UNIVERSITY OF
LIVERPOOL

A mobile EEG investigation of the neural dynamics underpinning real-world economic decisions during product purchasing.

Thesis submitted in accordance with the requirements of the
University of Liverpool for the degree of Doctor in Philosophy
by Hannah Roberts

May 2021

TABLE OF CONTENTS

FREQUENT ABBREVIATIONS

ACC	Anterior cingulate cortex
ANOVA	Analysis of variance
BCI	Brain-computer interface
BESA	Brain electrical source analysis
BOLD	Blood oxygen level dependent
BVS	Brain valuation system
DDM	Drift diffusion model
DLPFC	Dorsolateral prefrontal cortex
ECD	Equivalent current dipole
EEG	Electroencephalography
EMRP	Eye movement related potentials
ERP	Event related potential
EUT	Expected utility theory
fMRI	Functional magnetic resonance imaging
fNIRS	Functional near-infrared spectroscopy
FRN	Feedback-related negativity
IC	Independent component
ICA	Independent component analysis
LPP	Late positive potential
MoBI	Mobile brain/body imaging
NAcc	Nucleus accumbens
OFC	Orbitofrontal cortex
PCA	Principal component analysis
PCC	Posterior cingulate cortex
PT	Prospect theory
SD	Standard deviation
SV	Subjective value
VEP	Visual evoked potential
vmPFC	Ventromedial prefrontal cortex
WTP	Willingness to pay
2-D/3-D	2-Dimentional/3-Dimentional

DECLARATION

No part of the work presented was submitted in support of any other applications for degree or qualification at any other university or learning institution.

ACKNOWLEDGMENTS

I would like to express my deep gratitude to my supervisor, Dr Andrej Stancak, for his endlessly dedicated guidance, advice and support throughout my PhD. His unmatched passion for science, far-reaching knowledge of the brain and incredible attention to detail helped me to push past the many barriers which presented themselves throughout this ambitious work, making it possible for me to produce a thesis that I can be proud of. I am truly grateful and I will never be able to thank you enough for the opportunity of a lifetime. I would also like to express my deepest gratitude to Dr Nick Fallon for all of his amazing advice, support and insight, and Dr Timo Giesbrecht, for championing this ambitious PhD and for offering his incredible advice, support and guidance throughout the PhD.

I would like to express my sincerest gratitude to each member of my research group and, in particular, Dr Vicente Soto, for being an incredible MoBI and eye-tracking mentor for always helping me, and Dr John Tyson-Carr, for his patience and support with my many MATLAB queries and help with many aspects of the project. I would like to thank Martin Guest for the innumerable amount of help he has kindly given me throughout this project, far too much to name. I would also like to thank Dr Katerina Kokmotou, for her many hours assisting me with data collection, Alice Newton-Fenner for her advice about economics, proof reading skills and many hours assisting with data collection, and Dr Adam Byrne, for his many hours spent assisting me with data collection. It was wonderful to work with you all.

I would like to express my deepest thanks to EPSRC and Unilever for funding this project. I would also like to thank each and every participant who dedicated their time to taking part in these Studies.

I would like to thank my wonderful family; my Mum, Dad and my sisters, for always being there and cheering me on. I could not have gotten anywhere without you. I would like to thank my wonderful partner, Dr Paweł Jędras, who's advice and support during the write up of this thesis, in science and in life, went above and beyond what I could have ever asked for. Thank you so much. I would like to give a special thank you to my friend, Dr Moon Wilton, who taught me EEG in my bachelors and helped me to believe in myself, encouraging me to apply for this PhD in the first place. Thank you for your endless support. I would also like to thank my friend, Dr Beth Mead, for all of your proof reading and endless support, and my friend, Dr Lauren McGale, for your support throughout the PhD. I would also like to thank Dr Lana Jago, Dr Judit Fazekas, Dr Katherine Melling, Dr Charline List, Joanne Wilson, Dr Danni Zurinsky and Dr Eugenia Romano for your support and friendship.

I would like to dedicate this thesis to my Mum, Tracy Roberts, my Dad, David Roberts, my sisters Zoë and Ellie Roberts, my partner, Dr Paweł Jędras, and my kittens; Poppy and Cookie. Thank you all for all of your love, support and for everything you have all taught me, I could not have done this without your love and support.

ABSTRACT

Economic decisions are continuously made throughout daily life and involve subjective value (SV) assignment and subsequent selection of the option with the highest SV amongst competing alternatives. The precise temporal characteristics of early value computation are unknown, and, to date, no research has examined the neural dynamics of subjective valuation in naturalistic environments, which have different perceptual and motivational characteristics which could alter SV. The current thesis examined the spatiotemporal neural dynamics underpinning subjective valuation of products in naturalistic settings using mobile electroencephalography (EEG) and eye-tracking.

Eye-movement related potentials (EMRPs) underpinning SV of products were examined in a product gallery for 2-D images, and a custom-built mock shop for real 3-D products. Stimulus onset corresponded to the first instance of the gaze touching an object. Products were viewed and rated whilst mobile electroencephalography and eye-tracking recordings were taken. Willingness to pay (WTP) values were used as a measure of SV and were elicited using a Becker-DeGroot-Marschak (BDM) auction following the mobile EEG task. ICA was used to reduce contamination of eye-movement artefacts. Source dipole modelling was used to estimate cortical generators of EMRP components.

Results from three experimental chapters suggest early encoding of unique bands of SVs for 2-D and 3-D products in multiple distinct cortical clusters. Low- and high-value products were discriminated binarily in early latencies of EMRPs, with facilitated encoding of low-value items. Intermediate-value items were discriminated in later components of EMRPs, both within parietal/occipital cortex. Linear encoding of SV was observed for 3-D products.

The current thesis demonstrates, using novel methodologies and mobile EEG and eye-tracking recordings in realistic settings, that early SVs assigned to 2-D and 3-D products are computed on a coarse grid, within multiple distinct components of EMRPS within parietal/occipital cortex, with facilitated binary representations of low- and high-value products and later encoding of intermediate-value products.

1. GENERAL INTRODUCTION

1.1. Overview

Value-based decisions are a natural part of everyday life and subjective values (SVs) are continuously assigned, either consciously or unconsciously (Rangel et al., 2008). Value-based decisions involving the assignment of SVs to competing alternative options can range from the relatively trivial to the highly consequential and life-changing, with a whole spectrum of decisions in between (Clark et al., 2012; Rangel et al., 2008). Effective value-based decision making is essential for surviving and thriving in the world, and maladaptive patterns of salience attribution and value-based decision making can lead to issues of substance abuse (Galandra et al., 2018), hoarding, obsessive-compulsive disorder (Pushkarskaya et al., 2017) and pathological gambling (Kräplin et al., 2014) among other issues.

It is an important research agenda to understand how a decision maker processes and assigns SVs to competing alternatives (Rangel et al., 2008), how SVs are compared, how a decision is reached based on these comparisons (Brosch & Sander, 2013), and how the consequences of these decisions are evaluated and inform future choices (Rangel et al., 2008). The recently-emerged field of neuroeconomics combines disparate fields of neuroscience, psychology, economics and computer science to integrate theory and practice to determine the neurobiological underpinnings of value-based decisions (Camerer et al., 2004; Fehr & Rangel, 2011). The field of neuroeconomics has led to the comprehensive mapping of the neural substrates of the brain valuation system (BVS) (Rangel et al., 2008). However, as functional magnetic resonance imaging (fMRI) has been the dominant neuroeconomic technique for examining value-based decisions, questions of whether value-based decisions are processed within the same or distinct brain regions, and their time-course, remain unanswered due to the method’s limited temporal resolution. Therefore, some aspects of the BVS remain largely unknown, and investigation of the spatio-temporal dynamics of the BVS is essential to gain a more holistic insight into the ways in which the brain processes SV. Traditional laboratory-based neuroimaging experiments have also been criticised for their lack of ecological validity, preventing them from being generalised to real-world settings (Andrade, 2018).

Mobile brain/body imaging (MoBI) has emerged over the last decade to investigate embodied cognitive processes in their natural context (Parada, 2018), overcoming the limitations of previous research methodologies. Mobile neuroimaging has revolutionised the investigation of cognition by affording the opportunity to compare natural contextualised neural processing with findings generated in more restrictive laboratory-based studies to verify their generalisability (Ladouce et al., 2017). The MoBI approach can provide new insights into the neural dynamics underlying value-based decision making by allowing for examination of value-based processing in naturalistic contexts during free viewing. Examination of natural behaviours is essential as brain states differ during movement (Ladouce et al., 2017), information can be processed in the periphery of the visual field (Dias et al., 2013), and immediate availability of products can alter motivated behaviours (Jędras et al., 2019; Jones et al., 2012). However, to investigate value-based decisions using MoBI, methodological issues related to the recording and extracting of mobile EEG data need to be addressed, including the precise synchronisation of EEG and eye-tracking data streams and the minimisation and effective removal of movement-related artefacts. Therefore, the aim of the current thesis is to determine the spatio-temporal dynamics of value-based decisions for products in freely behaving participants in natural environments, whilst ensuring high-quality of recording by effective reduction of artefactual noise.

1.2. Purchasing decisions and consumer theory

1.2.1. Rational choice and utility maximisation

Buying decision making incorporates a series of stages which precede product purchase. Dewey (1910) described the five stages of buyer decision making as problem/need recognition, informative search, evaluation of options, purchase decision and post-purchase behaviour (Bruner & Pomazal, 1988). These stages are considered to be the central pillar of popular consumer behaviour model, and demonstrate that the purchase decision is a process of cost-benefit analysis which directs a customer from the initial identification of their needs to purchase behaviours, motivated by a desire to achieve homeostasis between the actual and desired state (Bruner & Pomazal, 1988). Consumer theory is a branch of microeconomics which examines how people make financial decisions considering their resources, preferences, the products available and their respective prices (Bondarenko, 2020; Hess et al., 2018). Consumer theory is built around the concept of utility maximisation and assumes that customers are inherently rational and make calculated purchase decisions (Bondarenko, 2020; Hess et al., 2018).

Pioneering the study of economic decision-making and purchase decisions in the 17th century, Smith (1759) proposed the invisible hand theory in his book ‘The Theory of Moral Sentiments’. Smith suggested that acting in one’s own self-interest, including its individual and social context, is one of the key principles governing rational individual economic decisions which drive a free market economy. Smith also argued that such self-interested behaviour actually maximises the interests of society as a whole and thus, is morally justified (Smith (1759) as cited in Bishop, (1995)). Smith is considered the founder of Rational Choice Theory, which proposes that individuals are fundamentally rational and are focused on expected utility maximisation; obtaining the best reward at the lowest price to satisfy motivation ranging from selfishness to altruism (Elster, 2001).

Utility maximisation can be modelled by the Marshallian demand function which illustrates rational customer decision-making (Marshall, 1890). The Marshallian model makes purchase predictions in the context of price and income and assumes that customers are able to provide a perfect solution to the utility maximisation problem by spending money whilst maximising utility (Marshall, 1890). The Marshallian demand curve demonstrates the relationship between price and demand under the assumptions that the prices of alternative products and consumers income are constant. However, critics of the Marshallian model point out that the model does not define what is in customer’s best interest, which is likely subjective, and offers logical norms for purely rational buyers. The normative stance may likely be appropriate for the purchase of the most expensive goods, such as a car, but may not be applicable to essential items such as which brand of tissues to purchase (Kotler, 1965). Additionally, human decision making can be inconsistent and irrational and the desire to purchase can be motivated by many different factors, both within and beyond conscious awareness, not just driven by the pursuit to maximise utility (Fine, 2008). For example, consumers might be less likely to purchase a previously favoured product when it is on offer, as they might perceive a price reduction as a reduction in product quality or in their social status (Kotler, 1965). Ultimately, the Marshallian model is unable to explain how product preferences are formed, highlighting the importance of investigating the decision-making process outside of the bounds of pure rationality.

1.2.2. Alternative models of consumer decision making; Pavlovian, Psychoanalytic, Veblenian and Maslow's theory of motivation

Psychological models and methods can be used to understand preference formation and decision irrationality, which is not considered in purely economic models of decision making. The Pavlovian model of decision making, named after the Russian physiologist Ivan Pavlov, offers a limited yet important insight into purchasing behaviour, indicating that purchasing is a form of learned behaviour which can be developed through repetitive actions and learned relationships between stimuli (Clark et al., 2012; Kotler, 1965). According to the Pavlovian model, conditioned stimuli trigger previously acquired behavioural responses which are capable of reinforcing novel behaviour acquisition, and can produce behaviours that act against optimal outcomes which would maximise utility (Clark et al., 2012). The Pavlovian model utilises four concepts to explain purchase decisions; drives, cues, responses and reinforcement (Dollard & Miller, 1950; Kotler, 1965). Drives refer to primary physiological or learned social internal motives which motivate purchase (e.g. acquisitiveness or fear). Cues and their intensity (e.g. promotions, discounts) are environmental or internal stimuli which can trigger buying behaviour. A response is a buyer's action which is activated by a combination of cues which may lead to purchase. Reinforcement learning means that purchase behaviours which were rewarding are more likely to be repeated (e.g. brand preference) (Dollard & Miller, 1950; Kotler, 1965). However, the Pavlovian model does not offer insight into perception or unconscious processes associated with purchasing decisions (Kotler, 1965).

