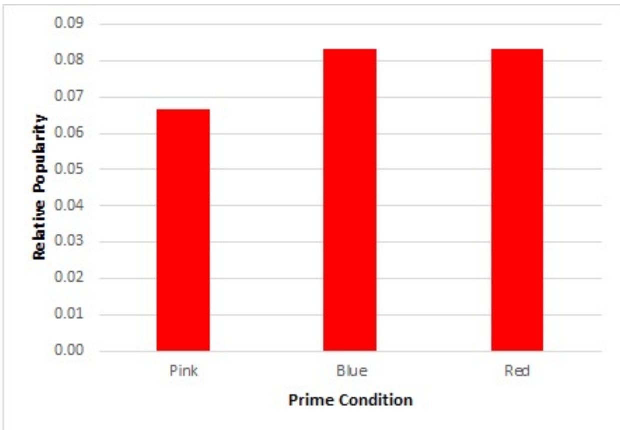

Figure 5.1.c: Red dresses popularity

Figure 5.1: Changes in relative popularity of the different coloured dresses during the three different prime conditions

There were also a number of interesting finding regarding the popularity of the green dresses within the study. As can be seen in Figure 5.2, the green dress was the most relatively popular dress throughout all of the colour conditions. There were two green dresses available, so a scaling factor of $\frac{2}{3}$ was used so that the green could be compared relatively to the pink, blue, and red dresses (2 green dresses; $2 \div \frac{2}{3} = 3$).

Figure 5.2.a: Dress popularities during the pink prime condition

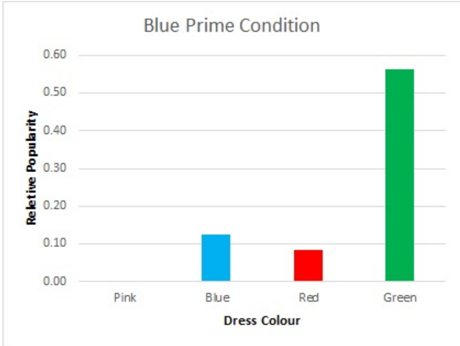

Figure 5.2.b: Dress popularities during the blue prime condition

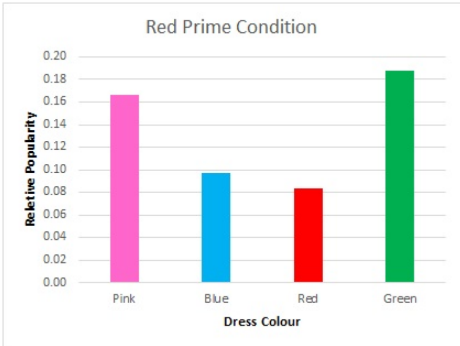

Figure 5.2.c: Dress popularities during the red prime condition

Figure 5.2: Comparison of different coloured dresses popularity during the three different prime conditions

The popularity of the green dress is likely because it was available in the most popular styles. There were eight different styles of dress available in the experiment; a suede dress, a shirt dress, a ribbed patterned dress, a dress with a rollneck, a skater style dress, a plain tee style dress, a dress with a belt and a dress made of chiffon material. The relative popularities of these dresses can be seen in Figure 5.3.

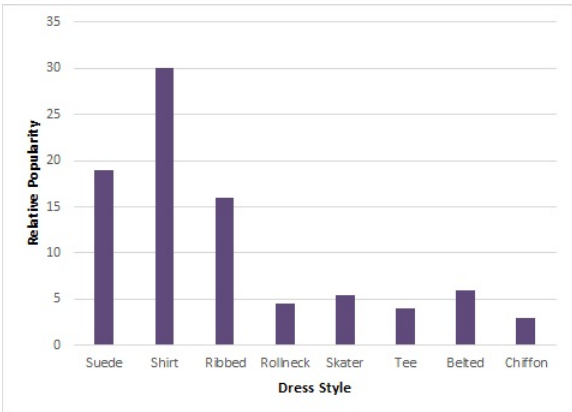

Figure 5.3: The relative popularities of the different styles of dresses available in the experiment

Another interesting finding of the popularity of the green dress, is that its relative popularity more than doubled during the blue priming condition, as can be seen in Figure 5.4. The popularity of the green dress increased to a relative popularity score of 0.56 during the blue prime condition, compared with a relative popularity of 0.20 during the pink prime condition, and 0.19 during the red prime condition. Although green was not a colour that the experiment was attempting to prime the participants towards, it appears that the blue priming techniques have had an influence on the popularity of the green dress. This may be due to the fact that blue and green are considered to be similar colours. Both blue and green have relatively short wavelengths, and are both theorised to be calm and agreeable colours(Goldstein 1942; Elliot and Maier 2007).

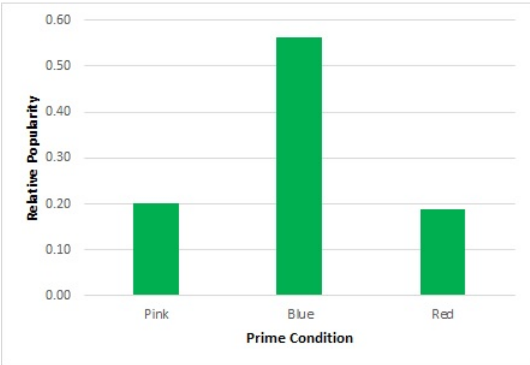

Figure 5.4: The relative popularity of the green dress during the three different prime conditions

5.3 Data Preparation

5.3.1 Introduction

The first stage of analysing the participants' eye-movements involves preparing the data, identifying the fixations and mapping these onto images that represent the scene that was viewed during the experiment. Areas Of Interest (AOIs) are drawn onto the two-dimensional images to highlight stimuli within the scene that are relevant for analysis. 31 AOIs were identified within the retail environment, 23 of these being the 23 dresses that the participant can choose from. The other highlighted AOIs included the visual displays, the mannequins and the images, and the handbags used to decorate the room. These additional AOIs were highlighted at an early stage so that additional analysis could be run if necessary. However, these additional AOIs were not relevant to the hypotheses of this research, so have not been included in the further analysis. Once the fixations have been identified and the AOIs have been highlighted, it is possible to quantify the gaze bias that each AOI received by using the fixation metrics, such as the total dwell time and the total fixation count. To ensure that the correct statistical comparisons are used, the frequency distribution of the data is tested. This demonstrates the distribution of the dwell times and fixation counts for all participants, for all AOIs.

5.3.2 Fixation Computation

The first stage of fixation computation is the I-VT algorithm, it determines whether a gaze point belongs to a fixation or a saccade based on the length of the gaze point, and the speed and direction in which the pupil is moving. (Salvucci and Goldberg 2000). The I-VT classification algorithm is one of the most common fixation classifications used in eye-tracking research (Munn et al. 2008; Salvucci and Goldberg 2000; Olsen 2012). The Tobii Pro Analyzer software uses the Velocity-Threshold Identification (I-VT) fixation classification algorithm to identify the wearers' eye-movements (Olsen 2012).

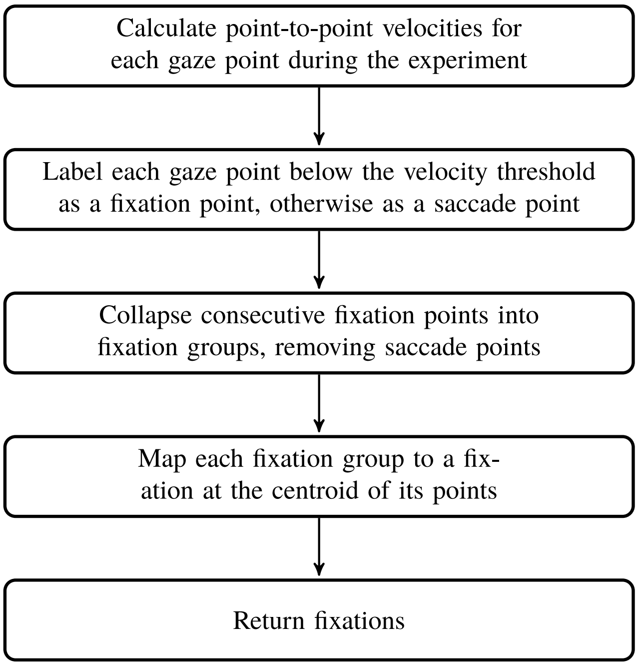

Figure 5.5: Pseudocode for the I-VT algorithm, adapted from Salvucci and Goldberg (2000, pg. 73)

The first stage of the I-VT algorithm is to calculate the velocity between each gaze point during the experiment (Salvucci and Goldberg 2000). The velocity is computed based on the distance between the two gaze points, and the time between them. Based on the velocity threshold set by the investigator, the algorithm then sorts each gaze point into either belonging to a fixation or belonging to a saccade. Gaze points which are identified as fixations are then combined with neighbouring gaze points to create fixations. For this research the velocity threshold was set such that the gaze points had to be less than 75ms apart, and at an angle of less than 0.5° to be grouped as a fixation.

Once a fixation is identified, the position of the fixation is set as the central position of the gaze points that it is made up of. The I-VT algorithm returns each fixation with values $<x,y,t,d>$, with x and y representing the fixation's location (taken as the central point of the grouped gaze points), t representing the time the fixation started, and d representing the duration of the fixation (Salvucci and Goldberg 2000). Fixations shorter than 60ms were removed, as the minimum length of fixation required to obtain any relevant information is believed to be 60ms (Pavlas et al. 2012). The psuedocode for these stages for the I-VT algorithm can be seen in Figure 5.5.

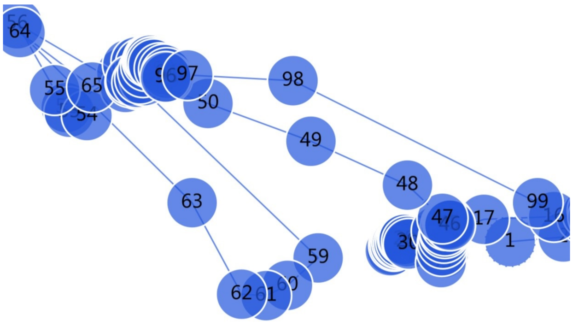

Figure 5.6.a: Raw gaze points of participant 1234

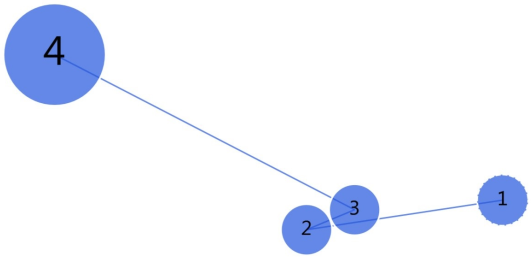

Figure 5.6.b: Fixations identified by the I-VT algorithm

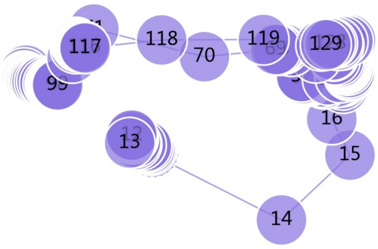

Figure 5.6.c: Raw gaze points of participant 1906

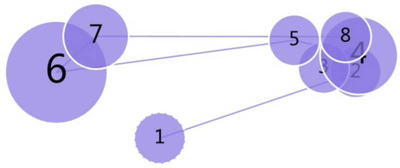

Figure 5.6.d: Fixations identified by the I-VT algorithm

Figure 5.6: Demonstration of the I-VT filter. Information taken from the first three seconds of the participants' data

Figure 5.6 uses gaze plots to demonstrate how the I-VT algorithm transforms a group of individual gaze points into identified fixations. In gaze plots each circle represents a point at which the eye was stationary, and the line between each circle is the movement in between. The number inside each circle demonstrates the order in which they took place. In the raw data, as can be seen in 5.6.a and 5.6.c, each circle represents a 20ms gaze point. Figures 5.6.b and 5.6.d show the identified fixations once the I-VT filter has been applied, and fixations shorter than 60ms are removed. In these illustrations the number in the circle is also indicative of the order in which the fixations took place, and the lines between represent the sacccades between the fixations. Each circle represents a fixation, they are different sizes as the longer a fixation is, the larger its representative circle will be. The data to create these illustrations come from the first three seconds of two participants' data, participants 1234 and 1906.

Unlike some other eye-trackers, the *Tobii Pro Glasses 2* records both of the wearer's eyes, and therefore an average position between both of the pupils' locations is used. Data from a single eye are therefore sufficient for investigating eye-movements, however binocular eye-movement recording can be used to enhance the precision and accuracy of the gaze sample data (Holmqvist et al. 2011).

5.3.3 Map Fixations

A key novelty of this research is the use of eye-tracking in a mobile environment, which allows the subject to walk around and act more naturally than computer based studies allow. However, one of the difficulties of conducting mobile eye-tracking studies is that after the experiment, the participants' fixations have to be manually mapped onto images of the scene that the participant was looking at. Fixation mapping involves watching the participants' videos and at each recognised fixation point, selecting the identical position on the two-dimensional image as it appears in the video. A key difficulty of mobile eye-tracking experiments is that in mobile settings the distance between the stimuli and the observer vary throughout the experiment (Kiefer et al. 2014). Another difficulty is that the observer is not looking at a two-dimensional image (such as a computer screen, or tablet), they are viewing a three-dimensional world. This makes it difficult to automatically map the participants' fixations onto the scene that they are viewing.

Figure 5.7: The three images of the simulated retail environment that the fixations were mapped onto

For this experiment images of the simulated retail environment were taken using a digital camera. To simplify the fixation mapping process, only three images of the simulated retail environment were used; one of the front wall, one of the side wall and one of the main wall. The images used for mapping the fixations on to can be seen in Figure 5.7. These images include all of the necessary areas of interest, therefore mapping the fixations onto these images can provides all of the relevant fixation metric data.

Figure 5.8 demonstrates the fixation mapping process using the Tobii Pro Analyzer software. The participant's fixation is highlighted in the eye-tracking video, as can be seen in Figure 5.8.a. The researcher then manually selects the location in the image that directly matches the location of the fixation position in the video, to plot the fixation. This can be seen in Figure 5.8.b.

Figure 5.8.a: Video of the participants view, fixation represented by the red and white circle

Figure 5.8.b: Fixation mapped onto images in corresponding position

Figure 5.8: Fixation mapping using the Tobii Pro Analyzer software. The circle on the video represents the participant's fixation. The circle in the image has been manually positioned by the researcher.

5.3.4 Areas Of Interest (AOIs)

Once the fixations have been identified heat maps and gaze plots can be created. These are visualisations of the participants' visual attention on the scene that the participants viewed, illustrated on the images that the fixations have been mapped on to. Visualisations give a quick and easy to understand overview of the participants' visual attention, and are popularly used to demonstrate the overall trends (Holmqvist et al. 2011). However, visualisations do not provide quantitative results regarding visual attention on specific stimuli. In order to conduct statistical analysis of the participants' eye-movements throughout the experiment it is essential to specify the Areas of Interest (AOIs) with the scene the participants' viewed. The Tobii Pro Analyzer software has a useful tool to draw AOIs onto the snapshop images.

AOIs are drawn onto the same snapshop images that the fixations are mapped onto, therefore data can be generated regarding the fixation metrics on each individual area. The specific AOIs drawn for this study can be seen in Figures 5.9.

Once the AOIs are drawn, it is possible to quantify the number of fixations or the duration of the fixations which the participants placed on the stimuli of interest. The two key metrics that can be used to indicate this; the AOI fixation count and the AOI dwell time. The AOI fixation count, also known as the AOI hit rate, is simply a measure of the number of fixations that occurred on each AOI. The dwell time, is a measure that shows the total amount of time, throughout the whole experiment or any selected time segment, spent looking at each AOI.

Figure 5.9: Areas of Interest (AOIs) drawn onto the image of Wall 1

5.3.5 Frequency Distribution

Eye-tracking data is very rarely normally distributed, so it is important to test normality within any eye-tracking data set. Determining whether data are normally distributed or not is essential to ensure that the correct statistical tests are used to compare groups of data. Normally distributed data allow the use of parametric tests, such as ANOVAs and t-tests, whereas data that are not normally distributed requires non-parametric tests such as the Mann Whitney U-test (Nachar 2008).

Table 5.3: Shapirio Wilks and Kolomgorov-Smirnov Test Results

	Dwell Time	Fixation Count
Shapiro-Wilks	p = 0.00	p= 0.00
Kolomgorov-Smirnov	p = 0.00	p = 0.00

The Shapirio Wilks test and the Kolomgorov-Smirnov test compare the distribution of the samples from that of a normally distributed data set with the same standard deviation and mean (Field 2013). A statistically significant result from either of these tests ($p < 0.05$) indicates that the data are not normally distributed.

The participants' dwell times and fixation counts on all AOIs were tested using the Shapirio Wilks test and the Kolomgorov-Smirnov test, and the results can be seen in table 5.3. All of the p values are 0, therefore indicating that the fixation metrics are far from normal distribution. This is supported by the visual representation in the form of a histogram in Figure 5.10.