The psychoanalytical approach to consumer behaviour and purchase decision originates in work of psychoanalyst and neurologist Sigmund Freud (Cluley, 2008). The psychoanalytical account suggests that many of the consumer decisions are motivated by drives and environmental conditions in response to symbolic concerns (e.g. feelings, attitudes), which can operate outside of awareness, indicating that customers may become receptive to a message even before experiencing it (Cialdini, 2016). Freud's nephew, Edward Bernays, pioneered the use of psychoanalytic tactics in sales and public relations (Bernays, 1928; Tye, 1998). Bernays realised that it was possible to manipulate the irrational forces that drive human behaviour to influence purchasing behaviours (Bernays, 1928). For example, during the Lucky Strike cigarette campaign, he convinced women to smoke despite the societal taboo by promoting the symbolism of female smoking as a challenge to male power and female independence, referring to them as 'torches of freedom' at a publicised parade in which female suffragettes smoked (Amos & Haglund, 2000). Bernays simultaneously tapped into the emerging stereotype that women should be 'slim' using the slogan 'reach for Lucky, instead of a sweet' (Amos & Haglund, 2000). Ultimately, Bernays used symbols to appeal to unconscious desires, suggesting that the product is able to fulfil them, and these tactics are still embedded within marketing, advertising, branding and public relations today (Cluley, 2008).

The Veblenian (Veblen, 1899) model of consumer behaviour emphasises the role of society and culture in shaping purchasing decisions (Hodgson, 2004; Rutherford, 2011). According to the Veblenian perspective, psychological habits, social institutions and anthropological and economic factors, such as income, all contribute to purchasing behaviour. Veblen argued that predatory and competitive habits led to the stratification of society into lower- and upper- socioeconomic classes, in which high-status members are involved in unproductive occupations and low-status individuals are economically productive. Consequently, the consumer's social and cultural background plays an important role in purchase decisions, as consumers purchase goods to emulate the higher-class which arguably uses the best and the most desirable goods available. Therefore, the conspicuous consumer does not purchase goods to satisfy physical needs but, rather, to provide social satisfaction, prestige and the maintenance of social class (Almeida, 2016; Kotler, 1965). Maslow's Theory of Motivation (Maslow et al., 1970; Maslow & Murphy, 1954) divides human needs into one of five hierarchical categories; physiological (e.g. food), security (e.g. safety), social (e.g. belongingness) Ego (e.g. success) and self-actualisation (e.g. self-fulfilment). According to the theory, individuals will first satisfy basic physiological needs, but once fulfilled, people then move up the hierarchy and are driven to satisfy the next need. The theory of motivation has been used to understand consumer behaviour by mapping each aspect of product marketing onto the hierarchy of human needs and relating this to purchasing decisions. For example, products that satisfy basic physiological needs are abundant and cheap, whereas products that map onto self-actualisation at the top of the hierarchy are more scarce, reflecting product supply and demand. WTP and product prices should also be reflected by the hierarchy, with consumers willing to pay more for products at the highest level of the hierarchy. Yalch & Brunel, (1996) applied the needs hierarchy in consumer evaluation of product designs and found that consumers were 30% more likely to pay more for an aesthetically pleasing shaver and 22% more likely to pay more for an aesthetically pleasing toothbrush compared to basic equivalent items, reflecting the higher value of items which are able to satisfy self-actualisation needs. More recently, Cui et al. (2021) showed that purchase of electric vehicles in China was significantly predicted by environmental concern then price, experience, social influence and finally self-esteem, reflecting Maslow's hierarchy of needs.

Contrary to the assumptions of early rational choice theories, the Pavlovian, Freudian model, the Veblenian model and Maslow's Needs Hierarchy highlight the complexity of the purchasing decisions and the multitude of factors that can influence consumer behaviour. Internal influences on consumer behaviour include perception, motivation, personality, learning, attitudes and needs, emotions and physiological states (Hawkins & Mothersbaugh, 2010; Vainikka, 2015). External factors include social (Akar et al., 2015; Kotler, 1965), cultural (and subcultural) (Nayeem, 2012) influences, the influence of family (Kaur & Singh, 2019), demographic (Martins et al., 2011) and socioeconomic factors (Kamakura & Mazzon, 2013). Situational factors include the amount of resources available in terms of money (as well as the economic situation) (Unger et al., 2014), time (Hornik & Zakay, 1996), mood, the presence of others, (Zhuang et al., 2006), price expectations (Puto, 1987), brand loyalty (Khan et al., 2014; Philiastides & Ratcliff, 2013), own product expertise or the presence of an expert (Cordell, 1997; Klucharev et al., 2008), previous experience (Gustafson et al., 2016) and any competing demands which could dominate attention. Many of these factors are subject to fluctuations according to the environment and can increase or decrease susceptibility to particular marketing strategies which can influence purchasing behaviours. Such strategies include packaging (size, shape, colour, information) (Silayoi & Speece, 2004), elicitation of emotion (Kemp et al., 2012), creating urgency (Childs & Jin, 2020), and shopping environment (Michon et al., 2005). Given the complexity of purchasing decisions, the current thesis will focus specifically on economic aspects of product purchasing decisions; specifically, on early economic value-based decisions for products in naturalistic environments.

1.3. Economic theory of value-based decisions

1.3.1. Expected utility theory

Most psychological, economic and neuroscientific research has investigated value-based decision making and purchasing decisions based on concepts outlined in expected utility theory (EUT) and later, prospect theory (PT). EUT (Bernoulli, 1738) is the dominant normative rational choice model of economic decisions and is used to describe decision making under conditions of risk and uncertainty (Savage, 1954; Von Neumann & Morgenstern, 1944). According to EUT, decision agents will consider the respective value of each alternative outcome, otherwise known as their utility, predict the probability of each outcome occurring, combine each options utility with their respective likelihoods into a single expected utility and select the option with the highest expected utility (Mongin, 1998; Moscati, 2016). EUT outlines four axioms for the rational decision maker; completeness, transitivity, independence and continuity. According to the completeness axiom, the decision maker has well defined preferences and can always decide between two alternatives. Transitivity refers to the consistency of decisions between the same two alternatives on different occasions. Independence is the assumption that when an irrelevant third alternative is presented, the two relevant decisions will maintain their order of preference. Finally, the continuity axiom is the assumption that preferences are continuous and linear, and therefore, there are no jumps in preferences (von Neumann & Morgenstern, 1944). While EUT has been incredibly influential in economics, it has come under criticism for failing to explain certain behaviours, particularly when participants did not behave in a rational and consistent way (e.g. the endowment effect, when participants value a possessed item more highly than it is worth). In these cases, most of EUTs axioms were violated and failed to explain outcome interpretation (Tversky, 1975). Being a normative model, EUT does not capture many aspects of natural human decision-making as it does not consider the decision makers subjective preferences, wants or needs (Bossaerts & Murawski, 2015), nor include intuitive or emotional responses, context or framing (De Martino et al., 2006).

1.3.2. Prospect theory

In order to make sense of decisions when the axioms of EUT were violated, such as under conditions of risk, Kahneman et al., (1979) developed PT. PT proposes that the decision maker evaluates the value of different decision prospects, and the prospect with the highest SV is subsequently chosen (Kahneman et al., 1979). Importantly, PT assumes that outcomes are evaluated as relative gains or losses to a subjective reference point, rather than objective states of wealth as considered by utility theory. PT describes maximisation of utility according to this reference point, and also incorporates how cognitive biases and heuristics can influence choices.

According to (Tversky & Kahneman 1974), when faced with conditions of uncertainty, decision makers often rely on heuristics, biases and intuition and attempt to match information with a stored representation. Tversky and Kahneman (1981) demonstrated that, although risky prospects are evaluated based on their potential outcomes and their relative probabilities, the same prospect can be framed differently and this will influence decisions. For example, if options are framed as possible gains (compared to a reference state of gaining nothing), preferences tend to favour risk aversion, whereas if options are framed as potential losses with a reference state in which nothing is lost, people tend to show risk seeking preference (Tversky & Kahneman, 1981).

In line with PT, the SV of an item is a concave function of the size of a gain, and the same applies to losses. When the value function for gains and losses are compared side by side, an S-shaped function illustrates the value function, which is concave for gains and convex for losses, and considerably steeper for losses compared to gains (Kahneman & Tversky, 1984), relative to a neutral reference point (Kahneman, 2011). Tversky and Kahneman (1974) refer to this as loss aversion, whereby the loss of monetary resources is evaluated more negatively than a gain of the same amount is considered attractive, or in other words, the response to losses is stronger than the response to corresponding gains (Kahneman, 2011). Therefore, the amount of money available to win must be greater than the amount that could be lost in order for a gamble to be accepted. PT is able to account for individual variations in risk seeking or risk aversive attitudes by explaining how cognitive biases and framing can influence choices.

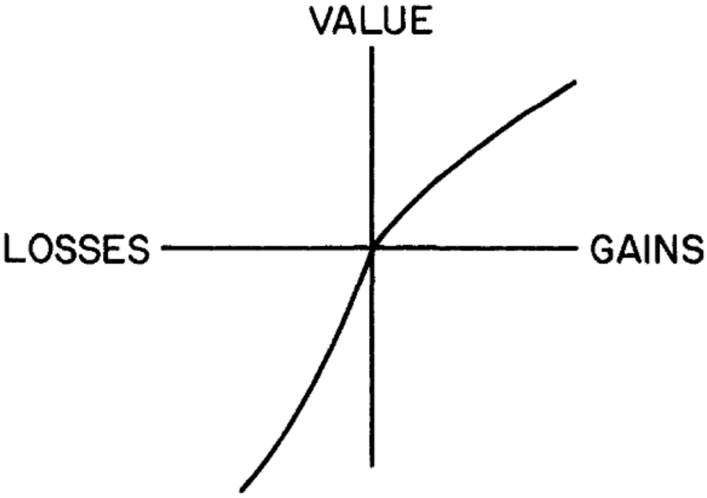

Figure 1. Hypothetic value function for gains and losses. Adapted from Tversky and Kahneman (1981).

Moreover, Kahneman and Tversky (1984) show that people tend to underweight moderate and high probabilities relative to a sure thing, contributing to risk aversion. However, for losses, people tend to overweight low probabilities which enhances the value of long shots in gambles in the case of severe loss, contributing to risk seeking. Ultimately, people tend to be risk seeking in the context of unlikely gains and risk averse in the context of unlikely loss. Loss aversion is considered to be a manifestation of negativity bias, as the motivation to avoid negative outcomes is much greater than to obtain positive outcomes (Kahneman, 2011). Additionally, Kahneman (1990; 1991) used features of the valuation function to explain the endowment effect, which is the reluctancy to part with a good that one owns for the same price that they are willing to pay for the same good. Rather, the value of a good increases when one owns the good, and more money is required to part with the good.

1.4. Neuroeconomics and the neural basis of economic value-based decisions

The discipline of neuroeconomics was formed in the 1990s to provide an encompassing perspective on the neurobiological mechanisms of decision making by utilising knowledge, theory and practice derived from the diverse fields of economics, psychology, neuroscience and computer science (Camerer et al., 2004). The neuroeconomic approach aims to answer the questions of how does the brain make different types of decisions, what are the brain structures underlying these processes, and how does this relate to real-world decision-making contexts (Fehr & Rangel, 2011).

The question of how humans make decisions has long evaded understanding (Sanfey et al., 2006). The multi-disciplinary field of neuroeconomics was an attempt to bring together the best theories and techniques from economics, psychology, neuroscience and computer science in an attempt to bridge the knowledge gap, to make better predictions and to ultimately determine the neurobiological mechanisms that underpin value-based decisions once and for all (Camerer et al., 2004). Since its conception, the neuroeconomic approach to decision making has led to an exponential increase in research publications and, consequently, a whole host of new insights regarding the neural dynamics of value-based decision making and avenues for further exploration (Glimcher & Fehr, 2013).

Primarily, neuroeconomic studies have endeavoured to comprehensively map out the neural structures of the BVS. Aiding empirical investigation, Rangel et al. (2008) devised a neuroeconomic framework describing the distinct stages of the neural valuation process, including; representation, valuation, action selection and outcome evaluation. Representation and valuation are subjected to internal and external demands, such as hunger or available resources, and outcome evaluation is fed back to inform future decisions about similar stimuli (Rangel et al., 2008). The discrete neural stages outlined by the model have been used to examine specific aspects of the brain valuation process (Chib et al., 2009; Kurniawan et al., 2013; Lin & Vartanian, 2017). According to Rangel et al. (2008), there are three value subsystems operating within the BVS which can operate independently or concurrently, and each subsystem has its unique brain activation patterns. These include the Pavlovian, habitual and goal-directed subsystems. The Pavlovian subsystem is activated during stimulus-response valuations for natural stimuli; mapping on to approach-avoidance behaviours (Wright et al., 2013). Consequently, the Pavlovian system includes a neural circuit of brain areas associated with emotion and reward, including the basolateral amygdala, the ventral striatum and the orbitofrontal cortex (Cardinal et al., 2002; Holland &

Gallagher, 2004). The habitual subsystem is responsible for valuation resulting from learned associations which are accumulated through repetition and includes brain structures such as the dorsolateral striatum and the thalamus (Ashby et al., 2010; Rangel et al., 2008). Lastly, the goal-directed subsystem is responsible for top-down outcome-based valuation and operates during novel situations, predicting and evaluating outcomes. The suggestion of discrete brain areas for the processing of different value-based decisions is supported by research which shows activation of unique voxels for discrete categories of stimuli (Bulthé et al., 2014; Diana et al., 2008; Haxby et al., 2001; Haxby et al., 2000; Howard et al., 2009; Kragel & LaBar, 2016). The Rangel et al. (2008) framework has been extensively used to investigate the BVS by examining neural correlates at each of the decision stages.

As an alternative to the proposal of discrete value systems within the brain set out by Rangel et al. (2008), the common neural currency hypothesis holds that all value-based decisions are computed within the same neural valuation system, which is domain general and generic, and SVs are assigned persistently and automatically to stimuli in the environment (Bartra et al., 2013; Levy & Glimcher, 2011; Westbrook et al., 2019). In line with the common neural currency hypothesis, SV computation involves comparison of costs and benefits across different domains for multiple competing alternatives on a common scale, which are then ranked to form a decision, and the BVS must account for this cross-domain comparison (Bartra et al., 2013; Westbrook et al., 2019). Support for the common neural currency hypothesis comes from research which shows activation of the BVS regardless of whether a valuation is explicitly needed, demonstrating the automaticity of the BVS (Lebreton et al., 2009; Tyson-Carr et al., 2018).

Kahneman (2011) proposed that there are two neural systems which govern consumer thought and decisions; System 1 and System 2, which are individually responsible for automatic and more conscious decisions, respectively. According to Kahneman (2011), System 1 is a ‘quick thinking’ system which is intuitive and relies on ‘gut response’. It is automatic and fast and requires little or no effort, has a high processing capacity, relies on biases, heuristics, habits and associative memory processes and is often emotionally charged (Kahneman, 2003). Importantly, Kahneman suggests that System 1 is in perpetual operation unless the individual’s attention is focussed elsewhere. System 1 can produce emotional reactions and physical behaviours in response to stimuli which replicate previous reactions to similar events, such as reacting with aversion to the word vomit, due to the fact that cognition is embodied. Conversely, System 2, the ‘slow thinking’ system, is conscious and controlled and relies on cognitive effort, deductive reasoning and conscious attention. Consequently, System 2 operates more infrequently and has a limited capacity, so it is deployed when System 1 is unable to provide an answer, and monitors the progress of System 1, exercising impulse control over System 1 when necessary. Kahneman (2011) argues that System 1 is innate and exists within most animal species, whereas System 2 is specific to humans. There can also be crossover between the two systems, for instance, System 1 creates impressions, intentions and feelings which can be endorsed by System 2 and turned into beliefs, making it more likely that System 2 will accept the impressions of System 1 in the future. Kahneman (2011) argues that in familiar situations, System 1 predictions are usually accurate and appropriate. System 1 and System 2 exist to maximise performance speed and accuracy, whilst exerting the minimum amount of effort. From an evolutionary perspective, System 1 provides continuous assessment of the environment to promote survival, therefore, it is associated with approach and avoidance and detecting threats and opportunities, which has been adapted to issues in the modern world.

In decision making, heuristics and biases are cognitive shortcuts based on stored examples which reduce cognitive load and facilitate fast responses to similar events, however, they deviate from rational judgement and can be flawed (Ehrlinger et al., 2016). Different heuristics and biases can influence decision making in both System 1 and 2. One such heuristic is the law of small numbers, i.e. the tendency to believe that a sample is highly representative of the population and that the law of large numbers (large samples will certainly be representative of the population) also applies to small numbers (Tversky & Kahneman, 1971). Furthermore, an anchoring effect can occur as a result of priming (System 1), or in a deliberate process of evidence gathering and estimate adjustment (System 2) (Kahneman, 2011). Additionally, the availability heuristic can produce biases that are more influential on system 1.

The Somatic-Marker Hypothesis (Damasio, 1994) provides neurobiological support for judgements made based on intuition, as in System 1 of Kahneman and Tversky's theory (Bechara & Damasio, 2005). The Somatic Marker Hypothesis is a neural theory of economic decision making, which stipulates that natural decisions must be quick and require less computation to be effective, therefore, they must be grounded in emotional 'gut' responses. Damasio (1994) suggested that emotions or 'gut instincts' are essential in guiding behaviour and decisions as they facilitate immediate rejection of aversive actions and reduce the amount of decision alternatives, protecting against future losses and supporting more efficient and accurate decisions (Damasio, 1994; Wilkinson & Klaes, 2012). Damasio argued that emotion, or somatic markers, can consciously and unconsciously assist cognitive processing during decisions and index subsequent decision making. Specifically, somatic markers function to assign initial values to decision alternatives, ultimately resulting in approach and avoidance and guiding later decisions (Bechara, 2013). If people are unable to activate the somatic states that facilitate early value attribution during decision making, for instance, in patients with ventromedial prefrontal cortex (vmPFC) impairment, this results in decision-making impairments and problems with emotion (Bechara, 2013).

An alternative explanation comes from drift diffusion model (DDM), which proposes that, in natural environments where multiple options are available, value-based decisions are made via noisy evidence accumulation over time, which is modulated by visual attention (Krajbich & Rangel, 2011; Milosavljevic et al., 2010). For a decision to be made, the costs and benefits of each alternative must be integrated and weighed against each other until a decision boundary is reached, stimulating the binary choice of acceptance or rejection based on anticipated rewards or losses (Basten et al., 2010). The DDM of value-based choices holds that relative value signals are persistently computed while evidence is gathered in favour of a heuristic-based ‘hypothesis’ that one item is more highly valued than another. Once a value signal reaches some upper or lower threshold following evidence integration, SV is reached (Milosavljevic et al., 2010). Therefore, according to the DDM approach, the brain assigns value sequentially and stochastically by extracting stimulus features through evidence accumulation and integrating the values over time (Milosavljevic et al., 2010). The DDM is conceptually similar to the embodied predictive processing account of embodied cognition (Clark, 2015; Friston et al., 2010), which holds that serial and hierarchical perception would take a long time and, thus, be disadvantageous in natural environments. In the real-world, information is accumulated in a continuous forward flow and constructs representations as more evidence is gathered, interacting with and updating stored representations as it goes, and is subject to top-down attention modulation (Clark, 2015). As a result, predictions and attempts to optimise predictions and minimise prediction errors are made (Friston et al., 2010; Kirchhoff, 2018). In this way, interactions with the world are akin to sensory experiments and hypotheses are tested by gathering further evidence through actions (Friston, 2012).

The DDM holds that the process of cost-benefit comparison is related to the competing behavioural tendencies of approach or avoidance, therefore, the cost-benefit comparison is modelled as drifting towards accept or reject decision boundaries (Basten et al., 2010). Basten et al. (2010) found evidence to support the DDM when examining the neural mechanisms underlying cost-benefit comparisons, with increased blood-oxygen-level-dependent (BOLD) activity in the nucleus accumbens (NAcc) and amygdala during evidence accumulation for costs and benefits, in the vmPFC, reflecting and comparison of reward and loss, and increased activity in the intraparietal sulcus reflecting integration of the difference signal, accumulated until a decision threshold is reached.

1.4.1. Neural substrates of the brain valuation system

The main priority for neuroeconomic research has been to comprehensively map out the BVS during the different value stages outlined by Rangel et al., (2008) using methods such as fMRI and single neuron recordings (Konovalov & Krajbich, 2019; Rangel et al., 2008). Studies have suggested that the BVS incorporates a diverse network of brain structures in the occipital, temporal and parietal cortices (Lebreton et al., 2009), including the striatum, the ventromedial prefrontal cortex, orbitofrontal cortex (OFC), posterior cingulate cortex (PCC), hippocampus, amygdala, insula, dorsolateral prefrontal cortex (DLPFC) and anterior cingulate cortex (ACC).

The striatum is thought to encode positive SVs of primary and secondary rewards at the time of choice and during outcome evaluation (Bartra et al., 2013), overall reward magnitude (Elliott et al., 2000), monetary gains and losses (Delgado et al., 2000), anticipation of an increasingly rewarding (Knutson et al., 2001) or aversive stimulus (Jensen et al., 2003) and prediction errors (Hare et al., 2008). Similarly, the vmPFC also plays a role in SV computation at the time of choice for primary and secondary rewards (Hare et al., 2010; Kable & Glimcher, 2007; Padoa-Schioppa & Assad, 2006; Plassman et al., 2007) and evaluation of decision outcomes (Clithero & Rangel, 2014; Levy & Glimcher, 2012; Padoa-Schioppa & Cai, 2011; Rangel & Hare, 2010) and correlates with subjective desirability of goods (Plassmann et al., 2007), expected value (Kable & Glimcher, 2009), reward outcome value (Knutson et al., 2003), experienced pleasure (Grabenhorst & Rolls, 2011), and the difference between chosen and unchosen options (Grabenhorst & Rolls, 2011). Moreover, different areas of the vmPFC might encode distinct aspects of the valuation process, with anterior vmPFC activity reflecting experienced value, and posterior vmPFC activity indexing decision value (Smith et al., 2010). Both the vmPFC and striatum activity elicited in the absence of value choices have been shown to predict subsequent choices, suggesting that these areas encode SV automatically (Levy et al., 2011) and activation of the vmPFC and striatum correlate with the value of fixated targets, suggesting that these value signals are modulated by visual attention (Lim et al., 2011).

The OFC is one of the main projection areas in dopaminergic pathways and is thought to index reward processing (Liu et al., 2011), particularly, reward learning and adaptive decision making in dynamic environments (Walton et al., 2011). OFC activity has been shown to correlate with positive rewards (Liu et al., 2011), reward availability and anticipation (Blechert et al., 2016; Jędras et al., 2013), expected value and experienced value, and subjective pleasantness (Grabenhorst & Rolls, 2009). In primates, neurones in the OFC encode SVs of alternative options and chosen options (Padoa-Schioppa & Assad, 2006), and reward amount (Wallis & Miller, 2003). Additionally, it has been shown that OFC lesions impair goal-directed decisions (Padoa-Schioppa & Conen, 2017) in uncertain environments (Walton et al., 2011). Moreover, OFC neurones encoded gaze position and value, which was amplified when primates fixated on a cue, demonstrating the importance of gaze behaviour in the neural mechanisms of value-based decisions in ecologically valid settings (McGinty et al., 2016). Therefore, the OFC is thought to be an essential structure in economic decision making (Padoa-Schioppa & Conen, 2017).

The PCC, involved in memory retrieval (Lebreton et al., 2009), has been linked to SV computation and information integration during decisions (Clithero & Rangel, 2014), and correlates with value coding for delayed rewards (Peters & Büchel, 2009), expected rewards, punishments, and planning of saccadic eye-movements to target stimuli in primates (Iyer et al., 2010). The PCC may also index decision salience and attention (Heilbronner et al., 2011). The hippocampus, another memory-related neural structure, also plays a role in the BVS. Hippocampal activity is modulated when preference decisions are based on brand information (McClure et al., 2004; Schaefer & Rotte, 2007), for example, increased preferences for Coca-Cola compared to Pepsi Cola correlated with hippocampal activation (McClure et al., 2004). Additionally, hippocampal activity is correlated with sensitivity to financial loss, and the hippocampus might have an inhibitory effect on reward experience, forming part of the behavioural inhibition system (Elliott et al., 2000).

The amygdala is associated with monetary loss aversion and there is evidence to suggest that it could be important in inhibiting behaviour which is likely to produce negative outcomes (De Martino et al., 2010). The amygdala is also thought to be involved in generating value expectancy (Holland & Gallagher, 2004). Alternatively, the insula is involved in the encoding of subjective unpleasantness (Grabenhorst & Rolls, 2009), and processing of aversive outcomes (Tanaka et al., 2004), including the encoding of low-value products (Tyson-Carr et al., 2018).

The DLPFC is known to be involved in working memory and mental manipulations, and is thought to index relative value computations according to contextual demands (Lee & Seo, 2007; Saraiva & Marshall, 2015). The DLPFC and VMPFC interact during value-guided decisions and the DLPFC might modulate the value encoded by the VMPFC when decision conflict occurs (Saraiva & Marshall, 2015) and during cost-benefit decisions (Basten et al., 2010). Moreover, DLPFC activity is thought to encode goal-value signal in primates and in humans (Rangel et al., 2008) and values of actions correlate with DLPFC (Morris et al., 2014).

Similarly, the ACC is thought to guide adaptive decision making and value through cognitive control mechanisms and integration of choice history and outcomes, particularly in dynamic naturalistic environments (Walton et al., 2007). ACC activity has been linked to processing of response conflict and adaptive modification of behaviour following reinforcement learning (Botvinick et al., 2001), as well as cognitive control, motivation, inhibitory control, surprise and reward-based decision-making (Shenhav et al., 2016; Vassena et al., 2020).

It has been suggested that because the vmPFC/OFC, striatum and insula show activation to a variety of rewarding stimuli in the same participants, these brain areas might represent a common neural currency for economic value decisions, allowing for comparison between different stimulus categories (Brosch & Sander, 2013). Complex decisions involving a cost-benefit analysis could involve interactions between the vmPFC/OFC and insula, whereas issues of delaying gratification and value discounting might be subject to interactions between vmPPFC/OFC and ventral striatum (Brosch & Sander, 2013).

Although not part of the BVS, brain areas responsible for visual attention may also play a role in early value-based decisions during free viewing, as crude, preliminary SVs, derived from learned values or heuristics, may be assigned to competing stimuli to selectively guide attention to salient stimuli (Itthipuripat et al., 2015). Supporting the role of visual attention in valuation, studies have demonstrated that highly rewarding stimuli receive neural prioritization of attention in the visual cortex, despite the fact that they are not physically salient (Itthipuripat et al., 2015). Therefore, visual attention could interact with the BVS during early automatic valuation to ensure facilitated attention to salient stimuli, promoting approach and avoidance behaviours.