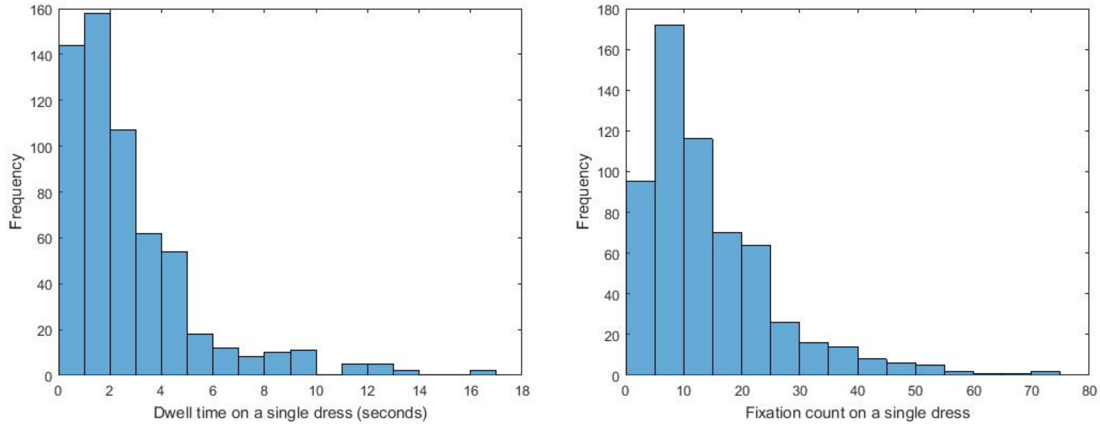

Figure 5.10: Histograms of the frequency of dwell times and fixations counts for each of the dresses for all of the participants

5.3.6 Summary

This section has demonstrated the stages of data preparation which are needed before eye-tracking analysis can take place. In order to conduct statistical analysis of mobile eye-tracking data it is essential for genuine fixations to be identified, for the fixations to be mapped onto two-dimensional images of the scene, and for the AOIs within the scene to be drawn onto these two dimensional images. Once these processes have been completed, the dwell time and fixation count metrics for each AOI can be calculated. It is these metrics that will be used for statistical analysis calculations. To ensure the correct statistical calculations are conducted, the data have been tested for normality. The data are not normally distributed, therefore non-parametric statistical tests will be used.

5.4 Chosen Versus Not Chosen Dresses

5.4.1 Introduction

According to the Gaze Cascade Theory (as discussed in section 3.3.5) the participants will spend more time looking at the products that they like the most. Therefore, it is hypothesised that as an indication of preference, there will be a statistically significant difference between the dwell time and fixation count on participants' chosen dresses and the dresses that they did not choose. The novelty of this research is applying this well known theory to a mobile experiment setting, allowing the participants to move naturally whilst they shop. The majority of the eye-tracking methodology is discussed in section 4.4.3, whereas in this section the specific statistical tests used are discussed in section 5.4.2. The results are presented in section 5.4.3 and discussed in section 5.4.4.

5.4.2 Method

To determine whether there is a difference between the amount of time spent looking at chosen dresses compared to not chosen dresses, a statistical comparison with a significance level of 5% was applied to the groups of data. The null hypothesis of the preference hypothesis (H1a) is that there will be no difference between the amount of time spent looking at the chosen dresses and the not chosen dresses. A rejection of the null hypothesis supports the preference hypothesis, and validates the application of the Gaze Cascade Theory to a mobile based experiment. Due to the irregular distribution of the eye-tracking data, as discussed in section 5.3.5, it was necessary to compare the data using non-parametric statistical comparisons, for this reason the Mann Whitney U-test was used. The Mann Whitney test is a non-parametric version of the commonly used t-test, and it determines whether there is a statistically significant difference between two sets of data (Nachar 2008). The data were loaded into MATLAB, and code was written to group the data into the necessary categories. The `ranksum` function was used to perform the Mann Whitney U-test, which is identical to the Wilcoxon rank sum calculation.

5.4.3 Results

The first hypothesis of this research, *the preference hypothesis*, is that there will be a statistically significant difference in the response towards the products that the participants chose and the products that they did not choose. In the eye-tracking data the response is being quantified by the dwell time and the fixation count on the AOIs relating to the 23 dresses (three chosen, 20 not chosen). Therefore the null hypothesis is that were will be no difference in the dwell time or fixation count on the chosen dresses compared to the not chosen dresses.

The results of the eye-tracking data have been compared for a difference between the chosen and not chosen dresses in two ways. Firstly the data were analysed collectively, for all participants' fixations on chosen dresses compared with all fixations on not chosen dresses. Following this, the data were separated into the three different colour conditions (pink, blue, and red) to determine whether the colour of the prime had any impact on the results. There were 10 participants who experienced the experiment in the pink condition, therefore the statistical comparison was of 30 data points (3 chosen dresses, therefore 3×10) compared with 200 data points (20 not chosen dresses, therefore 20×10). In the blue and red conditions there were eight participants, meaning that there were 24 data points compared with 160 data points for each of these conditions.

To clarify, each data point is the dwell time or fixation count that each individual dress received. It is not the collective amount of time spent looking at all chosen dresses or all of the not chosen dresses. If it were the collective time spent look at all of the chosen dresses against all other dresses, it could be assumed that looking randomly the participant would spend almost seven times as much time looking at the dresses they did not choose from, because there were almost seven times as many dresses in this group.

The first Mann Whitney calculation was applied to all of the participants' results combined. Therefore the dwell times and the fixation counts for all participants on their three chosen dresses was compared with the dwell times and counts on the 20 dresses they did not choose. For both the dwell time and the fixation count the p value was <0.001, meaning the null hypothesis was rejected.

Table 5.4: Comparison of the dwell times and fixation counts between the chosen and not chosen dresses

	Fixation Duaration		Fixation Count	
	h value	p value	h value	p value
All Participants	1	p <0.001	1	p <0.001
Pink Condition	1	p <0.001	1	p <0.001
Blue Condition	1	p <0.001	1	p = 0.002
Red Condition	1	p <0.001	1	p <0.001

To compare the results within the three different colour conditions (pink, blue and red), the participants' results were separated into these three groups. The dwell times and fixation counts on chosen dresses in the pink condition were statistically compared with the dwell time and counts on the not chosen dresses in the pink condition. This was then repeated for the blue and red conditions. The p value was <0.001 for all colour conditions, except for the fixation count for the blue condition, in which the p value was p = 0.002. These low p values indicate a strong support of the hypothesis that there is a difference in the amount of time spent looking at the dresses the participants chose and the dresses they did not choose.

5.4.4 Discussion

The first hypothesis being tested was that there will be a statistically significant difference in the dwell time and fixation count between the dresses that the participants chose, and the dresses that they did not choose. This is based on the Gaze Cascade Theory (Shimojo et al. 2003). The results demonstrate a strong significant difference and therefore support this hypothesis. The significant difference was found in all of the three colour conditions.

This strong support for the first hypothesis, demonstrated by exceptionally low p-values, validates the application of this research's methods and theory into a mobile retail environment. Researchers have commonly applied eye-tracking as a method to investigate aspects of consumer behaviour, such as the influence of the number of shelf facings and product positioning on consumers' attention and evaluation of brands (Chandon et al. 2009), or how the brightness of a product influences consumers' preference towards it Mormann et al. 2012. For more information on these studies, please see section 3.5.2. However, most of these experiments were conducted in laboratories with the participants viewing the stimuli on a computer screen. Whilst these experiments help to advance the field's understanding of consumer behaviour in a controlled environment, they do not offer the ecological validity of an experiment set in a realistic retail environment. Gidlöf et al. (2013) reviewed existing literature using eye-tracking to investigate decision-making and noted that whilst they found numerous studies investigating this topic ((Russo and Leclerc 1994; Chandon et al. 2009; Pieters and Warlop 1999), none of them was conducted in a natural environment. Shimojo et al. (2003) even introduced their Gaze Cascade Theory based on two experiments which were also conducted on computer screen. The novelty of this research is using eye-tracking to assess preference, using the Gaze Cascade Theory, in a realistic and mobile environment. This allows participants to act more naturally, as they would in a real shopping situation, therefore providing more ecological validity than previous research. Also, previous research has focussed predominantly on food based decision, where as this research has focused on fashion products.

5.5 Prime Versus Not Prime Dresses

5.5.1 Introduction

In this experiment the simulated retail environment contained priming material, such as visual displays and dressed mannequins, that were designed to influence the participants' responses towards a particular colour. There were three different colour conditions; pink, blue and red. The second hypothesis of this research, *the priming hypothesis*, is that there will be a measurable difference between the consumers' responses towards the products that match the prime colour, and products which do not match the prime colour. The Gaze Cascade Theory indicates that participants will have a gaze bias towards products that they prefer, therefore a more positive response towards prime coloured products could be indicated by an increase in gaze bias towards these products. Gaze bias can be quantified using the dwell time and the fixation count, meaning a statistically significant difference of these fixation metrics between the prime matching and non-prime matching products will support the priming hypothesis.

In this section the methods, which are the same as those used for testing the first hypothesis are discussed in section 5.5.2. The results are presented in section 5.5.3 and are discussed in section 5.5.4.

5.5.2 Method

Similarly to the chosen dresses versus non chosen dresses, the non-parametric Mann Whitney test will be used to determine whether the null hypothesis can be rejected, consequently supporting the priming hypothesis. The null hypothesis is that there will be no significant difference between the dwell time or the fixation count.

The method for analysing the difference between the prime coloured dresses and the non-prime coloured dresses was the same as the method for the participants' chosen and not chosen dresses. For details of this methods see 5.4.2. The Mann Whitney test was applied to groups of prime coloured and non-prime coloured dresses, with a significance level of 5%.

Table 5.5: The different number of data points in each of the three colour conditions when comparing the prime and non-prime dresses

		Prime		**Non-Prime**	
	n =	Dresses	Data points	Dresses	Data points
Pink Condition	10	3	30	20	200
Blue Condition	8	9	72	14	112
Red Condition	8	6	48	17	136
Total	26		150		448

The data were grouped in two different ways; firstly they were grouped to compare gaze bias on the prime coloured dresses against the non-prime coloured dresses for all of the participants combined. This created a group of 150 data points to compare against a group of 448 data points, as can be seen in table 5.5.

Secondly, the data were split into three pairs of groups of data, each representing a different colour condition. Statistical comparisons were calculated within each pair, not between pairs. The different colour conditions each had a different number of prime coloured dresses, so the groups of data compared for each condition are of different sizes. For example, in the blue condition there were nine prime coloured (blue) dresses, meaning there were 14 out of the 23 dresses which were not prime coloured. There were eight participants in the blue condition, so this meant a group of 72 data points (9×8) was statistically compared against a group of 112 data points (14×8).

5.5.3 Results

As with the chosen and not chosen dresses, to compare the prime coloured dresses and the dresses which were not prime coloured the Mann Whitney calculations were first applied to the dwell times and fixation counts of all of the participants combined. As can be seen in table 5.6, none of the results were statistically significant ($p<0.05$) between the primed and not-primed dresses.

Table 5.6: Comparison of the dwell times and fixation counts between the prime matching and not prime matching dresses

	Fixation Duaration		Fixation Count	
	h value	p value	h value	p value
All Participants	0	p = 0.06	0	p = 0.06
Pink	0	p = 0.83	0	p = 0.99
Blue	0	p = 0.14	0	p = 0.06
Red	0	p = 0.61	0	p = 0.89

When the data for each of the different prime colour conditions were analysed separately it was clear to see that one of the colour conditions demonstrated close to significance, whilst the other two colour conditions were not nearly significant at all. As can be seen in table 5.6, none of the colour conditions provided statistically significant results. The blue condition demonstrated close to significant results for the dwell time and fixation count, p = 0.14 and p = 0.06 respectively. However, the pink condition was far from significant with p values of p = 0.83 and p = 0.99, whilst the red condition had values of p = 0.61 and p = 0.89. These results are also illustrated in Figures 5.11.a and 5.11.b.

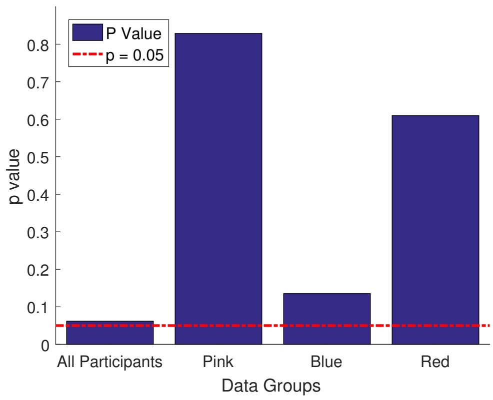

Figure 5.11.a: Dwell time

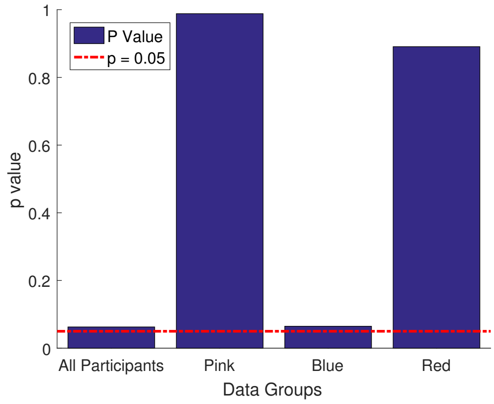

Figure 5.11.b: Fixation count

Figure 5.11: The p values of all participants, pink condition, blue condition and red condition. Prime coloured dresses versus non prime coloured dresses within each condition

5.5.4 Discussion

When looking at the collective results for all of the participants' dwell times and fixation counts on the prime matching dresses against the non prime matching dresses, despite the results being non-significant, they do appear to demonstrate a trend towards significance due to having such low p values (p = 0.06). Low p values such as these could be an indication that had the study used a larger sample size then it might have achieved significant results. However, when looking at the results for each of the colour conditions (as can be seen in table 5.6 and Figure 5.11), it is clear that the collective p values have been skewed by the results of a single condition group, the blue condition.

In the simulated retail environment, there were 23 dresses in total that the participants could choose from. Each of the colour conditions had a different number of dresses which matched the prime. There were three pink dresses in the shop, nine blue dresses and six red dresses. This disparity between the number of prime matching dresses means that the data in each condition were differently balanced or imbalanced. Whilst the data in the blue condition were not perfectly balanced (9 prime to 14 non-prime), they were more balanced than the pink condition (3 prime to 20 non-prime).

The different number of dresses was due to availability of suitable dresses in high street stores at the time. It was important for the dresses used in the experiment to be one block colour, relatively simple in style, and available in more then one colour. However, a variety of colours of dresses within the simulated retail environment is realistic compared to what would be found in a real store. Although having the exact same number of dresses in each of the three prime condition colours would have been a better design with regard to the statistical analysis, in the current experimental design it could have made the priming premise of the experiment quite obvious to the participant, consequently invalidating the results.

It can not be ignored, however, that the level of imbalance between the prime coloured and not prime coloured dresses within each colour condition appears to correlate with the p values. In the condition in which the prime to non-prime coloured dresses was most balanced (the blue condition) the p values were the lowest ($p = 0.14$ and $p = 0.06$). Conversely, the most imbalanced condition (the pink condition), demonstrated the highest p values ($p = 0.83$ and $p = 0.99$). One possible explanation for this is that the priming effect was reinforced by the number of blue dresses within the room, causing a stronger priming effect towards the blue products during the blue condition.

Despite the variance of p values, the overall finding from these results is that there are no statistically significant ($p<0.05$) differences in either the dwell times or the fixation counts between the prime coloured and non-prime coloured dresses, for any of the colour conditions or for all of the participants collectively. Therefore the null hypothesis can not be rejected, and there is no support for the second hypothesis (the priming hypothesis) of this research within the eye-tracking data.

5.6 Additional Eye-Tracking Metrics

The key eye-tracking metrics that have been analysed in this research are the dwell time and the fixation count on the AOIs of interest, comparing between the chosen and not chosen dresses, and the prime coloured and not prime coloured dresses. However, there are other eye-tracking metrics can provide insight into the participants cognitive processing throughout the experiment, such as the average dwell time. The average dwell time is the average length of the fixations on a particular AOI during a nominated time segment. The longer a fixation is, it is more likely that the viewer is cognitively processing information about the stimuli.

Table 5.7 shows the results of Mann Whitney comparisons of the average dwell times between the chosen and not chosen dresses, and between the prime and not prime dresses, during 6 different time segments. All Mann-Whitney comparisons were one-tailed in the right direction, therefore a statistically significant difference indicates that the chosen, or the prime coloured, dresses had significantly longer average dwell times on them than the not chosen, or not prime coloured, dresses.

Table 5.7: Comparison of average dwell time on chosen vs not chosen, and prime vs not prime coloured, within different time segments of the experiment

	Chosen vs Not Chosen		Prime vs Not Prime	
Time Segment Name	p	h	p	h
Whole experiment	0.44	0	0.09	0
During shopping task	0.30	0	0.06	0
After shopping task	**0.00**	**1**	0.15	0
During first 'Stop' segment (per wall)	**0.03**	**1**	**0.03**	**1**
During 'Shop' segment (per wall)	0.08	0	0.11	0
During last 'Stop' segment (per wall)	0.06	0	**0.01**	**1**

When looking at the average dwell time throughout the whole experiment, there were no statistically significant differences between the time chosen vs not chosen, and the prime vs not prime. However, during some stages of the shopping task there were significant differences. As can be seen in Table 5.7 during the first 'Stop' segment on each wall the participants had significantly longer average dwell times on the chosen and on the prime coloured dresses. This segment of the experiment was when the participants' had their first impression of the products available. This suggests that during their first impressions, the participants were taking in more information about both the chosen, and the prime products, during this stage.