1.4.2. Temporal dynamics of value-based decisions; electrophysiological evidence

The majority of neuroeconomic research has investigated the BVS using neuroimaging methods such as fMRI, providing an overview of brain regions that comprise the BVS (Bartra et al., 2013; Lebreton et al., 2009). However, the limited temporal resolution of fMRI cannot provide insight into the temporal properties of the brain valuation process during decision-making and, consequently, much less is known about the temporal dynamics underpinning valuation decisions (Larsen & O’Doherty, 2014). To date, a limited amount of research has targeted the electrophysiological correlates of valuation in evoked potentials, providing mixed results. MoBI research has found equivalents for some visual evoked potentials (VEPs). However, currently, no specific investigations of valuation decisions using eye movement related potentials (EMRPs) have been conducted. Such investigation is essential for uncovering the spatio-temporal dynamics of the BVS, which can help to reveal the ways in which the brain processes SV in realistic settings. The following paragraphs will provide an overview of visually evoked ERPs, or VEPs, associated with valuation and, where applicable, the EMRP or MoBI-derived equivalent ERPs.

1.4.2.1. P200

The P200 is an early VEP component showing a positivity in central-frontal and parietal-occipital scalp regions and peaking between 150–250 ms after the onset of a visual stimulus (Bourisly & Shuaib, 2018; Hu et al., 2017). The P200 is often associated with visual attention to salient stimuli (Carretié et al., 2001b). Specifically, research has shown modulation of P200 when attending to emotional stimuli (Carretié et al., 2001b; Gerdes et al., 2013; Schirmer et al., 2011), particularly negative cues, which might reflect a negativity bias in the brain (Carretié et al., 2001b; Correll et al., 2006; Gerdes et al., 2013; Huang & Luo, 2006; Rigoni et al., 2010; Wang & Han, 2014; Wang et al., 2012). Moreover, P200 is thought to index early valuation of rewards (Gui et al., 2016), as well as outcome evaluation, predictability of outcomes and risk (Polezzi et al., 2008; Rigoni et al., 2010; Schuermann et al., 2012), and desirability of products (Tyson-Carr et al., 2018). In wireless EEG recordings of natural behaviours, the P200 has been observed during piano playing (Zamm et al., 2019) and natural reading of unexpected words (Fjaellingsdal et al., 2020).

1.4.2.2. N200

The N200 is a negative evoked potential occurring between 180–325 ms in posterior electrodes and is thought to be essential for stimulus evaluation, discrimination, conflict processing and selective attention (Dennis & Chen, 2007; Gajewski et al., 2016; Hakim & Levy, 2019; Patel & Azzam, 2005), including attention encoding during free viewing (Natraj et al., 2018). The N200 might reflect a reinforcement learning signal for adaptive decision making, as it is sensitive to outcome valence and emotion processing (Hajihosseini & Holroyd, 2013; Kanske & Kotz, 2010). It has been suggested that the N200 indexes prediction errors and encoding of product preference (Goto et al., 2017; Schaefer et al., 2016; Telpaz et al., 2015; Tyson-Carr et al., 2018). In relation to MoBI research, the N200 has been shown to reflect automatic inhibition of motor control during sitting and walking in a go/no go task (De Sanctis et al., 2014), and has been investigated in the context of deviant stimuli during skateboarding and driving (Robles et al., 2020; Zander et al., 2017).

1.4.2.3. P300

Later event related potential (ERP) components such as the P300, a positive wave occurring 250–450 ms in midline electrodes (Pozharliev et al., 2015), have also been linked to value processing in the brain. Similarly to the N200, the P300 is thought to index attention (Polich, 2007; Schuermann et al., 2012), particularly for novel stimuli (Ladouce et al., 2019; Suwazono et al., 2000). Specifically, it has been suggested that the P300 represents a later revision or mismatch detection between incoming stimuli and the initial processing which occurred in earlier components such as the N100, P200 and N200 (Polich, 2007). Consequently, if the new stimulus aligns with the initial representation, the ‘schema’ outlined by earlier components is maintained, however if the stimulus is novel, additional P300 attention-related processes are needed to update previous stimulus representations (Polich, 2007). Therefore, P300 is thought to involve higher-level processing and working memory processes pertaining to attention (Polich, 2007). The P300 is also modulated by the positive or negative valence of stimuli (Cano et al., 2009; Conroy & Polich, 2007; Keil et al., 2002; Onishi & Nakagawa, 2019; Yeung & Sanfey, 2004), and allocation of attention when evaluating reward outcomes in terms of valence, magnitude and expectancy (Wu & Zhou, 2009; Yeung & Sanfey, 2004). In relation to MoBI research, the P300 has shown sensitivity for attentional resources for objects during dual-task walking (Shaw et al., 2018), and has been observed during sitting or walking (Debener et al., 2012), with reduced P300 amplitude during walking compared to standing still due to enhanced processing demands (Ladouce et al., 2019).

1.4.2.4. Late positive potential (LPP)/Feedback-related negativity (FRN)/Error-related negativity (ERN)

Other later components which are thought to be related to valuation include the LPP, the FRN and ERN, and these are thought to index valuation of outcomes. The LPP is a slow wave occurring 500–700 ms and is modulated by the emotional significance of stimulus valence (Hajcak & Olvet, 2008; Keil et al., 2002; Schupp et al., 2000), and reflects attention allocation for motivationally salient stimuli, including products (Goto et al., 2017; Lang & Bradley, 2010; Pozharliev et al., 2015). Findings regarding the LPP are mixed, however, as Pozharliev et al. (2015) only observed modulation of the LPP in a social context when others were present. The FRN is a negative deflection occurring in frontal-central electrodes with a peak latency of 250 ms (San Martín, 2012). Like the P300, the FRN is thought to encode aspects of outcome evaluation following feedback (Yeung & Sanfey, 2004), and is specific to negative feedback (Huang & Yu, 2014). The FRN is thought to reflect prediction errors and depend on the relationship between expected rewards and actual rewards, with worse than expected outcomes eliciting enhanced FRN (Huang & Yu, 2014). For example, the FRN is sensitive to price expectation violations during shopping (Schaefer et al., 2016), and aversion to monetary loss (Kokmotou et al., 2017). The ERN is a negative deflection which peaks approximately 80 ms in frontal scalp regions in response to errors (Chang, 2016; Holroyd & Coles, 2002), and is thought to reflect higher-level conflict monitoring and error detection (Holroyd & Coles, 2002; Wessel, 2012). MoBI research has reported modulation of the ERN for incorrect responses of a go/no-go task during sitting and treadmill walking (De Sanctis et al., 2012). Recently, the LPP for threatening faces has been observed in virtual reality (VR) conditions (Stolz et al., 2019). However, to date, modulations of the FRN have not been detected in MoBI studies in ecologically valid settings, which could indicate operation of different processes (Lange & Osinsky, 2020).

1.4.3. Exploratory data-driven analyses to examine value-based decisions

There is much research investigating the brain areas involved in value computation, however, much less research has investigated the activation of brain networks over time during value-based decisions, and the temporal dynamics of the brain valuation process remain elusive (Tyson-Carr et al., 2020). Converging neuroscientific evidence has suggested that choices involve initial assignment of SVs which are then compared, resulting in selection of the optimal option (Gold & Shadlen, 2007; Harris et al., 2011; Kable & Glimcher, 2009; Montague & Berns, 2002; Rangel et al., 2008; Rangel & Hare, 2010). In dynamic real-world environments, it may be essential to encode and compare information from the environment over time to successfully weigh alternatives and form a decision, which is in line with the DDM (Basten et al., 2010; Milosavljevic et al., 2010; Ratcliff, 1978; Tzovara et al., 2015).

It has been shown that modulation of value occurs across multiple time windows, ranging from 150 – 800 ms post stimulus onset (Harris et al., 2011). Categorisation of valence emerges from 120 ms (Smith et al., 2003), and value categorisation has been reported as early as 150 ms (Harris et al., 2011), suggesting that the BVS is capable of rapidly encoding stimulus value. Harris et al. (2011) conducted an exploratory analysis of EEG data over an extended time window and observed early cortical modulation of value between 150 – 250 ms in the parietal and temporal lobe, reflecting value signal computation, suggesting that early ERP components involved in early sensory processing can also encode stimulus value, not just salience. Later modulation of value (400 – 550 ms) was observed in the vmPFC, reflecting value comparison during decision making and, for the latest time bin (700 – 800 ms), value-related modulation was observed in the intraparietal sulcus, reflecting transformation of goal-value into motor action. Taken together, Harris et al's (2011) data demonstrated the temporal stages of valuation leading to action execution. Tzovara et al. (2015) examined the time course of single decisions following stimulus presentation to detect trial-to-trial level variation in decisions, allowing for identification of decision stages. A data-driven approach was utilised to avoid bias and overlooking decision-making phenomena occurring outside of a predefined time interval of interest. Results revealed an early time-locked component around 150 ms after stimulus presentation, reflecting evidence accumulation, and a later component which shifted across trials depending on level of difficulty of the decision. Easy decisions were detected at approximately 500 ms compared to hard decisions which were detected around 700 ms, and decision onset could be predicted 340 ms prior to the subject's behavioural response by detecting correlates of when single decisions were made.

The exploration of the time course of decision-making processes requires an exploratory or data-driven research approach utilising methods with a high temporal resolution such as EEG. Only a limited number of studies have specifically examined modulation of economic value, as determined by willingness to pay (WTP), across an extended time-course (Tyson-Carr et al., 2018, 2020). Tyson-Carr et al. (2018) conducted an exploratory analysis to examine the spatiotemporal characteristics of brain valuation, with WTP as a measure of SV for products in tasks where valuation was either relevant or irrelevant to ascertain the automaticity of valuation. The authors found an N200 component was modulated by value, with enhanced activation for low-value items in the anterior insula and OFC, regardless of valuation context, suggesting that an automatic valuation process operates in the brain which promotes avoidance of unwanted items. Furthermore, Tyson-Carr et al. (2020) extended previous findings by examining eye-fixation related potentials for products over the entire period of natural object viewing; separating viewing into 800 ms time bins to determine how neural valuation decision temporally evolved. Following an independent component analysis (ICA), results revealed distinct spatio-temporal encoding of value. Importantly, each of these independent components (ICs) distinctly encoded product value early in the viewing period, within the N200, and persisted throughout the viewing period in free- and forced-bid trials. Results also suggested that high-value items did not significantly vary throughout the valuation stage and received increased fixations, therefore, increased cognitive processing may be required for these items. Tyson-Carr et al.'s (2020) results suggest that products of different SVs receive unique neural encoding which begins as an automatic provisional value categorisation which persists across the decision period in successive fixations and is updated according to information gathered from the environment. These findings support the DDM perspective of valuation processing, whereby evidence is accumulated until a decision threshold is reached, and this can occur rapidly resulting in automatic value encoding in the brain (Harris et al., 2011; Milosavljevic et al., 2010; Tyson-Carr et al., 2020). Despite these initial findings, the identification of a decision-making timeline and neural correlates has been an important yet largely overlooked research avenue which could provide a better insight into decision-making processes in real-world settings.

1.4.4. Linear versus distinct neural encoding

Because the temporal dynamics of value-based decisions are not well understood, it is not known how the brain encodes SV. Studies have found some evidence for distinct SV encoding in unique spatio-temporal cortical clusters (Tyson-Carr et al., 2018, 2020). For example, Tyson-Carr et al (2020) observed distinct cortical clusters for products of different SV as measured by WTP, with one component encoding high-value products in the left parietal cortex, one encoding intermediate value items in the frontal-central region of the cortex, and one in the frontal cortex encoding intermediate and low-value products. Category specific neural selectivity has also been observed in other domains, such as for faces in the N170 component (Cao et al., 2014), and for negative stimuli in the P100, N100, P200 and N200 components (Huang & Luo, 2006; Lithari et al., 2010; Smith et al., 2003).

Alternatively, there is some evidence which contends that SV could be linearly encoded by the brain (Abitbol et al., 2015; Bartra et al., 2013; Lebreton et al., 2009). Bartra et al (2013) questioned whether neural correlates of SV follow a linear or nonlinear function, indicated by a monotonic increase in BOLD fMRI signal as a function of SV, compared to a U-shaped function showing maximal activation for at the polar ends of SVs. Bartra et al. (2013) found that some structures within the BVS demonstrated linear encoding, including the vmPFC and PCC, whereas the anterior insula displayed non-linear encoding. They also found evidence for distinctive neural structures encoding positive or negative value and combined encoding of valence in other structures. Therefore, further research is needed to determine whether SVs are encoded linearly or in distinct neural clusters within the BVS.

1.4.5. Automatic valuation processing in the brain

Decision-making was initially considered to be a conscious and deliberative process. However, because the real-world contains a multitude of complex information to be processed and because humans have limited attentional resources and higher order processing capacities including memory, in recent years is has been suggested that the BVS must assign some SVs automatically without conscious attention (Anderson, 2013).

Previous studies have reasoned that in order to adaptively and efficiently respond to stimuli in the environment, the BVS must automatically assign values to objects in the environment, and these SVs can influence behaviour even if the object is not explicitly attended to, or if they are choice irrelevant (Grueschow et al., 2015; Lebreton et al., 2009). This phenomenon is known as value-based attentional capture (Anderson, 2013), referring to the neural process of persistently monitoring the environment for behaviourally relevant or salient stimuli and automatically assigning SVs to efficiently guide choices promoting behavioural approach or avoidance. Rapid attention for a stimulus maximises the time that the decision-maker has to act upon the stimulus, making it more likely that they can obtain a reward or avoid a negative outcome, increasing the likelihood that the individual will survive or thrive (Anderson, 2013). In line with an adaptive response to stimuli, Cortese et al., (2020) demonstrated that value-based predictions drove motivated behaviours which allowed tasks to be solved more quickly, suggesting that decision-making in the brain is able to tap into higher-order summarisations of the task states. Furthermore, it has been suggested that an automatic BVS should be generic and encode both primary and secondary rewards, allowing for stimuli comparison across multiple dimensions (Lebreton et al., 2009). Additionally, it is unknown whether multiple distinct neural systems operating in parallel, one domain-general neural system, or a sequential evidence accumulation threshold mechanism operates in the brain when assigning SVs during value-based decisions. The automaticity of the BVS has been empirically supported, with studies finding activation of valuation neural circuits during explicit valuation and during distractor tasks when value computation was not required (Grueschow et al., 2015; Lebreton et al., 2009; Polanía et al., 2014), during forced choice tasks (Plassmann et al., 2007) or hypothetical purchase decisions (Tusche et al., 2010), suggesting that value is persistently and implicitly computed by the BVS (Lebreton et al., 2009).