Table 5.8: Comparison of average dwell time on chosen vs not chosen, and prime vs not prime coloured, between different time segments of the experiment

	Chosen vs Not Chosen		Prime vs Not Prime	
Time Segment Comparisons	p	h	p	h
First 'Stop' segment vs second 'Stop' segment	0.20	0	0.23	0
First 'Stop' segment vs 'Shop' segment	0.06	0	0.14	0
Second 'Stop' segment vs 'Shop' segment	0.63	0	0.94	0
During shopping task vs after shopping task	**0.00**	**1**	**0.00**	**1**

It is also possible to compare the length of the average dwell times on the chosen, not chosen, prime, and not prime dresses between different time segments. The results of these comparisons can be seen in Table 5.8. Throughout the Stop-Shop-Shop segments of the experiment there were no significant differences in the average dwell times. However, when comparing the average dwell time between during the task, and after the task, there is a significant difference for both the chosen and prime coloured dresses. The Mann Whitney was one-tailed in the right direction, meaning that the average fixations were longer during the task, and significantly shorter after the task. This indicates that the participants has sufficiently obtained enough information during the Stop-Shop-Shop segments of the task, that they were able to make the decision of which three dresses to choose with ease.

Table 5.9: Time to first fixation

Participant Number	Choice 1	Choice 2	Choice 3
2751	50.23	36.71	12.98
1994	1.48	14.42	5.88
6789	2.27	13.32	5.52
1906	37.59	15.00	36.93
1408	6.62	6.96	13.52
2511	8.68	16.84	5.22
1824	10.80	5.82	18.32
1996	14.42	15.16	7.34
2406	0.24	0.00	1.92
1901	48.09	0.00	58.95
9532	7.78	10.60	16.96
1992	34.47	0.38	4.86
2304	1.66	0.00	59.98
0212	0.80	0.00	18.12
2604	12.22	23.29	6.52
8000	7.82	4.36	5.48
9382	1.76	12.28	5.52
3537	40.43	6.30	14.98
0927	10.40	52.15	6.52
2413	27.45	9.68	6.60
0810	10.74	2.80	1.96
9421	35.55	9.24	37.29
7927	2.70	4.48	4.74
2021	1.60	20.25	15.34
1637	16.80	3.52	17.24
2911	8.30	5.92	5.96
Average	15.42	11.13	15.18

Another metric that can give insight into the participants' cognitive behaviour is the time to first fixation. The average time to first fixation on each of the dresses was 15.2 seconds. The time to each participants first fixation on their three chosen dresses can be seen in table 5.9. The average of the time to first fixation for first, second, and third choice dresses is also presented. Interesting, the average time to first fixation on the second choice dresses, was quicker than that on the first and third choice dresses. The average of the time to first fixation on the top three choices for each participant is 13.91 seconds, which is quicker than the average time to first fixation on other dresses in the retail environment. The shortest time to first fixation of all of the AOI's within the experiment, was on the main advert on wall one. This was at the centre of the room, and the advert included a human face, which are known to be highly salient.

5.7 Exploration of the Participants' Cognitive Control

5.7.1 Introduction

The two research hypotheses, the preference and priming hypotheses, have been tested based on the participants' eye-movements in this chapter. The eye-tracking analysis theories are based on the participants' eye-movements being largely controlled by their subtle preferences and subconscious responses within the retail environment. However, there are various factors that can attract or influence an individual's visual attention, whether it is a bottom-up influence of salient stimuli, or top-down control based on the experimental task. Top-down and bottom-up mechanisms of eye-movements have been discussed in more detail in section 3.3.6. To explore the data further, heat map and gaze plot visualisations can be used to give a qualitative overview of the data. It is important to explore the data further to determine what may have been influencing the participants' eye-movements during the experiment. Alternative controls or influences over the participants' eye-movements may override the theories that the hypotheses were based on.

5.7.2 Heat Maps

A heat map is an illustrative summary of the participants' eye-movements during an experiment (Blascheck et al. 2014). Figure 5.12 shows the heat map for all of the participants' fixations combined, on the first wall of the simulated retail environment. It can be seen that participants spent more time looking at the products on the rail in the centre of the room, instead of the forward facing products. It is also noticeable that participants' attention was often directed at the face of the woman in the visual display. It is common for forward facing faces to attract attention (Riby and Hancock 2009).

Figure 5.13 shows the heat map for all of the participants' fixations on the second wall of clothing within the simulated retail environment. As can be seen, the participants' eye-movements follow a similar pattern on this wall. There is a small amount of gaze drawn to the face of the model in the image, and the majority of the fixations are on the dresses themselves. For both the front wall and the side wall the heat maps demonstrated a similar pattern in all of the three colour conditions. The heat maps for the individual colour conditions can be found in the appendix D.1.

5.7.3 Gaze plots

A gaze plot is a visualisation of the fixations and the saccades in their chronological order, which makes up a scanpath (Holmqvist et al. 2011). In a gaze plot, each fixation is represented by a circle, the size of which is determined by the length of time of the fixa-

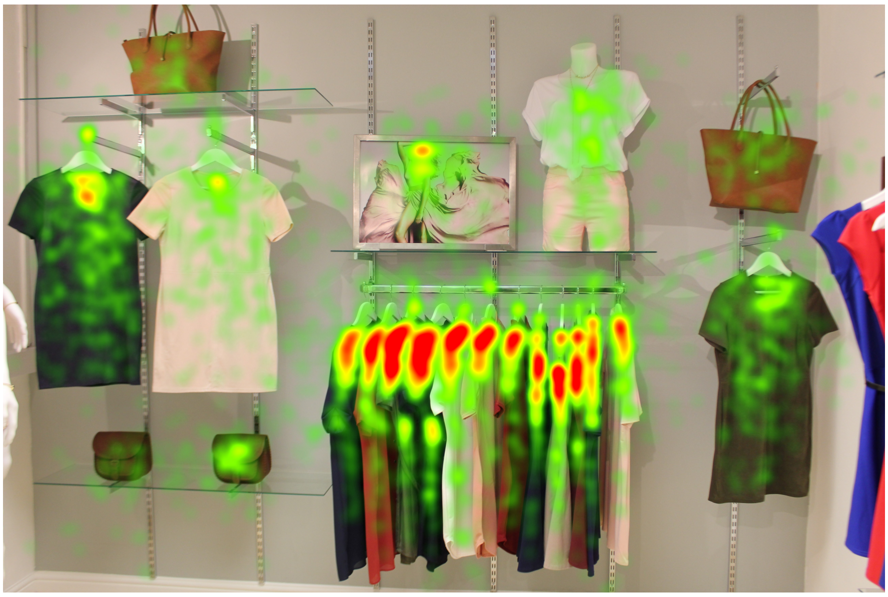

Figure 5.12: Heat map of all participants' data combined on the front wall in the simulated retail environment. Scale max value = 40 fixation counts

tion, and the saccades between the fixations are represented by the connecting lines between the circles (Blascheck et al. 2014).

Figure 5.14 shows the gaze plots of three different participants' scanpaths on the front wall during the experiment. Each participant's scanpath data are represented by a different colour. From this it can be clearly seen that participants' gaze often followed a pattern of scrolling their eyes through all of the products and objects in the room in a linear order, then moving their eyes more randomly around the scene. This was a common pattern amongst most participants. The similarity of the participants' eye-movements, as demonstrated by the gaze plots, indicates a level of cognitive control. This suggests that participants' eye-movements were top down controlled, based on the design of the experiment.

5.8 Discussion

The further exploratory examination of the data has demonstrated additional influences on the participants' attention. Understanding the factors which had an influence on the participants' eye-movements during the experiment is imperative to deciphering the results of this study.

Eye-tracking visualisations can give key insights into the mechanisms governing the participants' eye-movements. Heat-maps are a quick way to achieve an overview of the participants' gaze bias, collectively or individually. Looking at the heat maps can also reveal additional behaviours that may not be picked up in the direct statistical comparisons. For example, when looking at the heat maps for each wall within the simulated retail environment, it was evident that the participants attention was initially attracted

Figure 5.13: Heat map of all participants data combined on the front wall in the simulated retail environment. Scale max value = 40 fixation counts

to the face of the model in the visual display image. This is not unusual, as the human face naturally captures our visual attention due to its social and evolutionary importance (Riby and Hancock 2009). This is suggestive of a bottom-up controlled eye-movement.

Orquin and Loose (2013) argue that saliency and bottom-up control generally have a smaller effect on eye-movement than top-down control. There is evidence to suggest that semantic or contextual cues, such as task demands or rewards for task performance, will override visual saliency attention (Kowler 2011). The pioneer of eye-tracking Alfred Yarbus et al. (1967), first identified that eye-movements are highly task dependent. In his well-known study based on a photo of three people in a room, Yarbus gave different participants different tasks and monitored their eye-movements. The tasks included being asked to guess the age of the people in the photo, remembering the positions of the people and objects within the room and a free examination of the image. The results of these various tasks can be seen in Figure 5.15. His results showed that participants will focus on the most task relevant stimuli, and different tasks will elicit different scanpath results (Orquin and Loose 2013). The heatmaps presented in section 5.7.2 support this, such that the task-irrelevant stimuli, such as the handbags, did not receive as much attention as the dresses. The participants were instructed to choose their favourite three dresses, and therefore focused their attention on these products.

Figure 5.14.a: Gaze plot of participant 1906

Figure 5.14.b: Gaze plot of participant 1824

Figure 5.14.c: Gaze plot of participant 6789

Figure 5.14: Three different participants' gazeplots during the first standing still stage of the experiment. The circles represent a participant's fixation points, and the lines respresent the saccades between these fixations. The different colours represent different participants' data.

The two research hypotheses, the preference and the priming hypotheses, have been tested in this chapter with the eye-tracking data. The eye-tracking sub-hypotheses are that there will be a measurable difference in the gaze bias between the chosen and not chosen dresses

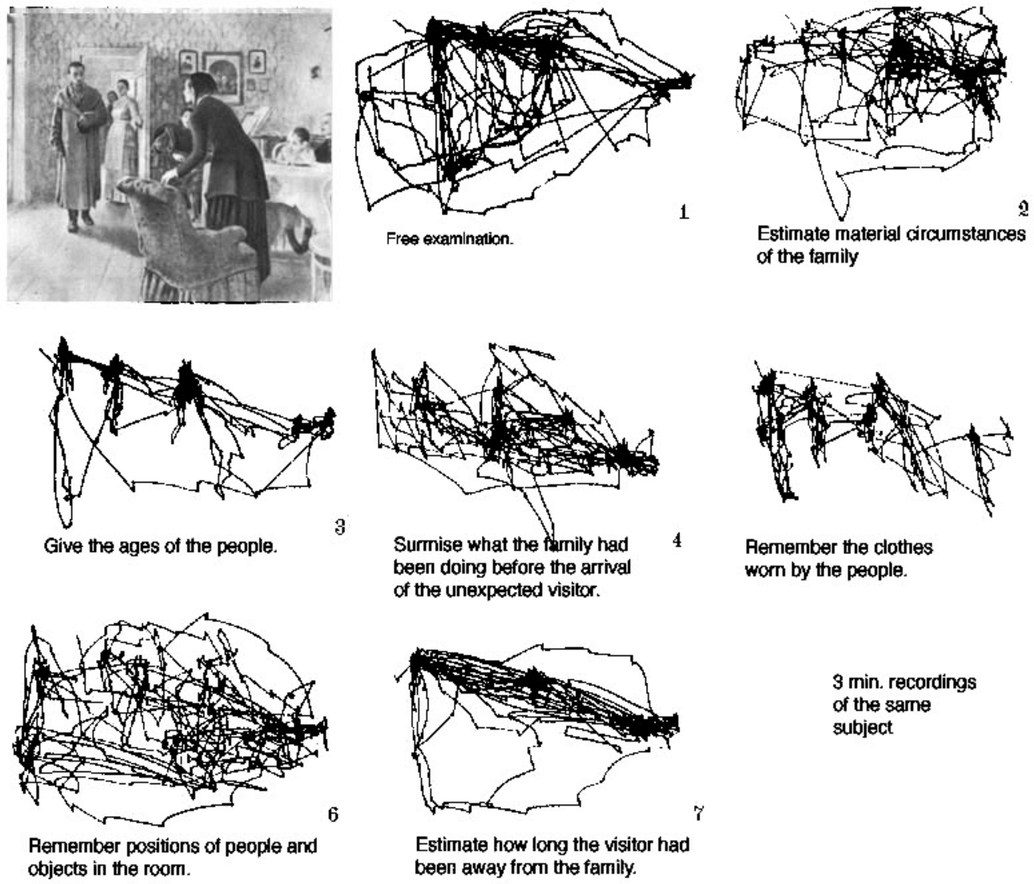

Figure 5.15: Yarbus et al. (1967)'s discovery of different search patterns based on different tasks

(H1a), and between the prime and not prime dresses (H2a). This was quantified using the participants' dwell times and fixation counts on AOIs that correspond with the dresses. The results presented support the first (preference) hypothesis, as a statistically significant difference was found between the chosen dresses and the not chosen dresses. However, the second (priming) hypothesis was not supported, as no significant difference was found between the prime coloured and not prime coloured dresses.

The balance of evidence suggests that the participants' eye-movements were predominantly cognitively controlled. As introduced in section 2.3, priming can cause either an affective, a cognitive, or a behavioural response. This is in line with the ABC model of attitudes introduced by Breckler (1984). The eye-tracking analysis methods have been validated by the statistically significant results presented between the chosen dresses and the not chosen dresses. Applying traditional eye-tracking analysis methods to a mobile setting for analysing consumers' responses towards their preferred products is one of the contributions of this research.

5.9 Chapter Summary

This chapter has demonstrated that the Gaze Cascade Theory for measuring consumers' preferences can be applied in a mobile setting, allowing participants to move freely and naturally in a simulated retail environment. This is supported by the results presented in section 5.4.3. This contribution means that it is possible to measure consumers' preference towards real products, as opposed to just simulated store images on a computer screen.

The priming hypothesis has not been supported by the eye-tracking data, as shown in the results in section 5.5.3. By qualitatively analysing the data using visualisations, such as heat maps and gaze plots, it is clear that the participants' eye-movements were largely top-down cognitively controlled. Whilst the participants have a high level of control over their eye movements, they are less likely to be influenced by subtle, subconscious primes. This also indicates that colour priming does not induce a cognitive response towards target stimuli within a preference based task.

As the participants' eye-movements have been established as highly cognitively controlled, this gives very little (if any) information about their emotional responses towards the products within the retail environment. Electroencephalogram (EEG) can be used to analyse consumer affective response. EEG measures brain waves, which are almost impossible for individuals to control consciously. By using EEG in conjunction with eye-tracking it should be possible to get a better picture of the participants' subconscious emotional responses, as it appears that eye-movements have been consciously controlled.

Chapter 6

EEG Methods and Results

6.1 Introduction

The electroencephalogram (EEG) has been used to investigate consumers' subconscious affective responses during the experiments. To analyse recorded EEG data, firstly the data need to be cropped, filtered and transformed from the time to the frequency domain.

This chapter begins with a thorough explanation of the data preparation required to clean the EEG data in section 6.2. This involves filtering the data to remove unwanted frequencies, cropping the data to the correct length to match the section of eye-tracking data recorded during the experiments, and extracting the alpha frequency band to be used in the emotional response algorithm later in this chapter.

A key contribution of this research is that the experimental design allows the participants to move freely within the retail environment, within browsing stages of the experiment. A novel methodology is proposed that uses the fixation times recorded by the eye-tracker to indicate which epochs of EEG data are relevant for statistical comparison. Section 6.3 and 6.4 highlight the challenges overcome to implement this methodology. In order for this method to work, the timings from the two different devices need to be highly accurately aligned; section 6.3 presents a thorough explanation of how this was achieved.

In a natural movement task a participant may be moving, or standing relatively still, at different times, causing different levels of movement disruption in the EEG signals. Focussing on the fixations from the eye-tracking means that highly time localised analysis can be conducted. Section 6.4 demonstrates how the correct fixation timings were selected, so that those which overlapped with motion artefacts could be removed.

Using Davidson's model of emotion, the EEG data are analysed to investigate the participants' affective (emotional) responses towards the chosen and not chosen dresses, and the primed and not primed dresses. Section 6.5 details the steps taken to apply the emotion algorithm to the data, and presents the results.

Full scripts and all EEG data are available at the following link: https://github.com/CASSON-LAB/Eleanor-PHD-EEG

6.2 EEG Data Preparation

6.2.1 Introduction

The first stage with any EEG analysis is to prepare the data; it is important that the data are as clean as possible, and as many noise artefacts are removed as possible. Filtering is a useful way to remove consistent unwanted noise at chosen frequencies. The EEG data that were recorded at the same time as the eye-tracking data are of interest to this research, so the EEG data were cropped to the point when the eye-tracking recording began, to ensure the same times were looked at. Section 6.2.2 describes the filters applied to the EEG data, and how the data were cropped. EEG data need to be transformed into the frequency domain to be interpreted, as difference levels of power within different frequency bands are indicative of different behaviours. This research requires the alpha power for analysis, in line with Davidson's model of emotion, so the alpha frequency band was extracted. Alternative frequency bands can be extracted simply by altering the parameters of the filter. The method for extracting the alpha power of the EEG data is outlined in section 6.2.3.

6.2.2 Filtering and Cropping

Filters are typically used to remove low-frequency drifts and high-frequency artefacts (Cohen 2014). This analysis used a high pass filter, low pass filter, and a bandstop (also known as a notch) filter were used. A high pass filter only retains data over a specified frequency, and in a similar manner a low pass filter only retains data below a specified frequency (Cohen 2014). The specified high pass frequency used in this analsis was 0.16 Hz, and the low pass frequency was 30 Hz. A bandstop filter will remove activity between two specified frequencies, in this analysis 52.5 Hz and 47.5 Hz were used to remove 50Hz mains noise.

The filters were applied to the data using transfer function coefficients of a first order Butterworth filter, using the MATLAB function `filtfilt`. The Butterworth filter is a commonly used filter that has a maximally flat frequency response within the passband, and does not cause much distortion of the signal's low frequency components (Roberts and Roberts 1978). The MATLAB `filtfilt` function is able to filter the data without causing any unwanted phase shift, because it filters the data first in the forward direction, then it filters it again in the reverse direction (Oppenheim 1999). It is especially important to use the `filtfilt` function for this EEG analysis, as precise timing and alignment between the two devices is imperative for the proposed methodology. Fixations are short (62 $\pm$ 235 ms in this experiment), therefore even a phase shift of 50ms could cause the incorrect segment of EEG data to be analysed.

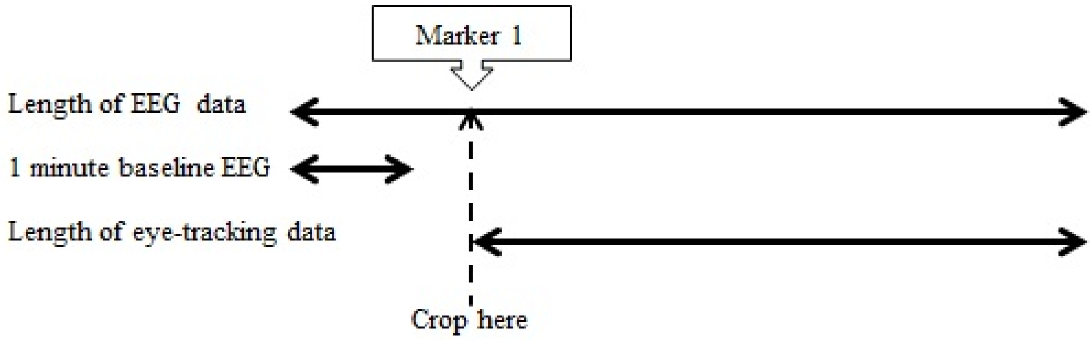

Figure 6.1: Illustration of where the EEG data were cropped in line with the start of the eye-tracking recording

During the experiments, the EEG device began recording before the eye-tracking device. The first section of the EEG recording is a minute of the participant sitting as still as possible, so their brain wave activity during this phase can be used as the baseline information. A Graphical User Interface (GUI) was used to operate an automatic hot keys script, that sent a marker to the EEG data at the exact same time as the eye-tracking recording was started. This is explained in more detail in section 4.5.5. The point at which the eye-tracker started recording is identified as marker 1. By identifying the marker 1 time in the EEG data, it was possible to crop the EEG data so that it starts at the same time as the Tobii recordings. This cropped version of the EEG data were used throughout the rest of the analysis.

6.2.3 Extracting Alpha

Although there are no precise boundaries that define frequency bands, they are most commonly grouped into delta between 2-4 Hz, theta between 4-8 Hz, alpha between 8-12 Hz, beta between 15-30 Hz, lower gamma between 30-80 Hz and upper gamma between 80-150 Hz (Cohen 2014).

A frequently used method for calculating alpha is to use the Fast Fourier Transform (FFT) method. The FFT method transforms EEG signals from the time domain to the frequency domain by decomposing the signal into its sinusoidal components (sine wave graphs of the different frequencies), breaking the time signals down into frequency subspectral components (Akin 2002). Typically with the Fast Fourier Transform the data window size would be ten times the time period of the lowest frequency to resolve. For 8 Hz alpha activity this would be 1.25s, which would mean that the highly time localized analysis required by the proposed methodology would not be possible.

An alternative method for extracting the alpha frequency is to extract the energy in the EEG trace at each time point using another first order Butterworth filter, using 8Hz and 12Hz as the cut-off points. This is implemented with the `filtfilt` command in Matlab, which, as mentioned previously, does not cause a temporal phase shift. The time fre-

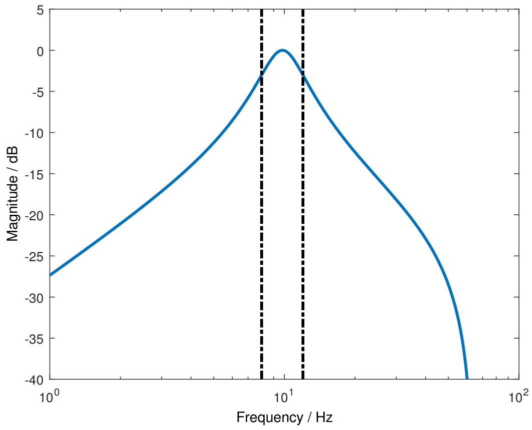

Figure 6.2.a: a

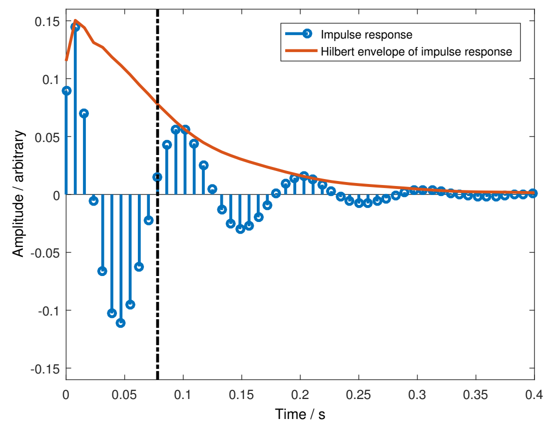

Figure 6.2.b: b

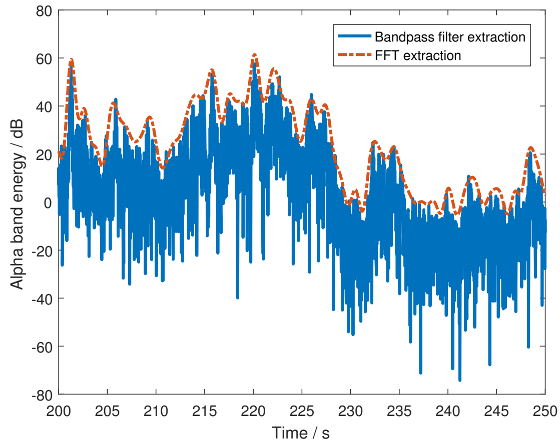

Figure 6.2.c: c

Figure 6.2: The time-frequency localisation used to extract alpha band activity during fixations as short at 100 ms. (a) Frequency localisation is concentrated within the non-flat pass-band. (b) Time localisation is concentrated within the full width half maximum of the impulse response. (c) Comparison of energy estimated from the bandpass filter and Fourier Transform method.

quency localisation provided in the alpha band is shown in Figure 6.2, where frequencies are constrained to be within the passband of the filter (8–12 Hz), while the time support is the duration of the impulse response, with a full-width half-maximum of 78 ms, showing that frequency information can be localized to within the 100 ms dwell time we consider. This comes at the cost of the non-flat passband seen in Figure 6.2.a for the extraction of frequency information.

Using the filter output the instantaneous EEG energy is then found in dB as

$$e_{dB} = 10 \log \left(\text{Filter output}^2 \right) \tag{6.1}$$

to give a sample-by-sample estimate which can be summed over any desired time span to find the total energy present in that span. Figure 6.2.c shows how the bandpass filter methods for alpha extraction compares to the FFT approach, using 1.25 s Hamming windows and a 50% overlap between the windows. The data shown in Figure 6.2.c are of the F3 EEG channel, although all channels demonstrated the same level of similarity to the FFT method. The Fourier Transform envelops the instantaneous band power extraction.

6.2.4 Summary

The data have been filtered using low pass, high pass and notch pass filters, and cropped in line with markers sent to the EEG data when the eye-tracking recording began. The alpha frequency band was extracted from the data using a second notch filter. The notch filter was used instead of FFT as it allows greater control of the temporal localisation of the data.

6.3 Device Synchronisation

6.3.1 Introduction

This research used the fixation times, recorded by the eye-tracker, as identifiers for which epochs of EEG data were of interest for analysis. This requires highly precise time synchronisation, especially as the fixations were short (62 $\pm$ 235 ms). However, unfortunately both devices were battery powered, and therefore susceptible to suffering from clock drift. Although they both report that they record at a fixed and constant sampling rate, the actual rate can be altered by the devices' temperature or battery voltage (Lasassmeh and Conrad 2010).

Fortunately both devices record gyroscope data which can be used to determine the level of drift between the signals throughout the recording. Despite the different locations of the gyroscopes, one at the front of the head and the other at the back, they both recorded very similar motion signals. Dynamic time warping was used to realign the motion signals based on the drift found between them. This realignment was also applied to the EEG extracted alpha, and the eye-tracking fixations times, so that the data from each device (EEG and eye-tracker) were highly accurately aligned.

6.3.2 Gyroscope Signal Pairing

Both the Tobii glasses 2 and the Emotiv EPOC EEG headset include a gyroscope that records the wearer's rotational head movement. The Tobii glasses 2 records movement in three directions, whilst the Emotiv EPOC headset only records movement in two directions. The gyroscope recordings from the different devices can be used to assess the misalignment between the two devices recordings, and correct for any differentiating drift over time.

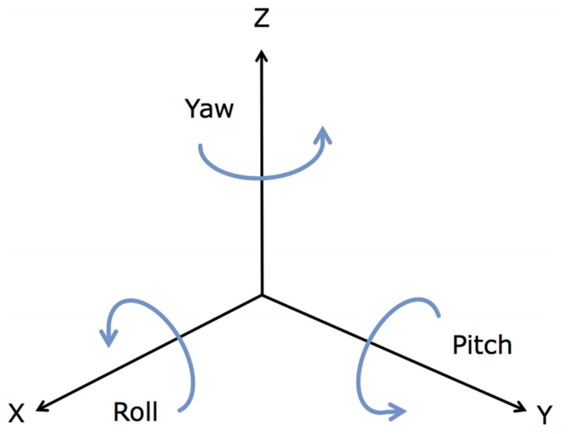

Figure 6.3: Typical angles that a gyroscope records (Ellis et al. 2014)

The Tobii gyroscope was positioned between the wearer's eyes at the front of the head, whereas the Emotiv gyroscope was positioned at the back of the wearer's head. Despite being positioned in different places on the wearer's head, the gyroscopes were well aligned in terms of rotational axis. If either of the gyroscopes was rotated by 45 degrees, then the axis of rotational movement would not have been the same, and the motion recordings may have been very different. Movement around the three axes X, Y, and Z, are roll, pitch and yaw (respectively).

6.3.3 Dynamic Time Warping

Once the most closely matching pair of gyroscope recordings had been identified, they first required a bulk shift. Maximum correlation was used between the two signals to bring them more closely time aligned, however they drift apart over time put them out of synchronisation at various points, as can be seen in Figure 6.4.

The drift that occurred between the two devices was corrected by applying Dynamic Time Warping to both of the gyroscope signals. MATLAB has a built in `dtw` function, which has been described by Paliwal et al. (1982). The `dtw` function provides indices which are used to apply a zero-order-hold to stretch both of the signals so that the key feature points within the signals are aligned. These indices can then be used to re-sample other data recorded during the experiment. The realigned signals can be seen together in Figure 6.5.

The EEG data, the EEG gyroscope data and the time base of the EEG device (as reported by the Emotiv device) were all realigned using the indices, as well as the fixation times on AOIs from the eye-tracking recording, the eye-tracker's gyroscope data and the time base of the eye-tracker (as reported by the Tobii device). The indices indicated where one of the signals needed to be stretched, and at these points the data would be repeated for the necessary length of the stretch. To demonstrate, if the time base reported by the Emotiv was originally [0 0.078125 0.015625 0.0234375 . . .] it might be changed to [0

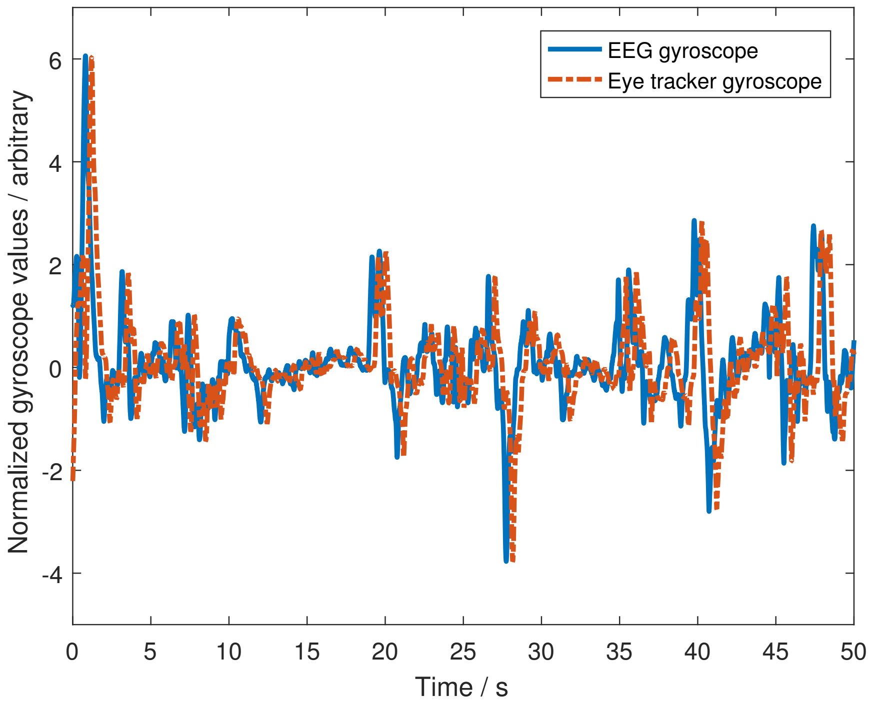

Figure 6.4: The gyroscope signals from the different devices begin in synchronisation but drift apart over time

0.078125 0.015625 0.015625 0.015625 0.0234375 . . .] after it has been stretched. In this case the 0.015625 is now repeated three times so that is is aligned with the Tobii time base. No information is removed from either of the traces, they are each extended (never cut or cropped) so that the different time points can match up.

The fixation times, which were provided in the Tobii time base, were looked up in the Emotiv time base once the time bases had been correctly aligned. Thus the fixation times could be accurately matched with the correct epoch of EEG data, based on the time warped Emotiv time base. Figure 6.6 shows the original eye-tracking fixation times (in yellow), and the fixations times after being corrected using the dtw indices (in red), over the EEG data.

6.3.4 Drift Between Devices

The average bulk shift required to bring the two gyroscope signals to near synchronisation was 0.6 second, with a standard deviation of 0.4 second. The bulk shift required for individual participants can be seen in table 6.1. After this bulk shift was applied, dynamic time warping was used to realign the signals where they had drifted apart throughout the recording. The average time warping correction that was needed to make the gyroscope signals match was 0.21 second, with a standard deviation of 0.12 second. This time warping corresponds to an average speed deviation from the time base provided by the devices of 53.66 milliseconds per minute of recording, with a standard deviation of

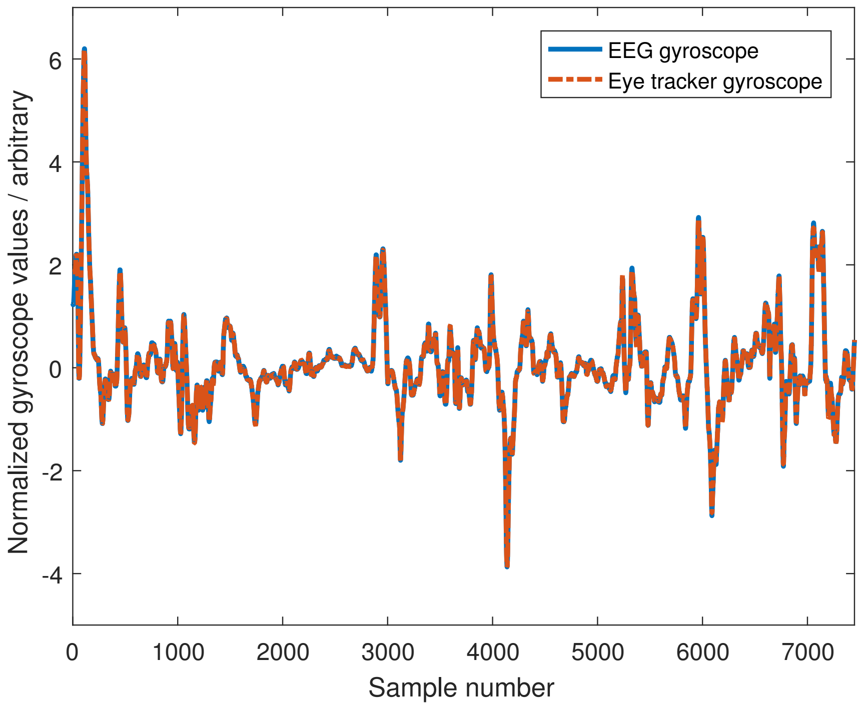

Figure 6.5: DTW has been used to realign the gyroscope signals from the two devices

22.3 milliseconds per minute of recording. The time warping correction, and the corresponding deviation from the original time base, for each participant can be seen in table 6.1. Due to the highly time localised nature of the analysis within this experiment, it is essential that the data recorded from the two devices are aligned precisely. From the level of shift and time warping that was required for these data, the highly time precise analysis would not have been possible without these dynamic adjustments of the effective sampling rate. If the bulk shift had been applied in isolation the data would have drifted further apart than the shortest fixation length, meaning that the incorrect epoch of EEG data would have been used for the analysis.