In addition to persistently encoding value, another indication of automatic valuation in the brain is rapid encoding of SV prior to conscious elaboration. Automatic processing and facilitated attention are allocated to motivationally salient stimuli to promote approach or avoidance, explaining the negativity bias. Additionally, target detection is facilitated when stimuli are associated with rewards (Kiss et al., 2009), and a history of previously rewarding or reward-associated stimuli can facilitate attentional priority for those items (Anderson, 2013). It has also been suggested that SV is closely linked to decision confidence, with high-value and low-value options linked to high confidence, thereby stimulating approach-avoidance behaviours, whereas medium-value options are associated with more uncertainty and lower confidence (Bobadilla-Suarez et al., 2020).

Previous ERP studies have shown facilitated processing of salient stimuli suggesting automatic value encoding. For example, research has shown that the amplitude of the P200, which is thought to reflect early automatic attention allocation, is modulated according to negative stimuli (Carretié et al., 2001b; Huang & Luo, 2006; Jin et al., 2017; Wang et al., 2012), and the N200 has been linked to automatic preference encoding (Goto et al., 2017; Kiss et al., 2009; Telpaz et al., 2015), as well as to automatic valuation for low-value products (Tyson-Carr et al., 2018) and low/medium-value products (Tyson-Carr et al., 2020).

The role of the body and the environment has been largely overlooked when investigating automatic valuation. Because automatic valuation forms part of a process which stimulates approach and avoidance, the body plays an essential role, however, all of the studies to date examine neural responses while participants are sitting or reclining, omitting opportunities for approach-avoidance. Additionally, cues in the environment which signal the availability of items can facilitate attentional bias and alter motivated behaviours (Jędras et al., 2019; Jones et al., 2012; Maas et al., 2012), necessitating investigation of automatic valuation in natural environments. Despite the influence of the body on valuation and motivated behaviour, to date, no studies have examined the automaticity of the BVS in natural conditions using methods with high temporal resolution such as mobile EEG, and this is the focus of the experiments in the current thesis.

1.4.6. Interim summary of electrophysiological studies investigating value

Many studies have examined the neural correlates of value, however, relatively fewer experiments have been dedicated to examining the temporal sequencing of value-based decisions. Most of the electrophysiological literature on valuation has focused on electrical potentials that occur during processing of choice outcomes, such as the FRN, ERN and LPP. ERP correlates of value that are time-locked to the onset of the stimulus highlighted the P200, N200 and P300 ERP components, which are also thought to index visual attention for salient stimuli, although the literature is divided on how or whether these components are related to value encoding. Studies have observed value-based neural modulation across multiple time windows, ranging from 150 – 800 ms post stimulus onset, with very early modulation of value in the brain at around 120 ms (Harris et al., 2011). Because the exact spatio-temporal dynamics of the neural valuation process are unknown, to avoid overlooking effects of valuation due to cherry picking the data, an exploratory-based data-driven approach investigating the entire time-course of the decision and utilisation of methods with a high temporal resolution, such as EEG, offers the most promising solution. A data-driven approach affords investigation of outstanding research questions regarding whether value is encoded distinctly by separate cortical clusters or linearly within the same neural structures, to what extent value is automatically encoded within the brain, and whether an environment that is concordant with shopping will impact the valuation processes and behaviours.

1.5. The mobile brain/body imaging (MoBI) approach for investigating real-world value-based decisions

1.5.1. MoBI and embodied cognition

The MoBI approach was introduced in the seminal paper by Makeig et al., (2009) as a way of combining high density EEG measurements with body and eye-movement recordings in freely moving participants. The approach was developed to better understand the complex and multidimensional brain dynamics supporting cognition and motivated behaviour in realistic environments (Gramann et al., 2010; Gramann et al., 2011; Gwin et al., 2010; Liao et al., 2012; Makeig et al., 2009; Ojeda et al., 2014). Although other MoBI techniques exist, including mobile magnetoencephalography (MEG) (Boto et al., 2018) and mobile functional near-infrared spectroscopy (fNIRS) (Krampe et al., 2018; Park et al., 2018), the high temporal resolution of mobile EEG recordings makes it well suited for examining natural cognitive processes in real time (Makeig et al., 2004; Parada et al., 2020).

Central to the MoBI approach is the issue of ecological validity, which is the question of whether data obtained in restrictive laboratory-based environments is generalisable to real-world conditions, and has been debated since the 1940s (Andrade, 2018; Brofenbrenner, 1977; Neisser, 1976). Despite static laboratory-based experiments affording enhanced control over experimental variables increasing internal validity, humans are active agents and cognitive processes are not made in isolation (Parada et al., 2020). Therefore, according to the MoBI approach, unimodal laboratory-based neural data can only inform about neural processes that occur in that specific environment and are not necessarily generalisable to real-world contexts (Ladouce et al., 2017; Neisser, 1976). Decision-making is strongly influenced by fluctuations in internal demands, such as needs and desires, which are updated according to contextual changes within a complex and multifaceted environment (Makeig et al., 2009).

The fundamental assumptions underlying the MoBI approach are consistent with the concept of embodied cognition, emphasising reciprocal interactions of agents' mind and body in their environmental context (Lepora & Pezzulo, 2015). Embodied cognition can be understood from an evolutionary perspective, whereby cognition is holistically built upon perceptual and motor functions of the body, which evolved together through interactions with the environment (Gallagher, 2018). Such systems progressively adapted to increase effective (i.e. action selection) and efficient (i.e. action performance) utilisation of the available internal and external resources (Anderson & College, 2016; Gallagher, 2018).

For instance, during natural cognition, many aspects of a human body interact with environmental stimuli, including hands for grasping, eyes for focusing on stimuli, an upright posture and many other bodily states (Gallagher, 2018). Therefore, contrary to the neurocentric view that it is only the brain in isolation which determines perception, cognition and behaviours, the embodied cognition account posits that perception, cognition and behaviour are intrinsically linked to many embodied processes, including the endocrine and autonomic systems, and can mutually influence each other, altering neural processes (Gallagher, 2018; Gallagher & Allen, 2018). Moreover, there is a bi-directional interplay between decisions, choices and actions during natural cognition in ecologically valid settings, and these are continuously updated according to changes in the environment (Lepora & Pezzulo, 2015; Makeig et al., 2009). Sensory input, introspective bodily states, perception, cognition and motor actions all interact to inform natural decisions (Lepora & Pezzulo, 2015; Petit et al., 2016) to facilitate actions within the environment (Makeig et al., 2009). Supporting the MoBI approach and embodied cognition perspective, research has demonstrated activation of the mirror neuron system in both humans and primates during action observation and execution, demonstrating the interdependence between visual perception (observation of action), cognition (inner representation of action) and action (mimicking the movement; Kilner & Lemon, 2013).

To successfully examine the brain dynamics supporting natural cognition, it is essential to extend the traditional structured and controlled laboratory setting towards less controlled unstructured or semi-structured experiments that are embedded within their natural context (Parada, 2018). Examination and imaging of cognition in more naturalistic settings was made possible by advancements in the MoBI approach over the last decade, owing to advancements in EEG hardware such as the development of lightweight wireless EEG systems (Gramann, 2014; Oliveira et al., 2016) and active shielded electrodes (Gramann, 2014). The implementation of advanced data processing techniques such as ICA and principal component analysis (PCA) to remove movement-related artefacts, and the co-registration of eye-tracking data, combined with methods for synchronising multimodal data, have led to a marked increase in MoBI research (Artoni et al., 2017; Delorme et al., 2007; Gramann et al., 2014; Ladouce et al., 2017; Makeig et al., 1996; Makeig et al., 1999; Parada, 2018). MoBI methods allow for examination of neural dynamics during a number of natural behaviours including walking (Gwin et al., 2010; Severens et al., 2012; Wagner et al., 2012), running (Gwin et al., 2010), cycling (Zink et al., 2016), driving a car (Protzak & Gramann, 2018) and piloting an airplane (Callan et al., 2015). MoBI methods have a wide spectrum of other applications and can be used to examine behaviours in a limitless number of natural contexts, such as during artistic performance (Cruz-Garza et al., 2020), dance (Barnstaple et al., 2020), military training exercises (Ko et al., 2015), an office work place (Wascher et al., 2014) and in brain-computer interfaces (BCI) for real-time game play (Liao et al., 2012). The broad applications of MoBI systems demonstrates their potential for investigation of novel settings, which expand research horizons beyond the scope of more conservative approaches.

1.5.2. Free viewing in natural environments

Real-world vision involves a multitude of information in the environment which must be selectively processed and attended to, necessitating many different types of eye-movements by the visual system (Dimigen, 2014). The most frequent form of eye-movement used to explore information in natural environments are rapid, planned movements of the eyes known as saccades (Dimigen, 2014). High visual acuity is limited to 1-2 degrees around the point of visual fixation, known as the fovea centralis, however, outside of the fovea, parafoveal and peripheral processing is still capable of detecting a lower resolution visual image. The function of saccades is to direct the fovea to the most salient information in the environment at each moment in time to produce the highest-resolution image allowing as much information as possible to be detected (Dimigen, 2014). As a result, visual processing in natural environments is an active, trans-saccadic and goal-directed process, involving persistent shifts of visual attention across saccades during exploration of the environment in order to attend to salient stimuli in line with task demands (Canosa, 2009; Jia & Tyler, 2019; Kretch & Adolph, 2015; Schall, 2013).

Traditional laboratory experiments have precluded eye-movements during EEG measurement due to eye artefacts distorting the EEG signal (Jia & Tyler, 2019). Restricting eye-movements using serial presentation of stimuli can prevent expression of natural behaviours and omit investigation of a large portion of visual information processing and associated neural responses, sacrificing external validity and not allowing for understanding of data in a broader context (Dimigen et al., 2011; Jia & Tyler, 2019). In order to truly understand early valuation responses (which as seen in the previous section are likely linked to visual selective attention) it is essential to examine natural viewing behaviours during free visual exploration without restricting the subject's gaze (Kretch & Adolph, 2015). MoBI and eye-tracking can be combined to examine co-registration of eye movements and neural dynamics during natural free viewing and uncover aspects of cognitive processing and attention that could not be observed under more restrictive conditions (Dimigen, 2014; Fischer et al., 2013; Nikolaev et al., 2014, 2016).

Data recorded during co-registration of EEG and eye movements have shown that the way in which information is processed in natural environments differs from responses elicited from laboratory and computer-based stimuli, demonstrating the complexity of oculomotor behaviour (Dimigen, 2014). In laboratory experiments, correlates of visual cognition examined using EEG are often recorded during periods of prolonged fixation (Dimigen, 2014). However, natural vision involves active sampling of environmental information across several saccadic eye movements per second (Dimigen, 2014), and not all information is processed serially as salient information can be pre-processed in the fovea from non-central viewing positions (Dimigen et al., 2011). Active, natural vision also involves the prediction and pre-selection of future saccade targets in parafovea and periphery, motor preparatory processes, and anticipation which facilitates the rapid processing of stimuli affording swift responses in a dynamic environment (Dimigen, 2014). Trans-saccadic processing during natural vision also means that multiple visual representations gathered over time need to be spatially integrated across saccades, and this cannot be accounted for by restrictive laboratory studies (Ray et al., 2011). As such, working memory must be involved in trans-saccadic processing to maintain information about salient objects across successive saccades in order to guide subsequent saccades through goal-directed visual attention (Melcher, 2007). Therefore, salient aspects of the scene can be encoded prior to fixation and used to guide visual behaviour (Nikolaev et al., 2013). Taken together, the complexity of natural, active vision necessitates the importance of examining cognition using co-registration of EEG and eye-tracking under naturalistic free eye-movement conditions.

1.5.3. The importance of context and physical product presence for real-world value-based decisions

When valuation decisions for products are made in natural shopping contexts, environmental information must be attended in order to facilitate goal-directed exploration. This will be updated during movement, facilitating goals through interdependent perception, cognition and action (Ladouce et al., 2017). The neuroeconomic literature has shown that context can significantly modulate valuation responses (Kahneman et al., 1979), which can alter underlying brain activity (Tymula & Plassmann, 2016). Context-dependent expectations surrounding a product, such as beliefs and predictions regarding price or quality (Tymula & Plassmann, 2016), modulation of expectation congruency (Noseworthy et al., 2014), or context-induced changes in arousal (Griskevicius et al., 2009), can influence product valuation even when the physical properties of the good remain constant. For example, modulation of the price of an identical wine altered beliefs about its taste and modulated value-related brain areas (Plassmann et al., 2008). Conceptual and perceptual congruence between products and the environment can facilitate their positive evaluation and purchase selection by making them more accessible and easier to process (Berger & Fitzsimons, 2008). Additionally, priming of fear or desire can influence product desirability ratings (Griskevicius et al., 2009). Therefore, because decisions are formed as part of a complex and dynamic interaction with an environment, conclusions drawn from highly controlled laboratory experiments which omit these interactions and context might be limited or misleading. MoBI affords the opportunity for examining value-based decisions within their natural contexts, and the neural dynamics that underpin natural decisions, thereby greatly improving external validity.

An additional issue to consider when examining value-based decisions for products in naturalistic environments is the type of visual stimuli used. 3-D products can be examined from multiple different angles, which can differ in visual features such as luminance, contrast, size and shape. The physical presence of a product can influence motivated behaviours, with objects that are within reach being more likely to stimulate a purchase (Painter et al., 2002). Moreover, with 3-D objects, the participant is able to properly appraise the product using all of their senses. Alternatively, 2-D images can be standardised on basic visual dimensions, ensuring that responses elicited during product valuation are not due to low-level visual features. Factors related to utilisation of 2-D and 3-D stimuli should be carefully considered when developing a naturalistic paradigm to investigate valuation responses using MoBI.

2. GENERAL METHODS

2.1. Electroencephalography (EEG)

EEG is a technology that can be used to examine brain waves, i.e., the electrical outputs of neurones in the brain (Borck, 2018; Luck, 2005). Hans Berger (1873-1941) pioneered this neuroscientific research method in humans. His seminal paper "On the Electroencephalographram of Man" demonstrated that the rhythmic firing of groups of neurones, called neural oscillations, could generate an electrical field which could be detected and measured using a scalp sensor (Berger, 1929; Luck, 2005). However, it was not until 1964 that modern cognitive event related potential (ERP) experiments were developed, allowing for measuring brain responses to specific events (Luck, 2005).

2.1.1. Physiological basis of the EEG signal

The human brain contains approximately 100 billion neurones (Freberg, 2016; Herculano-Houzel, 2009). EEG measures oscillating electrical potentials from the cerebral cortex that are generated when neurones fire by placing electrodes on the scalp. Each EEG scalp electrode records many cortical sources, as neurones are densely packed in 10^5 per mm^2 of surface, with broad synaptic interconnectivity (Nunez & Srinivasan, 2006).

Neurones are volume conductors, meaning that currents can flow through them. They can also generate a variety of currents, including receptor potentials, synaptic potentials and action potentials (Gazzaniga, Ivry & Mangun, 2002). Neurones are comprised of a soma, the presynaptic axon, receptor dendrites and the synapse (Lodish et al., 2000; Speckman et al., 2011). The intracellular space contains high concentrations of potassium (K^+) ions and small concentrations of sodium (Na^+) and chloride (Cl^-) ions. The extracellular space contains high concentrations of Na^+ and

Cl^-, with small concentrations of K^+ ions. These unequal distributions of ions from the inside relative to the outside of the neuronal membrane create a resting potential voltage ranging between -60 to -70 mV (Barnett & Larkman, 2007; Speckman et al., 2011). The action potential results from the rapid depolarization of the neuronal membrane caused by a rapid influx of positively charged ions across the cell membrane, reversing the resting potential polarity. When a threshold is reached (between -50 and -55 mV), the presynaptic neuron fires an action potential, releasing neurotransmitters across the synapse (Gazzaniga, Irvy & Magnun, 2002). The changes in the membrane potential of the post-synaptic neuron following signal transmission are referred to as postsynaptic potentials (PSPs) (Freberg, 2015). Excitatory PSPs (EPSPs) propagate positive charges to the postsynaptic cell increasing the likelihood of an action potential firing, producing local membrane current sinks with distributed passive sources, which preserves current conservation. Inhibitory PSPs (IPSPs) produce the opposite effect, making it less likely for an action potential to be triggered in the post synaptic neuron, producing local membrane current sources with distant distributed passive sinks. The source of EEG signals recorded on the scalp are largely represented by EPSPs and IPSPs, rather than the action potentials themselves, as synaptic potentials have a larger temporal duration of around 5 to 10 ms up to 100 ms compared to action potentials which only last for less than 2 ms (Freberg, 2015; Speckman et al., 2011).

2.1.2. EEG measurement of electrocortical activity on the scalp

EEG measures modulations of synaptic and action potential fields from their background levels (Nunez & Srinivasan, 2006). Current flows between two cortical areas with different potentials (Freberg, 2016; Olejniczak, 2006). At the peak of the action potential, within the axon segment, there is a positive potential compared to the axon segment downstream, which is inactive and more negative. Current flows within the axon from the active to the inactive part of the axon, and the inactive part of the axon then reaches the threshold and becomes active. Simultaneously, current flows across the membrane to the extracellular fluid and back into the cell, completing the loop. Because current follows the path of least resistance, the extracellular current will produce differences in potential at the scalp, which can be detected using electrodes (Freberg, 2015). Electrical fields of individual neurones are usually not powerful enough to be detected using scalp sensors (Woodman, 2010). It is thought that due to the short latency of the action potential (< 1 ms) and the high-frequency of the signal, action potentials are only measurable at short distances from the scalp. Postsynaptic potentials have a longer duration, increasing the likelihood of summation and greater local field potential. To create electrical fields that are strong enough to penetrate the brain, dura mater, skull and skin, large groups of neurones must fire synchronously (Woodman, 2010). As a result, the current view among neuroscientists is that EEG measures the postsynaptic low-frequency current resulting from the synchronized activation of groups of neurones in a local network (Nunez & Srinivasan 2006; Logothetis et al., 2001; Luck, 2005).

Local field potentials are recorded on the cortical surface when pyramidal cells are arranged orthogonally to the cortical surface (Luck, 2005; Nunez & Srinivasan, 2006; Speckman et al., 2011). Synchronous field activation across a cortical patch stimulates the far-field potentials that are subject to volume conduction, which is measured by scalp electrodes (Makeig & Onton, 2011). Only local field activity that is synchronous across a particular source domain will contribute to the potential registered by scalp electrodes. Therefore, the distance of the sensor from the cerebral source will determine accuracy of modelling for that particular source, along with interference from artefactual extra-cerebral sources (Makeig & Onton, 2011).

2.1.3. Source dipole modelling

Identification of cortical generators of scalp potentials and oscillations is a challenging issue in EEG research and practice. The need to identify cortical generators is essential, especially if EEG data are affected with extracerebral artefacts such as in wireless EEG recordings in freely behaving humans. Extracerebral artefacts, which can impede the ability to identify underlying neural events, include; eye-movement artefacts, muscle contractions, cardiac activity, cable sway, line noise and EEG sensor displacement. Broad local field potentials are attenuated by the different materials through which they must pass to be detected by scalp electrodes (Nunez & Srinivasan, 2006), including the scalp, the skull, cerebrospinal fluid (CSF) and the brain itself (Makeig & Onton, 2011; Nunez et al., 2019; Nunez & Srinivasan, 2009). These cortical field potentials are met with resistance at each of these materials, which spatially distorts and diminishes the signal, and the resulting signal is registered on scalp electrodes (Makeig & Onton, 2011).

Loci of neural activity that produce a particular voltage distribution on the scalp in event related potentials (ERPs) can be estimated using source localisation techniques (Slotnick, 2005). Source localisation estimation is hindered by the inverse problem, which refers to the fact that when researchers work backwards to predict accurate source locations, there are multiple possible configurations of cortical generators that can explain a particular scalp voltage topography (Grech et al., 2008; Lopez, Rincon & Shimoda, 2016; Slotnick, 2005). Therefore, there are many possible *inverse solutions*, and selecting a solution depends on a-priori information and additional mathematical or anatomical parameter constraints (Durka et al., 2005; Slotnick, 2005). The forward problem refers to estimation of electrical scalp potentials resulting from primary current sources using models (Mosher et al., 1999).

The forward solution modelling accounts for signal distortion and alterations caused by different tissue properties and assumes a specific model for cortical activity, since only certain configurations of neurons can produce far field potentials measurable at the scalp. The cortical activity is modelled using location of source activity, assuming a spherical head model with Cartesian coordinates (0, 0, 0) representing the centre and location coordinates of the dipole (x, y, z) are fitted in reference to the centre. As can be seen in Figure 2, to provide forward solution, vector *r* from the negative charge towards the positive charge is then fitted using spherical moment parameters (*m* - dipole magnitude, and Θ, Φ defining orientation) and *M* representing dipole moment (i.e., measure of separation between the positive and negative ends of the dipole), are used to calculate the area of interception of the dipole and the matrix of electrode coordinates defining their localisation on the surface of the spherical head model (Figure 2). While dipole moment, magnitude and orientation parameters can vary over time, it is assumed that a particular dipole is invariant in terms of location and orientation over time (Scherg, 1990; Slotnick, 2005), resulting in the forward solution.

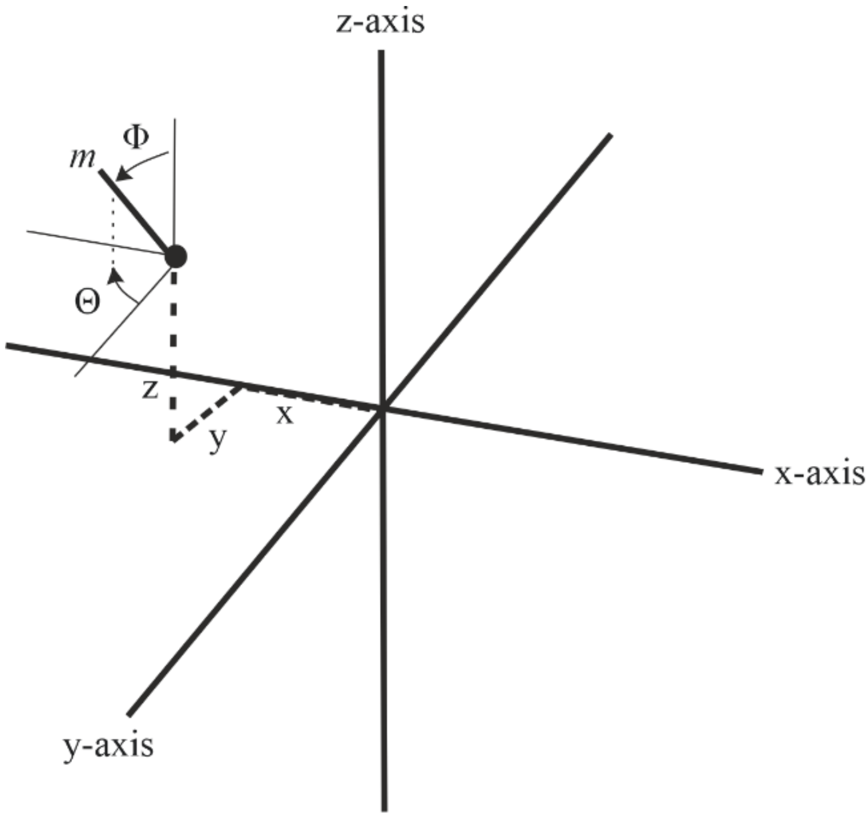

Figure 2. Dipole and matrix of electrode coordinates defining their localisation on the surface of the spherical head model, with Cartesian coordinate location parameters *r* (x, y, z), and dipole moment parameters *M* consisting of *m*, representing dipole magnitude and Θ, Φ defining orientation of the dipole. Reproduced from (Slotnick, 2005).

Building on the forward solution, the inverse solution involves non-linear model fitting algorithms to iteratively modify the parameters outlined by the forward solution, such as dipole location, time course, orientation and magnitude, in a way that minimises the sum of squares error, reducing the discrepancy between the model fit and the data (Slotnick, 2005). Specifically, the dipole fitting method of source localisation involves the iterative adjustment of the model voltage parameters (V_{model}), generated by the forward solution to best fit the neural data reflected in voltages recorded at the scalp electrodes (V_{data}). Dipole time course parameters can be fitted using a linear regression separately to the dipole fitting routine. Such parameter fitting routines include the Levenberg-Marquart method (Marquardt, 1963), the simplex method (Nelder & Mead, 1965), simulated annealing (Kirkpatrick, 1984) and generic algorithms (McNay et al., 1996; Slotnick, 2005).

The following factors are essential for the optimisation of the inverse solution: number of electrodes, solution constraining, head models and source localisation accuracy (Slotnick, 2005). An increased number of electrodes provides more information about underlying signal generators, thus, increases source localisation accuracy. It has been indicated that around 100 electrodes is likely to produce optimal source localisation as it allows adequate sampling of scalp voltage topographies (Laarne et al., 2000). Parameter constraints can increase the accuracy of source localisation, such as rejecting dipole solutions that are located outside of the head or limiting the number of dipoles by matching them to the expected number of neural sources. Initial dipole parameters can be randomly varied to reduce user involvement and convergent results represent the global minimum rather than the local minima of dipole parameters (Huang et al., 1998; Slotnick, 2005). Alternatively, a-priori knowledge regarding number of expected dipoles can be employed to specify initial parameters. Realistic head models, using the boundary element method or the finite element method, can provide more accurate approximations of head shape and conductivities of the skull, brain and scalp. However, such methods are extremely computationally demanding and still do not reflect accurate representations of the head, suffering from model misspecification and source localisation errors, particularly when multiple cortical sources are present. Source localisation has been shown to accurately predict sources up to approximately 1 cm using four-shell spherical head models (Slotnick, 2005).

Overall, while analysis of the voltage topography of an ERP can allow researchers to indicate underlying source generators of activation, source localisation techniques take this one step further, affording the accurate estimation of the location of the voltage source in the cortex (Slotnick, 2005). To estimate cortical sources, experimental chapter 1 in the current thesis estimated equivalent current dipoles using a sequential strategy describing the 3-dimensional source currents (Hoechstetter et al., 2010; Scherg & Von Cramon, 1986) and experimental chapters 2 and 3 used a spherical head model in Dipfit 2.