After applying the dynamic time warping to the gyroscope signals they became very highly correlated, with correlations between 0.992 and 0.009 (r^2 = 0.992 $\pm$ 0.009). Despite the different locations of the gyroscopes they both recorded very similar motion signals. The backward and forward motion of the two gyroscopes were very similar, despite the EEG gyroscope being positioned at the back of the head, and the eye-tracking gyroscope being positioned at the front. This demonstrates that in this direction of motion the head can be considered as a single moving entity, as the movements are so similar.

6.3.5 Summary

The novel methodology proposed in this thesis uses the fixation timings recorded and identified by the eye-tracking data to determine the correct epochs of EEG data to use for

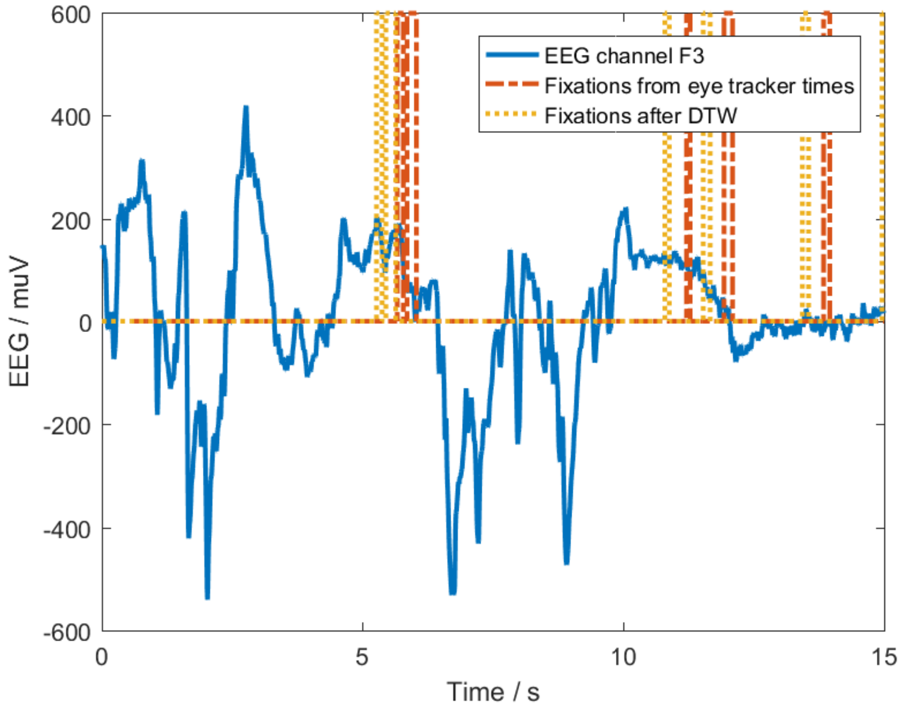

Figure 6.6: The fixation times recorded by the eye-tracker are corrected and repositioned using the `dtw` indices, shown here over the EEG data

statistical comparison. This requires near perfect temporal alignment of the signals. Due to both the EEG and eye-tracking devices being mobile, and therefore battery powered, the recordings were subject to clock drift. Realigning these signals was one of the key technical challenges and contributions of this research.

The devices both contain a gyroscope, which recorded the participants' head motion traces. These motion signals were able to be aligned offline using Dynamic Time Warping (DTW). The DTW provided indices which indicated the necessary stretch needed to be applied to either signal in order to realign them. These indices were subsequently applied to the other necessary signals to ensure everything matched up accurately.

The bulk delay between the devices ranged between 0.6 and 0.4 second for different recordings. The average amount of drift between the signals was 0.21$\pm$ 0.12s, which averages out as a deviation from real time of 53.6$\pm$ 22.3 milliseconds per minute of recording. The application of DTW brought the signals to almost perfect synchronisation, with correlations between the gyroscope signals of $r^2 = 0.992 \pm 0.009$.

Table 6.1: Amount of realignment required between the two gyroscope signals

Participant	Bulk delay (seconds)	Time warping required (seconds)	Deviation from time base in miliseconds per minute
1	0.07	0.24	85.36
2	0.52	0.15	34.04
3	0.10	0.24	94.24
4	0.21	0.20	59.19
5	0.64	0.20	45.89
6	0.72	0.23	36.15
7	1.06	0.15	32.74
8	0.00	0.15	55.46
9	0.41	0.12	50.26
10	0.92	0.16	45.14
11	0.65	0.16	38.85
12	0.54	0.11	47.71
13	0.33	0.20	57.95
14	0.72	0.16	50.35
15	0.70	0.37	72.31
16	0.48	0.23	49.54
17	0.31	0.73	132.47
18	0.32	0.22	36.56
19	0.68	0.21	41.60
20	0.54	0.15	46.81
21	2.27	0.22	35.24
22	0.84	0.20	72.43
23	0.53	0.20	40.82
24	0.64	0.14	46.96
25	0.99	0.18	38.06
26	0.34	0.17	47.70
Mean	0.6	0.21	53.61
Standard Deviation	0.4	0.12	22.34

6.4 Selecting Relevant EEG Epochs

6.4.1 Introduction

Once the time domains of the two devices have been accurately aligned, the epochs of EEG data which correspond to the eye-tracking fixations, and are motion artefact free, need to be identified.

Section 6.4.2 details how the fixation timings provided by the Tobii Pro Analyzer software were exported, imported, and stored in MATLAB. Following this section 6.4.3 describes the methods for detecting motion artefacts within the EEG data. Motion artefacts contaminate the data, and can invalidate the results. Section 6.4.4 presents the number of fixations that had to be removed due to motion artefacts, and section 6.4.5 presents the fixations which were removed due to being less than 0.1 second long.

6.4.2 Fixation Timings

In this experiment the fixations, recorded by the eye-tracker, were used to indicate which sections of EEG were of interest for analysis. The fixations were grouped depending on which participant they belonged to and which Area Of Interest (AOI) they fall upon. The AOIs have been drawn to correspond with the different stimuli within the retail environment, including one AOI per dress that the participants could choose from. For the different comparisons the AOI numbers have been grouped, for each participant, based on whether they correlate to a chosen dress, a not chosen dress, a prime coloured dress or a not prime coloured dress. These are the same fixation groupings as were used in chapter 5 for the eye-tracking analysis.

The Tobii Pro Analyzer software outputs the fixation data in an Excel document, which were separated into participant individual files. Within each document, there is a large table of 0 or 1 values. The top of each column identifies the AOI that the fixation could have been on, and the row information indicates the potential time stamp of that fixation. If a fixation did not occur on a particular AOI at the specified time stamp, there will be a 0 value in the correlating column. Alternatively, if a fixation did occur a 1 value will be present.

To store the fixation times within MATLAB, the 1 values were extracted, and stored with the participant number, the AOI, and the start and stop time stamp for every single fixation. The time stamp is provided by Tobii in milliseconds, this was converted to seconds to ensure a consistent time measure throughout the analysis. Once the start and stop times of all fixations had been identified, they were time warped using the traces calculated by applying dynamic time warping to the gyroscope signals. This ensures that the fixation timestamps accurately match up with the participants' brain activity that occurred at the exact same time.

6.4.3 Motion Detection

When a participant is mobile during an experiment, there will be an increase in the number of motion artefacts in the data. Participants' movements will create a much larger signal than brain activity will, therefore during a period of movement it is possible for the brain signal to be completely lost amongst the interference signals, or ”noise”. It is essential to identify these motion artefacts within the EEG data, so that the data analysed are purely brain activity, not corrupted or distorted by excessive movement.

Motion times within the data were detected by applying a threshold to the gyroscope signals from the Tobii eye-tracking device, and examining the EEG signal for any existing motion artefacts. Motion artefacts were detected in the EEG data by cross correlating the motion detection from both of these methods, providing a higher level of confidence in the results. At different levels of gyroscope thresholding, the level of agreement between the two methods differs. For example, when the gyroscope threshold is very low it marks the whole signal as motion. This causes a low level of agreement with the EEG motion detection, which does not mark all of the signal as motion. Increasing the gyroscope threshold increases the agreement between the gyroscope and EEG motion detection, because the gryoscope motion detection becomes more realistic. The agreement plateaus as the gyroscope threshold becomes high, as for most of the recording the EEG and gyroscope agree that there is no motion present. Increasing the threshold of the EEG motion detection further increases the agreement, as both methods presume there are no motion artefacts.

To determine which parts of the data contain motion artefacts a trade off is required between setting the gyroscope threshold too low or too high. Setting the threshold too low runs the risk of classifying everything as a motion artefact. Whereas setting the threshold too high could mean that genuine motion artefacts go undetected. The red lines in Figures 6.7.a, 6.7.b, and 6.7.c indicate the point 10% lower than the maximum agreement between the gyroscope and EEG detection, which was a good trade off balance.

The gyroscope records rotational motion around three axes; X, Y, and Z. The rotation on the three axes are also known as roll, yaw and pitch (see section 6.3.2, for Figure 6.3, which illustrates this). Figure 6.8 illustrates the directions that these axes correlate to on the human head. The X direction (roll) is the movement of rolling one's head from side to side. The Y direction is like shaking one's head to say no, and the Z direction is like nodding to say yes. For each participant, for each different gyroscope direction, the ideal gyroscope threshold point differs. The different gyroscope thresholds can be seen in table 6.2. Applying a Mann Whitney U-test to the ideal gyroscope thresholds for each of the three gyroscope directions identified that the thresholds required in the X (roll) direction were significantly lower than in the Y (yaw) direction ($p < 0.01$). Furthermore, the thresholds in the Z (pitch) direction were significantly lower than the x direction ($p < 0.01$). This indicates that EEG data are most sensitive to the nodding motion of the wearer's head.

6.4.4 Removal of Fixations That Include Artefacts

Once the fixation times and the motion times had been identified, and correctly time warped to ensure the correct time was selected, it was possible to remove the fixations which were contaminated by motion artefacts. Table 6.3 shows the percentage of the number of fixations and the percentage of the duration of the fixations that had to be removed due to motion artefacts.

When looking at the fixations on the chosen and the not chosen dresses, the highest proportion of fixations which had to be discarded for one participant was 45%, which corre-

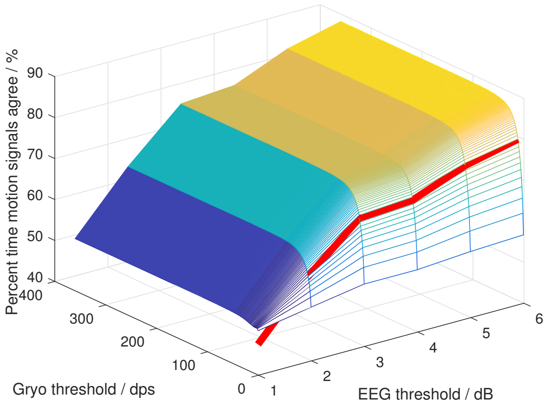

Figure 6.7.a: gyroscope x axis

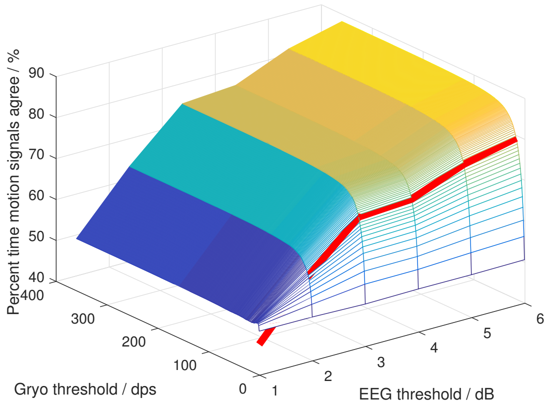

Figure 6.7.b: gyroscope y axis

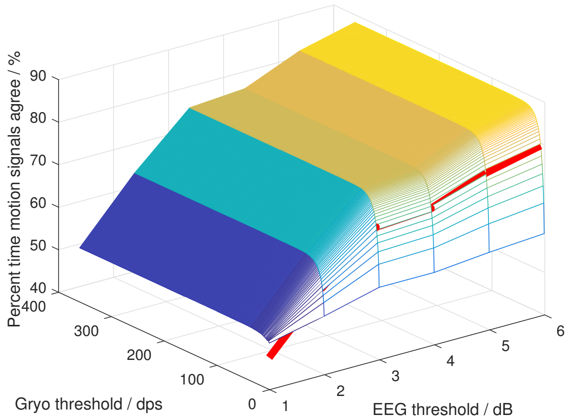

Figure 6.7.c: gyroscope z axis

Figure 6.7: Agreement between when the gyroscope signals indicate motion is present and when an artefact is present in the EEG trace using different thresholds for detection, for each of the three directional axes that the gyroscope records motion in. The red line indicates the gyroscope threshold to reach within 10% of the maximum agreement.

sponded to only 21% of the duration of the fixations. This was for the first participant, as can be seen in table 6.3. The average number of fixations when grouped into chosen and not chosen is 17% of the fixations, corresponding to only 8% of the duration of the total fixation time.

When comparing the fixations on the prime coloured dresses and the non prime coloured dresses, the highest amount of fixations that had to be discarded was 35%, which only corresponded to 21% of the total dwell time. This was for the ninth participant, as can be seen in table 6.3. The average amount of fixations removed between the prime and non prime fixations was 16%, and the amount of dwell time was only 8%.

Babiloni et al. (2013) conducted an experiment using EEG and eye-tracking to measure participants' responses to 20 paintings in an art gallery. Their method for minimising the amount of movement noise in the EEG data was to instruct the participants to stand still looking at each painting for exactly one minute. Whilst this may have been appropriate for an experiment involving art, it would not be appropriate in a consumer behaviour

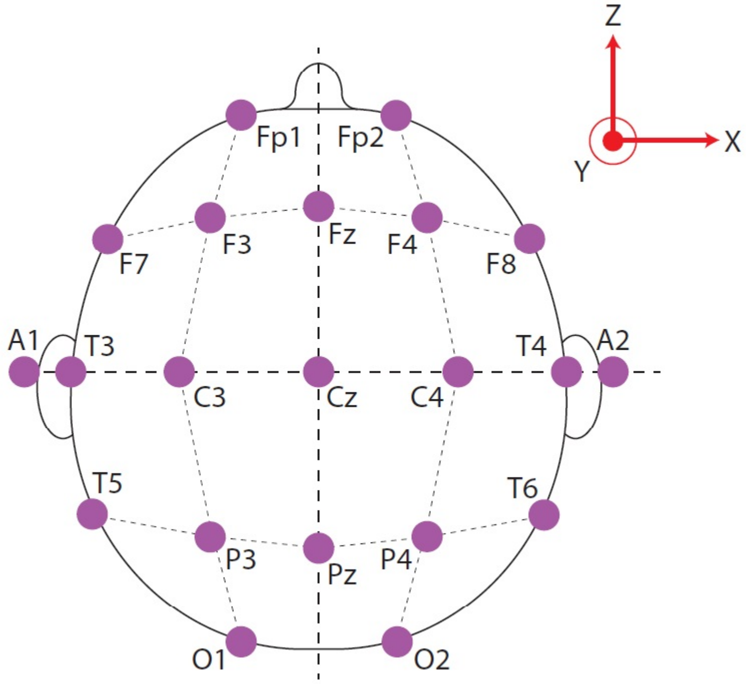

Figure 6.8: The 10-20 system next to the gyroscope motion axis for directional reference

study to dictate to the participants exactly how long they must look at each product. This would restrict and alter the participants' behaviour within the experiment, limiting the natural effect of their behaviour.

The EEG data from the current study is contaminated with large amounts of motion artefacts, due to allowing participants to move freely around the room and lifting dresses as they pleased. However, there are also many moments in which the participants are naturally stationary, or at least moving smoothly and slowly. This use of eye-tracking fixations as time of interest indicators, with the combined used of motion detection has allowed clean, motion free, segments of EEG data to be identified. This is a methodological contribution of this research.

6.4.5 Remove Short Fixations

To apply the emotional response algorithm the alpha power was identified for each of the motion artefact free EEG epochs that corresponded to eye-movement fixations. The alpha power for all channels of EEG data throughout the whole experiment have been extracted earlier in this chapter. Fixations which are less than 0.1 second are removed. The percentage of fixations that were kept because they are greater than 0.1 second can be seen in table 6.4. On average, approximately 70% of the fixations on the dresses were longer than 0.1 seconds, so were suitable to be kept for the statistical comparison analysis.

Table 6.2: Gyroscope thresholds that correspond to EEG motion artefact detection for each participant. Value in degrees per second (dps)

Participant	x	y	z
1	06	09	03
2	18	15	07
3	07	10	05
4	08	12	05
5	13	23	09
6	05	08	05
7	12	20	08
8	09	10	06
9	13	28	11
10	12	16	05
11	11	21	07
12	17	22	13
13	15	16	07
14	05	10	04
15	07	14	04
16	17	19	12
17	11	12	07
18	08	17	04
19	12	17	08
20	11	11	07
21	11	16	10
22	15	21	13
23	13	14	06
24	09	16	06
25	09	16	07
26	25	23	12
Mean	11	15	07
Standard Deviation	05	05	03

6.4.6 Summary

For this research the fixation times, provided by the eye-tracker, were used to identify the correct epochs of EEG data to use for statistical analysis. The fixation times were extracted in MATLAB from an Excel document provided by the *Tobii Analyzer Pro* software. The fixations were grouped according to the participant they belong to and the AOI that they fall on, along with the beginning and end times. These fixation times were time warped by the indices provided by the dynamic time warping, to ensure they accurately matched up with the EEG recorded data.

Once the correct fixation times were aligned to identify the relevant epochs of EEG data, the epochs contaminated with motion artefacts were removed. Motion artefacts were identified using a combination of EEG motion artefact detection and gyroscope motion thresholding. The gyroscope threshold required was set at 10% below the maximum agreement between the EEG motion detection and the gyroscope motion detection. The threshold for the gyroscope in the z direction (nodding motion) was identified as requiring the lowest threshold, showing that EEG data are most sensitive to movement in this direction.

	% of fixations				% of duration of fixations (seconds)			
Participant	Chosen	Not Chosen	Prime Coloured	Not Prime Coloured	Chosen	Not Chosen	Prime Coloured	Not Prime Coloured
1	45.16	32.33	33.33	33.91	21.47	18.40	20.83	18.42
2	18.10	16.61	13.04	17.50	08.97	06.64	04.93	07.62
3	11.48	23.53	22.73	20.10	05.99	09.69	13.00	08.20
4	30.49	21.58	31.34	21.88	15.76	9.27	10.57	11.09
5	26.51	15.55	08.47	19.32	16.25	07.43	03.04	09.73
6	05.00	04.09	00.00	04.92	03.94	01.77	00.00	02.24
7	13.64	8.51	02.78	11.62	05.56	04.19	01.85	05.19
8	13.79	11.11	09.52	12.68	11.08	06.28	07.45	07.51
9	20.83	09.49	35.48	09.55	07.78	03.81	20.74	03.31
10	09.52	23.47	30.00	20.18	10.43	08.39	11.02	08.47
11	13.89	18.11	16.10	17.77	06.07	06.75	06.77	06.51
12	20.00	07.50	13.00	07.00	09.66	02.85	05.05	03.04
13	21.05	12.10	12.68	13.33	20.00	07.10	08.77	08.09
14	32.08	14.50	19.74	15.29	17.85	06.46	09.94	07.28
15	36.11	25.21	25.08	30.25	10.78	06.93	07.27	08.06
16	12.37	16.04	20.62	09.36	03.86	07.83	09.47	04.09
17	10.29	14.56	14.67	12.58	01.97	05.05	04.18	03.63
18	16.42	13.98	12.04	15.73	10.24	06.69	05.23	08.56
19	24.21	14.14	06.58	21.43	10.03	06.96	03.66	09.56
20	11.59	17.71	10.53	19.91	03.98	08.19	05.05	08.46
21	12.03	14.65	11.41	14.81	05.14	05.50	04.74	05.61
22	05.71	19.16	29.82	11.03	03.07	12.59	17.27	08.77
23	12.61	13.95	15.11	12.97	07.29	05.97	06.25	06.30
24	27.12	17.87	18.07	19.85	11.80	08.10	08.06	08.89
25	22.73	16.67	10.67	21.34	12.32	08.09	06.94	10.42
26	17.46	09.57	03.28	13.36	06.05	03.53	00.29	05.15
Mean	18.85	15.85	16.39	16.45	09.51	07.10	07.78	07.47
SD	09.64	06.09	09.74	06.55	05.28	03.24	05.40	03.26

Table 6.3: Percentage of fixations and percentage of the duration of total fixation time, which had to be removed due to motion artefacts

The average percentage of fixations removed was 15.8 – 18.9%, with an average percentage duration of 7.1 – 9.5% when looking at the fixations relating to the chosen and not chosen dress AOIs. When looking at the fixations focused on the prime or non prime related AOIs, an average of 16.4 – 16.5% of fixations were removed, corresponding to 7.8 – 7.5% of the duration of fixation time.

6.5 Participants' Emotional Responses

6.5.1 Introduction

This section begins by reintroducing Davidson's model of emotion in section 6.5.2. The emotional response algorithm is then applied to the identified relevant epochs of EEG data, within the recorded baseline data in section 6.5.3, and to the epochs of EEG data that correspond to the fixation times during the experiment.

The results are presented in line with the two research hypotheses, the preference and priming hypotheses, and have been analysed based on the EEG data. Therefore the first

Participant	Chosen	Not Chosen	Prime	Not Prime
1	54.8	60.3	60.6	59.6
2	83.6	84.8	84.8	84.4
3	83.6	83.5	86.4	83.3
4	79.3	82.2	73.1	83.6
5	72.3	85.4	66.1	85.5
6	58.3	64.3	70.7	62.7
7	58.3	63.8	69.4	60.6
8	41.4	58.7	61.9	50.7
9	73.6	67.7	58.1	71.4
10	57.1	48.0	50.0	49.5
11	68.1	82.3	83.9	76.1
12	75.0	76.3	75.0	77.0
13	26.3	26.1	38.0	18.1
14	60.4	67.3	67.8	64.7
15	87.0	90.4	90.5	89.0
16	76.3	76.9	74.7	78.9
17	83.8	83.5	82.7	84.1
18	72.4	76.0	75.0	75.4
19	67.4	66.5	71.1	65.2
20	82.6	73.8	81.6	72.6
21	74.7	72.6	73.8	72.9
22	51.4	58.1	54.4	57.9
23	74.8	69.2	80.6	66.1
24	61.0	74.6	77.1	70.8
25	52.7	60.8	61.3	56.9
26	68.3	66.5	57.4	69.4
Mean	67.1	70.0	70.2	68.7
Standard Deviation	14.6	13.7	12.6	15.0

Table 6.4: Percentage of fixations >0.1seconds, and therefore suitable for use in analysis

hypothesis being tested in this chapter is H1b, that there will be a statistically significant difference in the participants' emotional response algorithm output when looking at the products that they chose, compared with the products that they did not choose. The second hypothesis tested in this chapter is H2b, which expects to find a statistically significant difference in the emotional response algorithm output when looking at the prime matching dresses, compared to the not prime matching dresses. The results of these statistical comparisons are presented in section 6.5.4, and discussed in section 6.5.5.

6.5.2 Emotional Response Algorithm

The emotional response algorithm used in this research is based on Davidson's model of emotion, (Davidson et al. 1979) (See section 3.4.6 for more details), in which the alpha in the left prefrontal cortex is subtracted from the alpha in the right prefrontal cortex. The most commonly used electrode locations for this asymmetry index are F3 and F4, and these locations were used in this research. The equation used was:

$$10 \log_{10} \sqrt{(RightAlpha)} - 10 \log_{10} \sqrt{(LeftAlpha)}$$

This algorithm was applied to all of the fixations made by all of the participants on all of the AOIs of the dresses. It was applied to all of the channels of the EEG data so that various channels could be analysed. The algorithm is essentially an asymmetry index, indicating the difference in activity between the different halves of the brain. Due to the inverse nature of alpha power and cortical activity, a positive value indicates an increase in activity in the left hemisphere, and a negative value is indicative of increased activity in the right hemisphere. According to Davidson's model of emotion, increased activity in the left hemisphere is indicative of a positive approach response, therefore it is hypothesised that there will be a more positive asymmetry index score when the participants are looking at their chosen dresses, compared to the non chosen dresses, and the prime matching dresses compared to the non prime matching dresses.

6.5.3 Baseline Value

During the first 60 seconds of the EEG recording the participants were asked to sit still whilst facing a plain blank wall. This was to record baseline data so that the participants' data can be normalised, based on their resting brain activity. This research is interested in the participants' state emotional responses, their *change* in emotions in response to the presented stimuli. Removing the individual baseline values from each participant's data normalises the results so that they can be grouped together for statistical comparisons. The recorded baseline data were split into 100 ms epochs, and the emotional response algorithm was applied to each epoch. Then the algorithm output for each of the 100ms epoch was averaged, to give one baseline output value per participant. The participants' baseline asymmetry index values ranged from 5.33 to 10.69 (mean, 0.57, SD 2.90); all values can be seen in Figure 6.9. The large difference between the different participants' baseline asymmetry index values highlights the importance of subtracting the baseline value from the participant's final emotional response value.

6.5.4 Results

The participants' affective responses during each fixation have been calculated, using the emotional response algorithm. Those fixations containing motion artefacts or which are less than 0.1 second long have been removed. The remaining fixations are grouped and compared to determine the difference in the participants' affective (emotional) responses towards the chosen and not chosen dresses, and the prime matching and not prime matching dresses. Reporting EEG results collectively is the most common method of reporting results when analysing changes in EEG activity (Smith et al. 2017; Coan et al. 2001; Killeen and Teti 2012; Davidson et al. 1990; Harmon-Jones and Sigelman 2001; Stylios and Chen 2016).

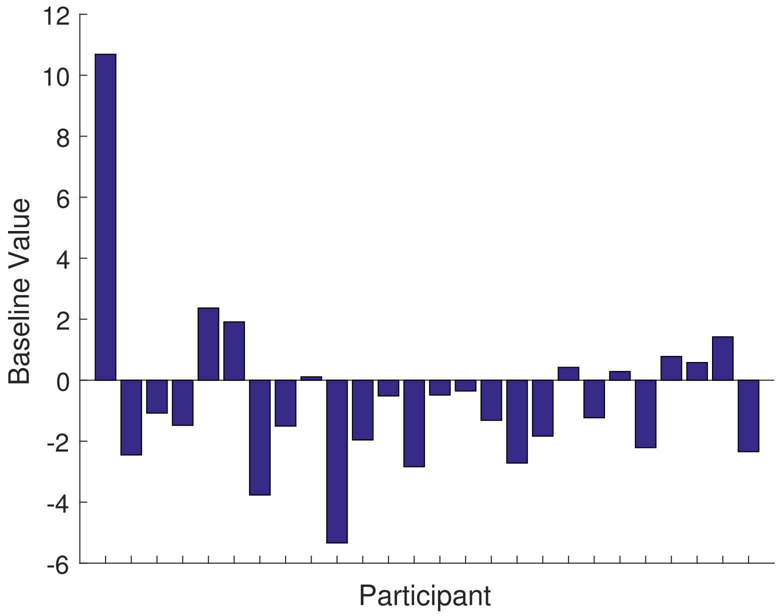

Figure 6.9: Baseline asymmetry index value for each participant

Frequency Distribution

To determine whether to use a parametric or non-parametric test for statistical comparison, the four groups of data (chosen, not chosen, prime and not prime) have been tested for normality using the Shapiro Wilks and Kolomgorov Smirnov tests. The results can be seen in table 6.5. All groups of data demonstrate non-normal distribution, therefore the Mann Whitney U-test will be used for the statistical comparison.

Table 6.5: Frequency distribution of the four groups of EEG data

	Chosen	Not Chosen	Prime	Not Prime
Shapiro-Wilks	p = 0.00	p = 0.00	p = 0.00	p = 0.00
Kolomgorov-Smirnov	p < 0.00	p < 0.00	p < 0.00	p < 0.00

Chosen Versus Not Chosen Results

To statistically compare the emotional responses during fixations made by each individual participant on the chosen and not chosen dresses a one-tailed Mann Whitney U-test was used. This tested for a statistically significant difference (p <0.05) in the emotion algorithm outputs for the epochs of data that correlate to fixations on chosen or not chosen dresses for each participant. The one-tailed direction is calculated so that the median of the responses towards chosen dresses is higher than responses towards non-chosen dresses, demonstrating a more positive response towards the chosen dresses.

The results showed that there was a statistically significant difference between the emotional responses of the combined participants towards the chosen dresses and the non chosen dresses (p = 0.0058). In all cases the mean values of the chosen dresses were significantly higher than the non chosen, confirming a more positive approach response towards the chosen dresses.

Prime Versus Not Prime Results

The participants' emotional responses when looking at either a prime coloured dress or a not prime coloured dress were also statistically compared using a one-tailed Mann Whitney U-test. It is hypothesised that the priming effect, induced by the coloured visual stimuli within the simulated retail environment, will cause the participants to have a positive emotional response towards the prime coloured dresses, compared to their response towards the not prime coloured dresses. This is demonstrated by a higher median of emotional response algorithm outputs corresponding to the fixations on the prime coloured dresses, than on non-prime coloured dresses.

The combined participants emotional responses were significantly higher ($p = 0.0167$) when participants were looking at the prime coloured dresses than when they were looking at the not prime coloured dresses.

6.5.5 Discussion

Many academics have used EEG to measure emotional responses (Davidson and Fox 1982; Allen et al. 2001; Kop et al. 2011; Waldstein et al. 2000; Ohme et al. 2009; Goodman et al. 2013). Specifically, Davidson's model of emotion is used to indicate approach or withdrawal tendencies within a participant's responses (Davidson et al. 1979). Based on the previous literature, the first hypothesis of this research is that there will be a measurable difference in responses towards chosen and not chosen dresses. A sub-hypothesis of this preference hypothesis is that the difference can be measured using EEG. Therefore the first hypothesis that has been tested in this chapter is hypothesis H1b, which is that there will be a statistically significant ($p<0.05$) difference between the asymmetry index scores when the participants were looking at the dresses they chose and the dresses that they did not choose. The results found a statistically significant difference between the chosen and not chosen dresses, with a p value of 0.0058.

The affective primacy hypothesis states that individuals' emotional responses towards target stimuli can be influenced by minimal stimulus input (Zajonc 1980; Murphy and Zajonc 1993). That is that even a small level of exposure to a priming stimulus can have an influence on the emotion response towards a target stimulus. Additionally, even priming influences that individuals are not consciously aware of can impact the emotional responses (Murphy and Zajonc 1993). This theory informed the second sub-hypothesis that has been tested in this chapter, hypothesis H2b. This hypothesis states that the colour priming within the simulated retail environment will cause a positive emotional response towards the matching coloured dresses. Specifically, there will be a statistically significant difference between the emotional responses towards the prime coloured dresses and the not prime coloured dresses.

In the experiment the priming stimulus was the colour of the visual merchandising within the store, including the mannequins' clothing and the colour of the models' dresses in the images within the room. The target stimuli were the dresses within the retail environment, specifically the dresses which matched the colour of the priming stimuli. The results showed a statistically significant difference in emotional response when looking at the prime coloured dresses and the not prime coloured dresses ($p = 0.0167$).

The results presented in this chapter provide two contributions to this research. Firstly, the significant results in support of hypothesis H1b validate the proposed methodology. The novel method presented in this thesis uses multimodal sensing of EEG, eye-tracking and motion to conduct highly time-localised analysis of participants' brain activity in a free-moving shopping experiment. This research has applied theories and methods that are are most commonly constrained to laboratory based studies, with participants reacting to stimuli on a computer screen, to a more realistic retail environment, allowing the participants to act more naturally, as they would in a real store. This technical contribution allows researchers to conduct studies with more ecological validity.

Secondly, the significant results in support of hypothesis H2b signify that colour priming can induce an emotional response towards target stimuli, and that this response can be physiologically measured using EEG. These results show that marketers and shop designers can use colour in the retail environment to influence consumers' responses towards particular products, which may lead to an increase in sales of said products. Being able to measure participants' emotional responses to affective priming can allow researchers to test priming effects with objective quantifiable methods, instead of relying on the subjective verbal responses of the participants. This is the first experiment to demonstrate these findings in a fashion retail environment, whilst allowing participants to move freely during the experiment.

6.5.6 Summary

The participants' emotional responses towards stimuli within the retail environment have been analysed in accordance with Davidson's model of emotion. The emotional response algorithm provided an asymmetry score between the brain data recorded at the F3 and F4 electrode locations. These baseline scores were subtracted from each participant's asymmetry scores, to normalise the data for comparison. Statistical comparisons between the groups of data were calculated using a Mann Whitney U-test.