2.1.4. Independent component analysis (ICA)

ICA is a higher order statistical spatial-filtering technique which can be used to linearly decompose mixed EEG signals recorded on the scalp into independent source components, allowing researchers to detect signal sources and to measure the spatio-temporal characteristics of the brain (Calhoun et al., 2009; Ullsperger & Debener, 2010). Importantly, ICA affords separation of cerebral from extra-cerebral artefactual activity facilitating the removal of artefactual noise, and is able to linearly decompose neural activity into independent sources, assisting the interpretation of distinct spatial-temporal components that comprise the EEG signal (Vigârio et al., 2000). There are a number of different ICA techniques available including InfoMax (Bell & Sejnowski, 1995), joint approximation diagonalization of eigen-matrices (Cardoso & Souloumiac, 1993), FastICA (Hyvärinen, 1999), second-order blind identification (Belouchrani & Abed-meraim, 1997) and adaptive mixture ICA (Palmer et al., 2011).

ICA does not assume prior knowledge and uses blind source separation to decompose the multi-channel EEG signal (Bell & Sejnowski, 1995). Unlike PCA, there is no order of magnitude associated with the components in ICA (Langlois et al., 2010). The ICA method assumes that scalp signals are an amalgamation of constituent signals, both neural and artefactual, with spatially-fixed scalp distributions and independent temporal properties (Jung et al., 2000). When applied to multiple electrodes, ICA trains spatial filters which each focus on a single source in the data (Makeig & Onton, 2011). ICA assumes that the number of components that comprise the signal should be equal to the number of channels utilised during the recording and does not impose conditions on spatial filters, enabling IC components that overlap spatially to be separated temporally (Jung et al., 2000). Consequently, this provides more precise measurement of individual EEG source potentials and reduction of source signal mixing despite broad spread due to conduction through the brain, skull, and scalp (Makeig & Onton, 2012). When PCA cannot be used because amplitudes are comparable, ICA is an effective method for separating intra-cerebral neural data from a wide range of extra-cerebral artefacts (Jung et al., 2000). Central to the assumption of applying ICA to artefact removal in EEG data is the idea that artefacts and neural components are temporally distinct at the statistical level (Jung et al., 2000), allowing for removal of stereotypical ocular artefacts such as eye-blinks, vertical and horizontal saccades (Nikolaev et al., 2016). ICA is the gold standard routinely used in EEG artefact removal, particularly for mobile brain/body imaging (MoBI) data obtained in naturalistic settings, which is prone to an increased number of artefacts associated with free movement of the body and eyes (Delorme & Makeig, 2004a; Nikolaev et al., 2016; Protzak & Gramann, 2018). However, artefacts with atypical topographies and waveforms must be precisely marked in order to be detected using blind source separation methods such as ICA. ICA decomposition is influenced by multiple factors including movement, number of EEG channels and high-pass filter, which can affect estimation of neural sources (Klug & Gramann, 2020). To ensure adequate ICA decomposition, high-density EEG recordings should be obtained from no less than 64 electrodes and a high-pass filter of 1 – 2 Hz should be used depending on noise level (Klug & Gramann, 2020).

2.1.5. Principal component analysis (PCA)

PCA is a statistical technique used to decompose averaged ERPs into their component parts to extract linear combinations of variables whilst accounting for covariance in the data, particularly when the EEG signal is an amalgamation of many highly correlated variables (Dien & Frishkoff, 2005; Dien, 2012). PCA is a type of factor analysis applied across time points and electrodes to extract latent components associated with separate ERPs, providing statistical separation of neural data detected at the scalp (Dien & Frishkoff, 2005). PCA is useful for reducing data dimensionallity, data cleaning and filtering prior to analysis, and can also be applied to detect events by using spatial patterns to decompose the data into latent temporal patterns (Dien & Frishkoff, 2005). There are a number of PCA techniques, including temporal (Dien & Frishkoff, 2005), spatial (Dien, 1998), sequential (Spencer et al., 2001) PCAs and partial least squares (Lobaugh et al., 2001).

There are three stages to a PCA. Firstly, the continuous variables are standardised to prevent distortion due to extended ranges between variables, a covariance matrix is computed which allows investigation of the relationship between continuous variables and whether they co-vary with respect to the mean. Next, eigenvectors (direction of axes where there is maximal variance) and eigenvalues (amount of variance in each principal component) are computed from the covariance matrix to determine the principal components. The principal components which explain the largest amount of variance in the data are presented first, with other principal components arranged in descending order of amount of variance explained. Eigenvalues of each component are divided by the sum of eigenvalues to determine the percentage variance explained by each principal component. Principal components that explain less variance in the data can be disregarded at this stage to reduce data dimensionality in the feature vector. Finally, the feature vector created from selected principal components reorients the data from the original axis to the one represented by only selected principal components by multiplying the transpose of the original data by the transpose of the feature vector (Jaadi, 2019).

In Brain Electrical Source Analysis (BESA, MEGIS Software GmbH, Munich, Germany, version 6.1), the EEG data can be reduced using PCA prior to ICA decomposition, with components that explain less than 1% of variance ignored. Additionally, artefacts can be removed using adaptive spatial filtering in BESA. The adaptive artefact correction method involves scanning of specific defined epochs considered to represent artefactual activity, and the segment is thought to reflect artefactual activity if the correlation between data and the artefact exceeds a certain threshold and the signal amplitudes are above a certain threshold. Subsequently, a PCA (Berg & Scherg, 1994) is then performed on the segments and the components that explain more than the minimum variance specified by the adaptive model have their topographies maintained. The PCA decomposes the matched components and the component with the highest *p* value explaining the least variance (e.g., below 5 to 10% of data variance) is then subtracted from the EEG data (Ille et al., 2002), effectively removing the artefactual signals from the continuous EEG data. Overall, PCA can be an effective tool allowing for decomposition of EEG data in order to determine their temporally or spatially distinct components (Dien & Frishkoff, 2005).

2.1.6. Placement of EEG electrodes

EEG is a technology that measures the modulation of local field potentials on the cortical surface over time using specialised sensors placed at specified locations across the scalp. As standard practice, EEG electrodes are placed into elasticated caps which are developed based on the internationally recognised 10-20 system, a standardised guideline for distribution of electrodes on the scalp based on proximity to anatomical landmarks of the skull, including the nasion, the inion, and the left and right pre-auricular points (Jasper, 1958; Klem et al., 1999). The 10-20 system affords equal spacing of electrodes relative to each other across the scalp. It is vital that electrodes are placed consistently across participants, as even small errors in electrode positioning can lead to large changes in the measurement of electrical potentials on the scalp.

To place the caps in a standardized manner across participants, a measurement of the circumference of the head is made to determine cap size. If the subject is in between cap sizes, the experimenter rounds down the measurement and the smaller cap is selected to receive a better connection between the scalp and the sensor. To place the cap according to the 10-20 system, a measurement is taken from the anterior (nasion) to the posterior plane (inion) through the vertex and a vertical line is marked at the midpoint using a blunt water-soluble pen. Following this, a measurement is made between the left and right pre-auricular points and a horizontal line is marked at the midpoint, converging with the vertical line to form a cross in the centre of the head. Electrode Cz is then positioned at the intersection where the two lines converge, indicating that the horizontal and vertical planes of the head have been correctly aligned (Figure 3).

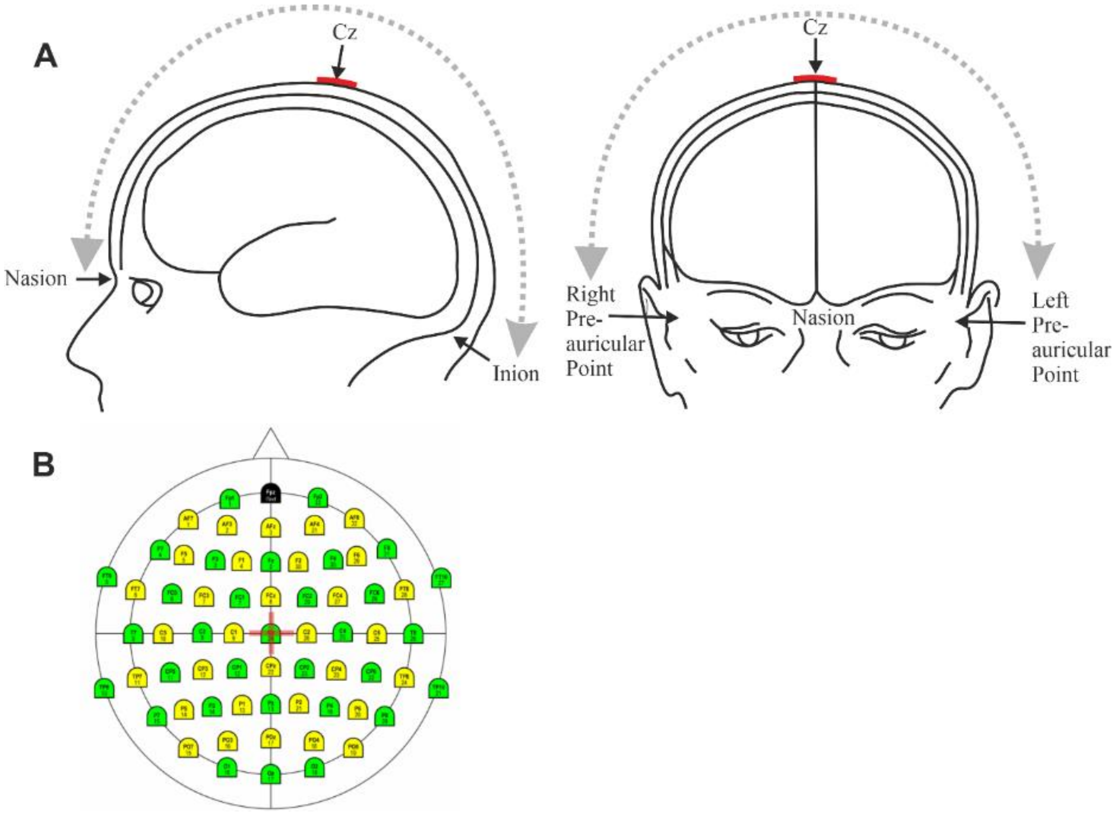

Figure 3. (A) Diagram illustrating how the cap is placed according to the standardized 10:20 system, relative to the midpoint between known anatomical landmarks. Red line indicates pen marks made in order to identify the midpoint and consequently Cz location on the X and Y axis. (B) Schematic representation of the Brain Products actiCHamp standardized 64-electrode layout (Brain Products, GmbH, Munich, Germany), with the red cross indicating a central placement of the cap on the participants head.

Adequate scalp connection is important for maintenance of EEG signal quality which allows for optimal ICA decomposition and source localisation. The highly viscous Super Visc electrolyte gel (Brain Products) creates a column of gel between the hair within the electrode holder, reducing the gap between the sensor and the scalp, helping to maintain stable signal quality and low impedance levels during the task. Less viscous electrolyte gels tend to degrade over the course of the experiment, requiring the addition of more gel to maintain signal quality, which can produce electrical bridging between nearby electrodes and this can reduce the ICA decomposition accuracy (Alschuler et al., 2014).

Although as few as 35 channels are sufficient for identification of some dominant neural sources (Lau et al., 2012), a minimum of 64 electrodes are required for optimal ICA decomposition and identification of underlying source components (Klug & Gramann, 2020; Lau et al., 2012). 64 electrodes are more applicable in the mobile settings than more precise 128-channels as they significantly reduce time for equipment application and experimental set-ups, reducing likelihood of signal degradation.

The EEG signal reflects the voltage potential difference between an electrode and a reference electrode (Luck, 2005), which can be a unipolar reference electrode (Cz, Fz, Oz, FCz are commonly used), the nose, or linked mastoids. Moreover, a Laplacian reference can be used, which detects the difference between the potential at each electrode and the averaged potential of nearest four neighbouring electrodes, or averaged reference can be utilised, which is an average potential over all electrodes (Yao et al., 2019).

2.2. Mobile EEG signal acquisition and pre-processing

A new generation of neuroscientific research has sought to examine the neural dynamics underlying natural cognition in more ecologically valid environments utilising mobile neuroimaging techniques such as mobile fNIRS (Krampe et al., 2018) and mobile EEG (Lau-Zhu et al., 2019). The MoBI approach typically investigates natural cognition and embodied dynamics using mobile EEG whilst participants freely move and behave, often in conjunction with other body imaging methods such movement analysis or eye-tracking. The MoBI approach affords investigation of the relationship between movement, cognition and the brain in natural settings (Jungnickel & Gramann, 2016). A number of different mobile EEG systems exist, ranging from consumer grade wearable systems with a low number of electrodes such as Muse, (Interaxon, Toronto, Canada), Mindwave (Neurosky, San Jose, USA) and Epoch (Emotiv, California, USA), to electrode dense research grade systems such as Brain Products MOVE (Brain Products, GmbH, Munich, Germany), LiveAmp 64 (Brain Products), eego (Ant Neuro, Hengelo, Netherlands), SMARTING mobile EEG amplifier (mBrainTrain, Beograd, Serbia) and Quick wireless headset (Cognionics, San Diago, USA).