Hypotheses H1b and H2b have been tested. H1b hypothesises that the participants will have a statistically significantly higher asymmetry score when looking at the item they chose than when looking at the items they did not choose. This hypothesis is strongly supported by the data (p = 0.0058), and therefore validates the novel method that has been proposed in this thesis. H2b hypothesises that the participants will be influenced by the priming stimuli and have a higher emotional asymmetry score when looking at the prime target stimuli than when looking at the non prime target stimuli. This hypothesis was also strongly supported by the data (p = 0.0167), showing that colour priming can induce an emotional response, and this response is measurable with EEG data.

6.6 Chapter Summary

Multiple steps have been taken to analyse the EEG data. Initially the data have been preprocessed, filtered, and transformed from the time into the frequency domain. Both recording devices were mobile, and battery powered, and therefore susceptible to clock drift throughout recording. The gyroscope data from both devices were used to ensure that the timing of all events throughout the experiments were realigned. Firstly the signals were bulk shifted, to almost synchronisation and then DTW was applied to correct for the drift between the devices over time.

Once the signals from the different machines are aligned, it is also important to identify and remove motion artefacts from the EEG data. The motion artefacts were detected with confidence by correlating the detected motion artefacts in the EEG data with detected levels of movement in the eye-tracker's gyroscope data. Once the uncorrupted epochs of EEG data were identified these were grouped together dependent on whether they were at the same time as fixations on the participants' chosen dresses, the dresses they did not choose, dresses that match the prime colour or dresses that don't match the prime colour. Within these grouped fixations, the alpha asymmetry was calculated, and statistical comparisons were applied.

There were two key hypotheses tested in this chapter, both of which were supported by statistically significant results. The results clearly supported the preference hypothesis: that EEG data can be used to measure participants' choice preferences. The results also supported the priming hypothesis: that EEG data can be used to measure participants' responses to colour priming.

These findings provide two key contributions to this area of research. Firstly, they demonstrate that it is possible to obtain significant results using mobile equipment in a simulated retail environment, thus increasing the ecological validity of the experimental process. Secondly, when contrasted with the negative findings of the eye-tracking analysis (see section 5.4), the positive EEG findings in response to colour priming suggest that this technique can be used to measure subtle emotional responses, even in a controlled experimental setting.

Chapter 7

Conclusions

7.1 Introduction

This research has investigated consumers' physiological responses in a retail environment. Specifically, the participants' eye-movements and brain activity have been measured. Responses towards their preferred garments have been compared with the responses towards the other garments, and the influence of the colour priming stimuli on the consumers responses towards matching coloured products has also been explored.

A novel method for conducting highly time localised analysis of EEG data during a free movement task, by using eye-tracking fixation data, has been introduced in this thesis. Additionally, another method to ensure the important synchronisation of the two mobile devices has also been introduced. This involved aligning the gyroscope data from each of the different devices by applying dynamic time warping to the gyroscope signals, and then stretching the time stamps for both the EEG and eye-tracking data accordingly. This made it possible to ensure almost perfect synchronisation between the timings of the two devices, meaning that the correct epochs of EEG data can be analysed.

Chapter 2 highlighted the way consumers make decisions, by reviewing literature regarding consumer consciousness, the influence of priming, and consumers' emotional responses. It is widely acknowledged that consumers' unconscious responses and processes have an impact on the purchase decisions that they make. The literature is clear that priming effects have an influence on these decisions. Within consumers' subconscious processing emotions can play a huge role. Therefore being able to measure consumers' subconscious and emotional responses when making purchase decisions can provide clear unbiased insight into consumer behaviour. However, this has never previously been applied to colour priming in fashion. This research has endeavoured to examine these responses.

To allow this chapter 3 identified a theoretical background to enable investigation into the consumers' subconscious emotional responses, by reviewing existing literature using biometric measurements to inspect and categorise consumer responses. Theories accompanying eye-tracking and EEG technologies were reviewed, to determine the appropriate methods to use for data collection and data analysis. A review of existing consumer studies was presented, and gaps in the literature were identified such as a lack of studies focussing on the influence of visual priming. There was also a lack of studies based in realistic environments, allowing participants to engage in a natural shopping task. This inspired the use of a realistic retail environment for the experimental setting for this research. It became apparent that it is important to apply and test the existing eye-tracking and EEG consumer response theories in a more authentic environment, representative of a real shopping situation.

In Chapter 4 the overarching theoretical framework for this research was introduced, Mehrabian and Russell (1974)'s Stimulus-Organism-Response (S-O-R) framework, which is a commonly used context for studying the influence of the environment on human behaviour. A key novelty of this research's use of the S-O-R framework was the focus on measuring the participants' internal *Organism* processes, by using biometric measures. As opposed to the common focus on consumers' *Responses*, which are traditionally investigated using self reported measures such as questionnaires and surveys. Following the theoretical framework, chapter four outlined the equipment and data collection methods that would be applied in this research.

Chapters 5 and 6 explored and analysed the data, presented the results and provided a discussion of each of the findings. In these two chapters the answers to the hypotheses were explored, and discussed.

Hypothesis 1 ***Preference Hypothesis.*** *There will be a measurable difference in the participants' physiological responses towards the products that they choose and the products that they do not choose.*

The first hypothesis (H1) is based on existing literature using eye-tracking and EEG to monitor consumer responses. Data supporting this hypothesis validates the methods and algorithms for analysis that have been used in this research. The hypothesis was measured in two ways; by a difference in gaze bias based on the eye-tracking data (H1a), and a difference in pre-frontal cortical activity based on the EEG data (H1b). The former being indicative of the participants' cognitive responses, the latter being indicative of affective (emotional) responses.

In both the eye-tracking data and the EEG data there was a statistically significant difference between the dresses that the participants chose and the dresses that they did not choose. Therefore, the data support the first hypothesis (H1), as both sub hypotheses (H1a and H1b) are also supported. This provides validity of this method, and determines that eye-tracking and EEG in a mobile environment are reliable tools for measuring participants' increased preference towards particular stimuli. Where previous consumer behaviour studies applied analysis theories in a laboratory environment, this study has applied them in a simulated real-life environment. The positive results for the first hypothesis legitimises the method as a measure of consumers' internal processes caused by the influence of priming effects. These methods can be applied to various consumer behaviour experiments, allowing researchers to examine consumer subconscious responses in a more ecologically valid environment.

Hypothesis 2 ***Priming Hypothesis.*** *There will be a measurable difference in the participants' physiological responses towards products that were prime coloured and those that were not prime coloured.*

The second hypothesis (H2) is that the priming stimuli will influence the participants' preferences towards prime matching coloured products, which will also be measurable using eye-tracking (H2a) and EEG (H2b). This hypothesis is based on literature regarding the non-conscious nature of consumers' purchase decisions and details of the priming phenomenon, which can influence an individual's behaviour even if they are unaware of the prime. This second hypothesis is dependent on the findings of the first hypothesis. In order to measure the consumers' physiological responses towards primed target stimuli, it is essential for the methods to be validated by the first hypothesis.

With the second hypothesis, the EEG data exhibited a statistically significant difference between the prime matching and non-prime matching coloured stimuli. However, the eye-tracking results were not significant. This suggests that EEG is better equipped at analysing subconscious responses which the participants have no control over, whilst eye-tracking, whilst indicative of subconscious processes, is still largely controlled by the participant in a conscious manner. Eye-tracking has been found to demonstrate preference in previous studies (Shimojo et al. 2003), however these are often computer or laboratory based short studies. While eye-tracking has been used extensively in consumer behaviour research, this new result suggests that additional findings and insights into behaviour may be possible by using both EEG and eye-tracking in future studies by others. It is possible the initial subconscious behaviour of eye-movements has been diluted by the length of the current experiment. The participants' eye-movements were not quick initial reactions to a scene, or analysed only in the final moments before a decision. They were considered over the full period of the experiment, partially diluting the Gaze Cascade Effect. Gidlöf et al. (2013) noted that the Gaze Cascade Effect is often most prominent during the last five seconds before a decision is made.

As discussed in section 5.8 eye-movements are highly cognitive in nature, whereas the EEG data were being examined for the participants' affective (emotional) responses. Therefore these findings could imply that colour priming has more of an influence on affective processes than it does on cognitive processes. There was a stronger effect in responses between the chosen and not chosen dresses, than the prime matching and not prime matched dresses. Priming effects are subtle, and whilst they can influence an individual's preference, or response towards a product, there are many other external and internal factors which will dictate a consumer's final purchase decision. In the case of this research, whilst the priming has been shown to increase the participants' affective reaction towards the prime matching products, there are also uncontrollable variables which will affect a consumer's decision, such as their personal style and previous primes they have experienced.

7.2 Contributions

7.2.1 Methodological Contribution

This research has tackled the challenge of analysing highly time localised EEG data within a free moving simulated retail environment, allowing the participants to browse the retail environment as naturally as they would when they really shop. The use of eye-tracking as an indicator of times of interest for EEG analysis allowed the participants to have completely free movement, unrestricted by pre-set experimental timings. A key aim of this research was to observe consumer behaviour in an as natural an environment as possible.

The improved ecological validity of the current study is a key novelty of this research, and highly important for improving the understanding of consumer behaviour and priming effects in the real world. Many theories can be developed based on computer screen experiments, however ultimately they need to be tested in real-world, artefact prone situations. In this research the participants were able to touch, and feel the clothes that they were choosing from. This research has built upon eye-tracking and EEG theories used in consumer research, and taken them into a more natural and ecologically valid environment.

7.2.2 Theoretical Contribution

This research has tested the priming phenomenon using new methods, in a realistic consumer environment. Numerous theories have been amalgamated to develop the entire theoretical framework in which this research sits.

Using the S-O-R model as the overarching theoretical framework for this research, and applying the understanding that consumers' decisions are heavily influenced by things that happen outside the individual's conscious awareness, this research has focussed on the consumer's internal subconscious processes within a retail environment. This research has shown that it is possible to measure consumers' internal processes by measuring physiological changes that indicate preference or, approach or withdrawal emotional responses. This has been indicated by the statistically significant difference in the prefrontal cortical activity when looking at different groups of dresses, as measured by the EEG.

This research has also discovered that colour priming can have an impact on a consumer's affective response towards a product, and that this priming effect can be measured using EEG. This highlights the influence of environmental stimuli on consumers' fashion choices. Marketers and retailers can use this information to help align consumers' preferences with their products. For example, retailers could use the colour of their visual merchandising displays to help improve the sales of their ethical and sustainable range of clothing, or to increase sales of the new season's most fashionable colour. It is also important information for consumers to be aware of. Understanding the influence that the retail environment could be having on the decisions being made can help consumers ensure that they are purchasing products that they genuinely want, and meet their needs, instead of being subconsciously influenced to make impulsive purchases.

7.3 Impact

The novel methods proposed by this thesis can have an impact not only on the field of consumer behaviour, but also in other research fields. The ability to explore consumer behaviour in free-moving contexts, such as a real-world shopping task, will allow researchers to gain a more realistic understanding of how consumers behave. Much consumer behaviour research has been confined to computer based, laboratory style settings if the researched wished to investigate physiological responses during the task. With these methods consumer behaviour research could be applied to real in-store contexts, and additional variables could be included if the researcher has sufficient budget and access to retailers.

Outside of the field of consumer behaviour, the combination of eye-tracking and EEG to enable accurate analysis of EEG data at different periods of time throughout an experiment, may be used in many fields. Any researcher who wishes to understand more about human behaviour in a mobile context may apply these methods. The use of the two technologies together allows researchers to have free roaming participants, not restricted by time segments to partition their EEG data based on the task at hand. Rather, the eye-tracking data can inform of the participants' actions and behaviours throughout the task, and the EEG can be analysed in line with this information.

7.4 Future Work

The application of off-line signal processing to accurately synchronise eye-tracking and EEG data opens possibilities for other researchers to conduct mobile experiments, enhanced by the use of the two technologies. By using eye-tracking as the indicator of times of interest, researchers can develop experimental conditions which allow participants to move freely.

In addition to the attraction of being able to assess consumers' responses in a more natural environment, the evidence that priming can be measured using EEG opens the possibility for further exploration that could be computer based. Different people are affected by different primes to varying extents. This study has shown that EEG can be used as a quantifiable measure of the priming affect. However, to understand one's susceptibility to priming stimuli, multiple repeats for each individual should be used. The findings of this study, based on only one experiment, with one product group to choose from and one primed construct (colour), is not enough to confirm susceptibility. It would be interesting to determine whether it is possible to measure how heavily influenced different individuals might be by different advertising techniques.

7.5 Summary

The findings of this research have verified the application of previous models to new research environments, providing ecological validity and enabling consumer behaviour research to branch out of the lab and away from computer screen based studies. Both the eye-tracking and EEG data supported the hypothesis that there would be a significantly different physiological response towards the garments that the participants preferred. Following this validation of research methods, the data were analysed to determine the impact of colour priming on consumers' physiological responses towards the prime target stimuli, compared to the non-target stimuli. The influence of the colour priming on the participants was supported by the EEG data, which analysed the internal emotional responses. However the eye-tracking data did not identify evidence of any priming effect.

This thesis has generated a methodological and a theoretical contribution to this area of knowledge. The methodological contribution is the application of eye-tracking and EEG to a realistic simulated retail environment, providing ecological validity for consumer research. The theoretical contribution lies in the combination of understanding the influence of the subconscious on consumer decisions, and quantifying this by measuring the influence of colour priming using physiological measures such as eye-tracking and EEG. This research has shown that it is possible to measure a discernible difference between consumers' subconscious internal emotional responses towards primed stimuli using EEG.

A key possibility for future research have been highlighted by this work, namely the opportunity to combine EEG and eye-tracking to allow researchers to examine consumer behaviour in a more natural environment.

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Appendices

Appendix A

Search for Colour Priming Literature

Detailed literature review searches were carried out for a number of terms to verify the lack of literature in each area. These are detailed in the tables below, together the most relevant papers that could be found. This search was updated in August 2017. When searching for the terms “consumer colour priming” and “consumer colour influence”, although this returns many results, few are relevant to the research presented in this thesis. When looking at the titles of the papers, some seem potentially relevant, however at closer inspection they are not. The papers which seem almost relevant are briefly summarised below.

Table A.1: Number of results search term: *Consumer colour priming*.

Database	Search term	Search results	Number of relevant results
Emerald Insight	Consumer colour priming	2,249	0
Science Direct	Consumer colour priming	0,934	0

Table A.2: Identified potentially relevant results: *Consumer colour priming*.

Reference	Relevance (or lack of)
Chou et al. (2016)	The effects of priming on consumers were studied, however no relation to colour.
Baxter et al. (2017)	Semantic priming, not the use of colour as a prime.
Beneke et al. (2015)	Looking at the impact of colour of the product on preference, however not the influence of different primes to influence said preference.
Mantovani and Galvão (2017)	Influence of priming on consumers, prime used was audacity traits of sports brands.
Kliger and Gilad (2012)	Colour is used as a prime, but for financial investment decisions not product preferences.
Kristensson et al. (2017)	The paper discusses using primes to influence consumers purchasing behaviour, however the primes used are verbal suggestions and signage around the store, not colour.
Kristensson et al. (2017)	The paper discusses using primes to influence consumers purchasing behaviour, however the primes used are verbal suggestions and signage around the store, not colour.

Table A.3: Number of results search term: *Consumer colour influence*.

Database	Search term	Search results	Number of relevant results
Emerald Insight	Consumer colour influence	08,633	0
Science Direct	Consumer colour influence	49,886	0

Table A.4: Identified potentially relevant results: *Consumer colour influence*.

Reference	Relevance (or lack of)
Kauppinen-Räisänen and Luomala (2010)	Similar to water bottle colour paper, looking at the impact of the colour of products on consumer preference, however not using colours as a prime.
Grossman and Wisenblit (1999)	Similar to previous paper, looking at the influence of the colour of products, not colour as a prime.
Nitse et al. (2004)	Title sounds promising, however article is more about the issue of colour metamerism than colour preference or choice.

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Appendix B

Additional Data Collection Details

B.1 Detailed Experiment Plan

The detail experiment plan was created as a document to aid the explanation of the process of the experiment to the participants. The participants were sent this document, along with the consent form, when they signed up to take part in the experiments. Page one and two of the detail expriment plan can be seen in Figures B.1 and B.2. This document was printed out, laminated and kept in the experiment room at all times. When participant's entered the experiment set-up room, this document was the first thing the investigator showed them, and discussed thoroughly.

<u>Detailed Experiment Plan</u>

<u>Step 1: Setting up the Equipment</u>

The EEG device: The Emotiv EPOC EEG headset, with 14 electrodes.


The Eye-tracker: The Tobii Pro Glasses 2.


The first step for setting up the equipment is to wipe the skin where the electrodes will be placed on your face, which is across the forehead. This done with Nuprep skin prep gel, which is like a light exfoliator, taking away makeup and any dead skin which may be in the area. Following this we will put the EEG headset onto your head first, then we will put on the eye-tracker, sliding the glasses frame arms underneath the EEG. Once these are on comfortably we will begin calibrating.

<u>Calibrating the EEG</u>: When the EEG device is put on your head, you might be able to feel that the felt pads of the electrodes are wet. They have been wet using a saline solution, which is just contact lens solution, to improve the conductivity between the electrodes and the scalp. During the experiment the electrodes can start to dry which reduces the conductivity and can cause problems with the quality of the recorded EEG data. To combat this a small amount of watery gel will be placed on your scalp. This gel brushes out easily and will not be noticeable in your hair after the experiment.

<u>Calibrating the eye-tracker:</u> Calibrating the eye-tracker is much quicker and easier than calibrating the EEG headset. All you will need to do for this is to look at a bullseye shaped target whilst I click calibrate on the screen.

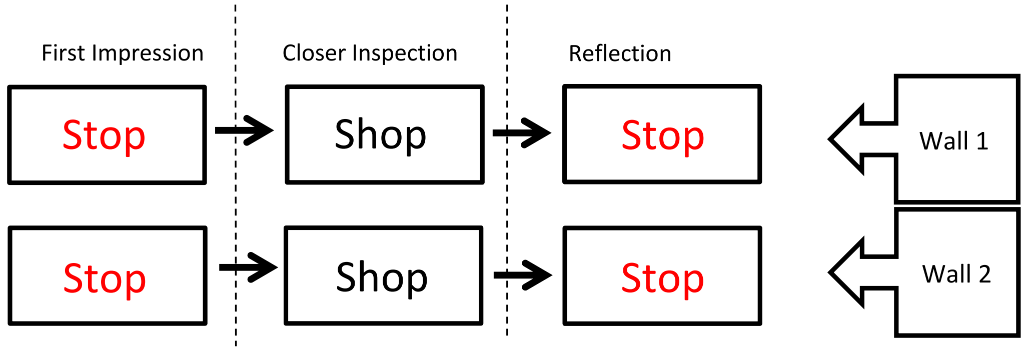
Once all of the equipment is calibrated we are ready to record! The first thing we will record is a minute of baseline EEG data, which I can use as a reference point during my analysis. Then I will start the eye-tracker recording, and let you into the shop.

Figure B.1: Page 1 of detailed experiment plan

Step 2: The Shopping Experience

EEG measures changes in the electrical potential in the brain near the scalp, happens when brain cells send messages to each other. The signals are so small that they have to be amplified before we can analyse them. However the EEG can also pick up other artefacts, such as muscle movement, which produces much larger signals than the brain does. If there is too much muscle movement the brain signals can be completely lost or corrupted. For this reason I am going to have to ask you to stand still a few times during the shopping experience.

There are two walls of clothing inside the shop. The first thing I would like you to do when you enter the shop is to stop in front of the biggest wall, stand still, and have a look at what you can see in front of you. Whilst you are standing still here I will be able to record some clean EEG data of your first impressions of the products. Once you feel you have had a good look at everything on the wall, please step closer and have a browse through all of the clothes on that wall. Then after you have had a closer inspection of the clothes, please step back to your original stop position and look at the products on the wall again. At this point I will be able to record clean EEG data of your reflection of the clothes. After you have done this for wall one, please repeat, doing the exact same thing but looking at the smaller wall to the right of the biggest wall. We'll call this wall two.



After you have completed the Stop-Shop-Stop stages for both of the walls, please choose your favourite dress out of the range. If you like more than one dress then feel free to bring up to three dresses out of the shop with you.

Step 3: The Interview

After you leave the shop we will take the equipment off your head and have a semi-structured interview about the shopping experience. This interview will be recording using an app on my phone, so for data privacy reason we will not mention your name during the interview, only the randomly assigned 4 digit participant number.

Figure B.2: Page 2 of detailed experiment plan

Appendix C

Eye-Tracking Data Preparation

C.1 Introduction

The first stage of analysing the participants' eye-movements involves preparing the data, identifying the fixations and mapping these onto images that represent the scene that they viewed throughout the experiment. Areas Of Interest (AOIs) are drawn onto the images to highlighting stimuli within the scene that is relevant for analysis. 31 AOIs were identified within the retail environment, 23 of these being on the 23 dresses that the participant can choose from. Once the fixation have been identified and the AOIs have been highlighted, it is possible to quantify the gaze bias that each AOI received by using the fixation metrics, such as the total dwell time and the total fixation count. To ensure that the correct statistical comparisons are used, the frequency distribution of the data is tested.

C.2 Import Data

The eye-tracking was recorded using the Tobii Pro Glasses 2, therefore the initial stages of the eye-tracking data preparation will be conducted using the supporting Tobii Pro Analyzer software. The software includes functions to import data, map fixations, generate visualisations such as heat maps and gaze plots, create Area's of Interest (AOI's) and export data metrics regarding relationships between the participants' fixations and the AOI's. The software is provided with a license that is purchased alongside the eye-tracking hardware.

The first stage is to import the necessary data into the *Tobii Pro Analyzer* software, including the experiment video clips with eye-movements and the snapshot images of the participants' environment. The Tobii Glasses contain five cameras, one forward facing camera that records the participants view, and four eye-facing cameras (two for each eye) that record the participants' pupils. All of the data recorded by the multiple cameras is stored onto a SD card that is stowed in the recording unit during the experiments. The combined data is then stored together as a single file on the SD card, which can be accessed via the Tobii Pro Analyzer software. The recordings are imported with a recording number, the participant name (generated at the time of recording by the investigator), the recording duration, the date of recording, and the gaze samples. The gaze samples value is calculated as a percentage of the eye position samples that could be correctly identified, converted and stored by the software as gaze points. For example the Tobii Pro Glasses 2 have a sampling frequency of 50 Hz, if the gaze samples was 100% this would mean that 50 samples per second were identified and able to be stored as gaze points (TobiiPro, 2017, lab manual). Within this experiment the gaze samples ranged from 62-96%.

C.3 I-VT Classifier Threshold

As previously discussed, the Tobii Pro Analyzer software uses a Velocity-Threshold Identification (I-VT) fixation classification algorithm to classify participants' fixations during the experiments. In it's simplest terms, the I-VT algorithm checks the velocity of every gaze sample and then categorises it as either belonging to a fixation or a saccade (Olsen 2012). Determining whether a sample is part of a fixation or a saccades depends on whether the samples velocity is above or below a predetermined threshold. If the velocity is larger than the specified *velocity threshold* then the sample is classified as part of a saccade, if it is lower than the threshold then it is part of a fixation. Once a sample is classified, the I-VT algorithm will group consecutive samples together if they are either both part of a fixation, or both part of a saccade. When a group of samples are grouped together as a fixation, the I-VT algorithm will also calculate the position and the duration of the fixation, based on the number of samples and velocity of these. The velocity threshold was set at 30°/sec for this research, as recommended by TobiiPro (Olsen 2012).

C.4 Noise Filter

When analysing eye-movements, and focussing on the participants' fixations, minuscule eye movements such as microsaccades and tremors, will create unwanted noise in the data (Duchowski, 2007). To calculate the velocity of eye-movements, the angle between two consecutive sample points is divided by the eye-tracker's sampling frequency. Microsaccades and tremors are incredibly fast and small intra-fixation eye-movements, which when picked up by the eye-tracker as gaze points, can disrupt the velocity calculations, and therefore make it difficult to determine whether samples are correct gaze points, and subsequently when a fixation has occurred.

To reduce the issue with noise, the Tobii Pro Analyzer software offers either a moving average or median function that can smooth out the unwanted noise samples whilst maintaining important gaze data that is needed for the fixation classification. The moving average function takes the average value between a defined number of samples before and after the current sample (TobiiPro, 2017). The defined number of samples is set as the "window size". The median function also uses a sliding window method, however the current sample is replaced with a median value of the surrounding samples, instead of an average value. The window size is automatically adjusted at the beginning or end of the recording, when there are not enough samples either side of the current sample to create the average value with. In this research the median function, with a window size of three samples, was used. This does not reduce the velocity peaks as severely as the moving average algorithm (TobiiPro, 2017).

The Tobii Pro Analyzer software also offers another filter to reduce the effect of noise, which calculates the angle velocity of each sample, as an average of the other samples velocities withing a specified period of time. The *window length* parameter sets the length of time that will be used. The benefit of using a measure of time instead of samples for this filter, is that the parameter can remain consistent even if the sampling frequency varies throughout the experiment. In this research a window of 20ms was used for the velocity calculator. This length was recommended by TobiiPro (2017) as it is able to with a reasonable amount of noise, whilst maintaining enough features of the original data.

C.5 Eye-Selection

The Tobii Pro Glasses 2 records the movement of both pupils, from four cameras, however the I-VT classification algorithm only requires one data input. Therefore, the software needs to merge the information from all cameras into one data set. There is an option for the software to only use data collected from either the left or the right eye. Many eye-tracking devices only record one eye, based on the belief that both eyes make almost identical movements and focus on roughly the same positions (Holmqvist et al. 2011).

To merge the data from the binocular recording from the Tobii Pro Glasses 2, an average position between both eye's gaze points can be calculated. The Tobii Pro Analyzer software offers an *average* and a *strict average* option. Both average settings take a combination of the left and right eye gaze positions and output an average gaze position between these, however the *average* setting includes samples when only one eye is detected, however the *strict average* setting would discard samples when only one eye is detected (TobbiPro, 2017, I-VT filter manual). In this research the "average" eye-selection option was selected.

C.6 Merge Adjacent and Discard Short Fixations

Once the software has filtered out unwanted noise, calculated the correct velocity of each sample, and categorised samples to determine which belong to a fixation, there are another couple of options available to ensure that only correct fixations are identified. The first of these is the option to merge adjacent fixations, if the difference between them is less than a predetermined time and angle. If there is a microsaccade during a fixation, this can cause the fixation classification algorithm to become slightly distorted and it may split a fixation up into multiple shorter fixations. The thresholds for merging adjacent fixations used in this research were a maximum time of 75ms and a maximum angle of 0.5°. Additionally, if fixations are too short they can be removed by setting a minimum dwell time parameter. the minimum length of fixation required to obtain any relevant information is believed to be 60ms. Therefore 60ms is set as the minimum fixation length for this analysis.

C.7 Fixation Mapping

The fixations were mapped onto the images of the scenes manually. The Tobii Pro Analyzer software displays the video of the recording, with the fixations visually displayed on top of the image, side-by-side with the snapshot image that the fixations want to be mapped on to. The video will automatically pause on the first fixation that the participant has made. To map a fixation onto the snapshot image the user simply has to click the position in the image that matches the location of the fixation on the video. Once a fixation has been mapped, the video will automatically step to the next fixation point and pause in that position, so the following fixation can be mapped. To ensure to minimise any potential human error during the fixation mapping process, all videos were double checked to ensure the correct positioning.

C.8 Create Intervals

During the experiment the participants were instructed to have times in which they stood still, facing either of the walls of clothing, or times during which they browsed through the clothes more closely. These can be separated into six key intervals, four of which they were stood still. More details of the participants process and intervals can be found in section REF. Using the Tobii Pro Analyzer software these intervals can be manually indicated in the videos as *Times of Interest*. The stages in which the participant were standing still were highlighted as *Times of Interest*. As were three time sections that will be used for the eye-tracking analysis. These three time sections were firstly the whole experiment from the fixation fixation in the first standing still stage until the participant turned to leave the retail environment. The second only included the task stages of the experiment, therefore lasted from the first fixation in the first standing still stage, to the last fixation during the last standing still stage. The final time section was the very end of the experiment, from after the last fixation in the final standing still stage until the participant turned to leave the store. These three time selections are explained and discussed in more detail in section REF.

C.9 Frequency Distribution

C.9.1 Histogram

Plotting a histogram is a method to visually represent the frequency distribution within a set of data. Figure C.1 shows the frequency distribution of the dwell times or fixation counts on the 23 AOIs, that correlate with the 23 dresses. It is clear, that for both dwell time and fixation count the data is not normally distributed, as it does not follow the classic bell-shaped curve that would be expected with normally distributed data.

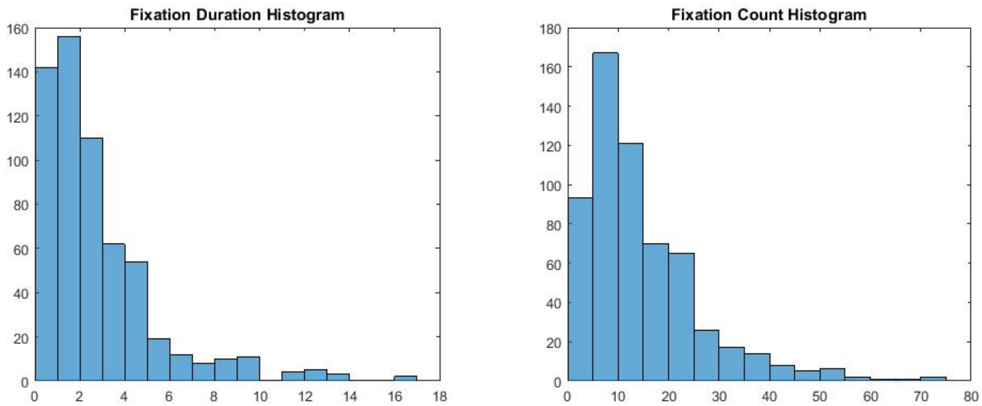


Figure C.1: Histogram of eye-tracking data

C.9.2 Skewness and Kurtosis Tests

The histogram is a useful visual representation of the data's frequency distribution.If data is not normally distributed it will either lack the symmetry of a normally distributed histogram, or it will be more or less pointy (Field 2013). These deviations from normal can be defined as the skew, or the kurtosis of the data. The skew value of the data determines if the data is distributed more frequently at either ends of the scale. Positively skewed data is has more frequent scores at the lower end of the scale, and negatively skewed data has more frequent scores at the higher end of the scale. By looking at the histogram in C.1, it can be seen that the data is positively skewed. The level of skew of the data can be calculated, and the value if shown in table C.1. The kurtosis value determines the 'pointyness' of the frequency distribution curve (Field 2013). If the distribution of the data has a positive kurtosis then it will appear more pointy, and negative kurtosis values will cause a flatter than normal curve. The kurtisos values for the dwell time and fixation count on each dress AOI can be seen in C.1.

	Dwell Time	Fixation Count
Skewness	2.1610	1.8658
Kurtosis	8.9581	7.6938

Table C.1: Skewness and Kurtosis Test Results

C.9.3 Normal Quantile-Quantile plot

A normal Quantile-Quantile plot (Q-Q plot) shows how the target data deviates from a more comparable normal distribution, by comparing the frequency distribution against a normal distribution with the same mean and standard deviation Field (2013).

The graph plots the quantities of each value within the data against the what the quantities would be if the data were normally distributed. This can be seen in Figure C.2, the blue points representing the dwell time or fixation count value quantities. The curve of this blue line further supports the evidence that the data is not normally distributed.

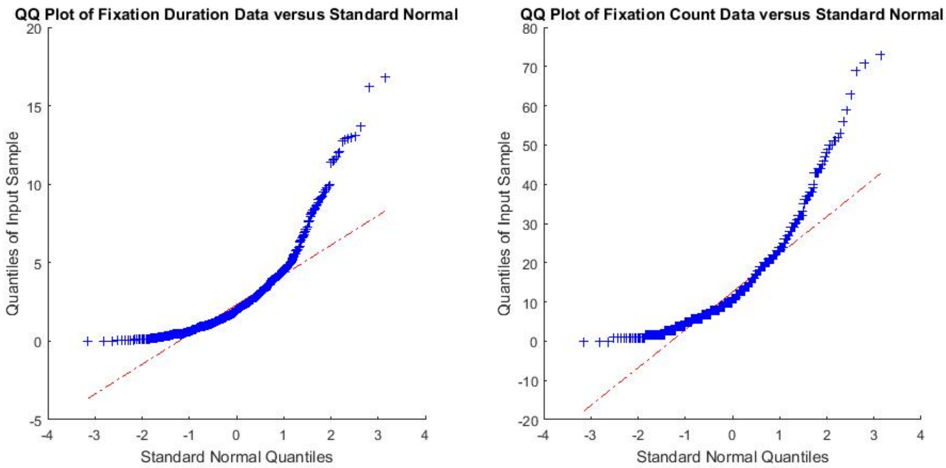


Figure C.2: QQ plot of eye-tracking data

Appendix D

Eye-Tracking Visualisations

D.1 Heat Maps

Figure D.1 shows the heat maps of the participants' fixations on the main wall of the simulated retail environment, separated into the three different colour conditions; pink, blue, and red. The overall pattern of the heat maps remains the same throughout the three different conditions.

Figure D.2 shows the heat maps of the participants' fixations on the second wall of the simulated retail environment, separated into the three different colour conditions. As with the heat maps for the front wall, the heat maps on the side wall demonstrate a similar pattern in all three different conditions.

All heatmaps here have a scale max value of 30 fixation counts.

Figure D.1.a: Heat map of participants' fixations during the pink condition

Figure D.1.b: Heat map of participants' fixations during the blue condition

Figure D.1.c: Heat map of participants' fixations during the red condition

Figure D.1: Heat maps of the participants' fixations, separated out into the three different colour conditions

Figure D.2.a: Heat map of participants' fixations during the pink condition

Figure D.2.b: Heat map of participants' fixations during the blue condition

Figure D.2.c: Heat map of participants' fixations during the red condition

Figure D.2: Heat maps of the participants' fixations, separated out into the three different colour conditions