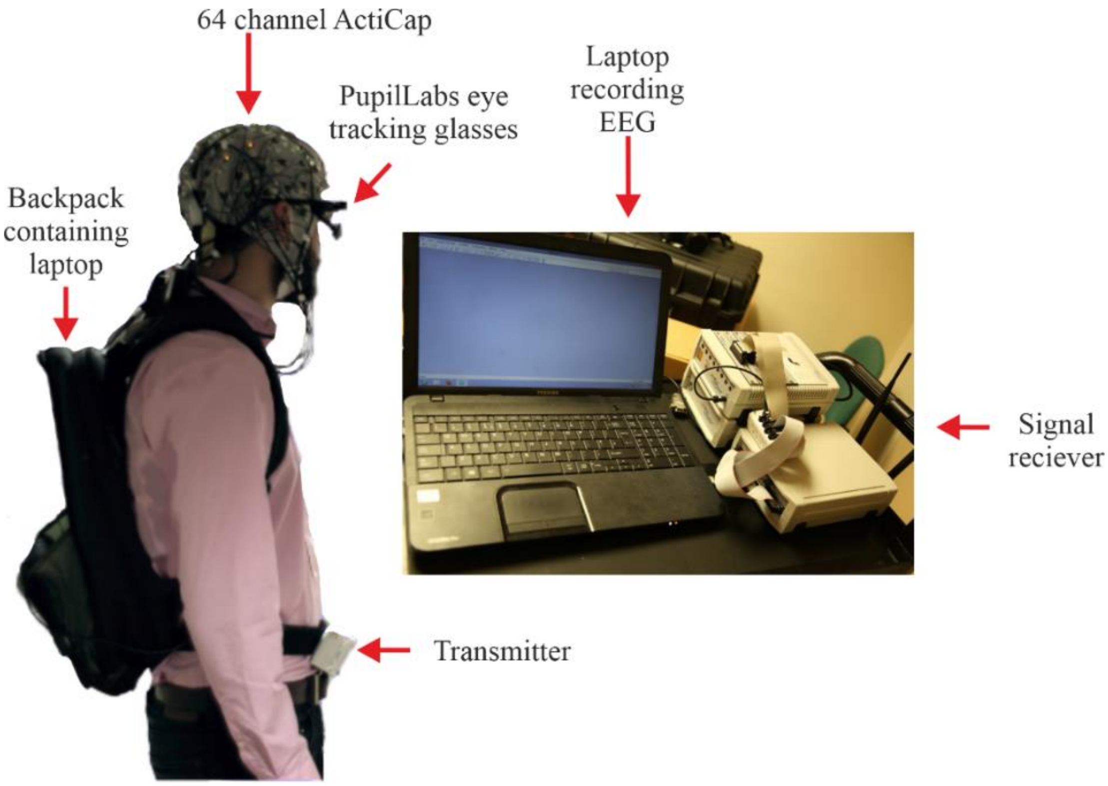

Figure 4. A participant wearing the 64 channel Brain Products actiCap, 64 active shielded electrodes which are plugged into the Brain Products MOVE system transmitter, attached to a Velcro belt worn by the participant. The MOVE system receiver is attached to the actiChamp amplifier.

The Brain Products 64 channel MOVE system is a commonly used research grade mobile EEG system (Gramann, 2014; Jungnickel & Gramann, 2016; Marini et al., 2019), see Figure 4. The Brain Products MOVE system utilises active Ag/AgCl electrodes which contain active circuits called impedance converters which make it possible to record high quality EEG signals in situations where high impedance levels are likely, such as during walking. Optimising the connection between the scalp and the electrode is even more essential in mobile EEG recordings as participants are walking and the signal quality could suffer from high-impedances due to electrode movement. Active electrodes reduce resistance between the sensor and the scalp using a voltage divider, which acts as a 1:1 amplifier, reducing the impedance of the signal and not allowing any feedback from the output of the conversion. By decreasing the resistance, the signal is amplified, and protected from electrode lines and external source interference; see Figure 5. Mobile EEG systems often utilise active electrodes to reduce the presence of line noise and movement artefacts in the EEG data.

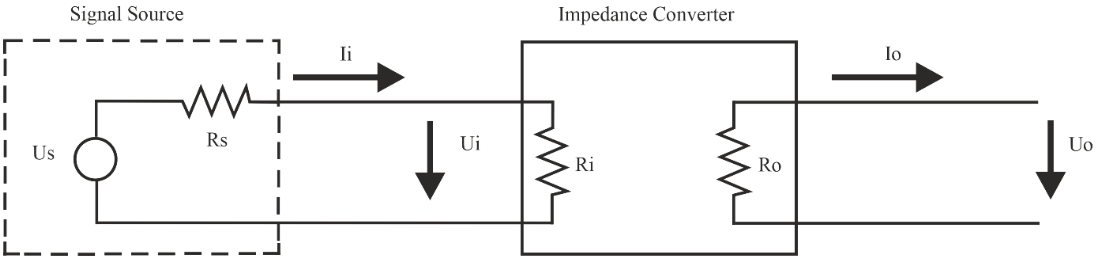

Figure 5. Schematic representation of an impedance converter inputs and outputs signals in active shielded electrodes, adapted from the actiCHamp documentation (2016, Brain Products, GmbH). Us and Rs refer to source current and source resistance, respectively. Ui refers to the input voltage at the input resistance Ri. Ii refers to impedance input and Io refers to impedance output. Ro is output resistance, which is smaller, and acts as a power amplifier. Uo is the output voltage.

2.2.1. Methods for synchronisation of eye-tracking and mobile EEG data streams

The inability to control stimulus onset in natural conditions presents a methodological issue for mobile EEG, and, as such, a secondary eye-tracking data stream is necessary to provide natural stimulus onsets when the subject's gaze touches an object. The addition of an eye-tracking data stream is one of the biggest challenges within the field of MoBI, as it must be precisely synchronised to the EEG data stream in order for ERPs to be accurately time-locked to the onset of the visual stimulus (Artoni et al., 2018). Synchronisation of multimodal data is challenging as different data streams are likely to have different sampling rates, and there could be sporadic delays in the individual equipment, the recording software, the operating system, or if using an online platform, the network, which can all introduce temporal jitter (Delorme et al., 2011). Different methods have been proposed to overcome the issue of data stream synchronisation in MoBI research, including online synchronisation platforms (lab streaming layer, LSL); the experimental real-time interactive control and analysis (ERICA) framework, and hardware (combined TTL and light pulse) solutions.

LSL (Kothe, 2014) is an online open source synchronisation platform which is capable of synchronising multimodal data streams over a network in real time during recording. LSL consists of an LSL application programming interface and a core library (liblsl) available across programming platforms for communication between multiple systems. Liblsl incorporates a suite of tools such as a recording program, file importer, viewing recorder, and apps for acquisition software such as eye-tracking, EEG, motion capture audio and video. Data is provided to LSL by creating a program which pushes a data stream through an outlet sample by sample as a multichannel vector. Receiving data involves discovering the stream on the network by the type of data stream; once discovered, an inlet is opened and samples of the data stream are pulled out.

A limitation of LSL is that it relies on optimal network latency, a strong battery life and a high bandwidth for reliable transmission of data over the network and, ultimately, accurate synchronisation of data streams. A major issue with LSL is that because it is reliant on the network, it is possible to fall out of network range which can result in data loss. Furthermore, differences in refresh rates can cause temporal jitter in the time stamps of the data sets during synchronisation and even refresh rates of up to 120 Hz are unable to account for this issue (Ladouce et al., 2017). Additionally, not all hardware is currently supported by LSL. EEG hardware supported include Biosemi, Cognionics, Mindo, EGI Ampserver and eye-tracking hardware supported include SR Research Eyelink and custom 2 camera setup. Therefore, LSL only provides a solution for certain MoBI systems (Artoni et al., 2018).

The ERICA framework (Delorme et al., 2011) consists of an online multimodal data collection, synchronisation and processing platform which synchronises multimodal data in real time using an application called DataRiver which streams from Matlab (Delorme et al., 2011). Within the ERICA framework, data streams are individually converted into a device-independent stream which is merged in real time into a river over a local area network or internet subnet. The data can be viewed and processed in real time using the DataRiver client running in MATLAB. The framework offers a high synchronisation accuracy of up to 2 ms between data streams

(Delorme et al., 2011). However, the DataRiver application is available for a limited number of EEG systems (Biosemi) and relies on local network connection.

An alternative method of EEG and eye-tracking data synchronisation which is not dependent on network performance or recording hardware involves delivery of a transistor-transistor logic (TTL) pulse to the EEG with a simultaneous light pulse delivered to the eye-tracker. The TTL light pulse method has proved effective for synchronisation of EEG, magnetoencephalography and eye-tracking data streams in naturalistic settings (Artoni et al., 2018; Soto et al., 2018). The combined TTL and light hardware solution to data stream synchronisation provides a useful alternative to online synchronisation techniques and can be used as a backup method of synchronisation in all instances so that data is never lost due to network dropout. Consequently, a combined TTL and light synchronization method was utilised in the experimental chapters of the current thesis.

2.2.2. EMRPs

EMRPs, or saccadic eye-movement related potentials, afford investigation of cognitive processes elicited during free eye-movement, such as sensorimotor integration (Jagla et al., 2007). Traditional laboratory-based experiments have limited saccade-related eye-movements due to the large number of associated artefacts that are produced. However, saccades can carry important information as natural cognition involves rapid shifting of the gaze and integration of visual information over successive saccades (Jagla et al., 2007; Melcher & Colby, 2008; Prime et al., 2011), short-term memory processes (Hollingworth et al., 2008) anticipation and prediction of visual information (Dias et al., 2013) and parafoveal processing of information prior to fixation (Degno & Liversedge, 2020).

In accordance with VEPs, EMRPs encompass averaged electro-encephalographic cortical potentials time-locked to the onset or offset of a saccade (Jagla et al., 2007; Nikolaev et al., 2014; Thickbroom et al., 1991; Yagi, 1979), rather than to a static visual image. EMRPs display similar characteristics to VEPs as they are both thought to be generated by retinal stimulation and elicit voltage potential deflections relative to baseline (Thickbroom et al., 1991). Conversely, fixation-related potentials are time-locked to the onset or offset of a fixation, when the eye-movement is ceased (Wenzel et al., 2016). The earliest reported EMRP was a positive occipital wave in occipital cortex following rapid saccades, known as the lambda potential (Green., 1957). The well documented lambda component is an EMRP that is elicited in response to visual stimuli with a peak around 100 ms post stimulus onset and an occipital positive maximum (Kazai & Yagi, 2003; Thickbroom et al., 1991; Yagi, 1979; Yagi, 1981). The lambda potential is known to be modulated by the structure of the visual background and illumination (Gaarder et al., 1964).

Saccadic EMRPs time-locked to the onset of saccades have been recorded over the occipital and posterior parietal cortex, reflecting premotor eye-activity known as the saccadic spike potential (SSP) (Thickbroom & Mastaglia, 1986). SSP reflects the use of oculomotor muscles initiating the saccadic eye-movement, peaking shortly after the onset of the saccade (Jagla et al., 2007). The SSP can modulate the amplitude of the lambda component (Yagi, 1979). Other EMRP components have been reported in posterior parietal cortex and frontal eye-fields, with modulation according to attention, information processing and command-related functions (Jagla et al., 2007; Kurtzberg & Vaughan, 1982). Saccades have been shown to represent important indexes of selective attention in natural environments, and have been investigated in the scanning of scenes, pictures, and during reading (Liversedge & Findlay, 2000).

Experiments investigating saccade-related potentials have demonstrated the influence of lower-level and higher-level semantic influences on eye movements and the processing of information (Liversedge & Findlay, 2000) and pre-saccadic extra-foveal neural activity has been linked to trans-saccadic prediction of stimulus category (Buonocore et al., 2020).

2.2.3. Technical and methodological issues in MoBI research

There are a wide range of hardware and software solutions available for recording and analysing brain activity during active behaviour (Jungnickel & Gramann, 2016) and a standard MoBI approach is yet to be determined. However, a number of methodological and technical issues have already been identified, and each must be considered when examining neural dynamics in natural environments using the MoBI approach (Gramann, 2014; Gramann et al., 2010; Gwin et al., 2010; Makeig et al., 2009; Ojeda et al., 2014) to ensure high-quality data reflected in its accuracy, completeness, consistency and reliability.

One of the most challenging issues for MoBI research is minimising the large amount of artefactual noise associated with free-movement in unconstrained environments (Gramann, 2014; Gramann et al., 2010; Gwin et al., 2010; Makeig et al., 2009; Ojeda et al., 2014) to increase the signal to noise ratio (Gwin et al., 2010; Ladouce et al., 2017). The EEG signal can become contaminated by many artefacts, both within and outside of the body, which can fluctuate during movement in natural paradigms. Extra-cerebral artefacts originating from non-neural events include movement of the head and neck when the subject orients their head towards a stimulus in the environment (Gwin et al., 2010). Eye-movement artefacts including blinks, saccades or the saccadic spike potential can distort underlying neural data and are generated by an eyelid movement, rotation of the corneo-retinal dipole or extra-ocular muscle contractions (Keren et al., 2010). Further biological artefacts include cardiac activity, movement and muscle contractions (Jung et al., 2000). Artefacts originating from non-biological sources which can occur during movement and through the use of natural paradigms include cable sway artefacts, line noise, and displacement of EEG sensors during movement which can alter ICA decomposition (Makoto, EEGLAB Wiki, SCCN 2019) and limit the ability to estimate neural sources of evoked potentials.

Other issues associated with recording natural behaviours concern the inherent trade-off between maintaining experimental control to limit artefactual noise and maintain a high signal-to-noise-ratio, and enhancing ecological validity by the facilitation of free behaviours and associated neural responses within natural environments (Ladouce et al., 2017). For example, in comparison to standard EEG, MoBI set-ups are longer, which can cause electroconductive gel to dry out contributing to the degradation of signal quality over the course of the experiment. Addressing the conductivity issues by topping up electroconductive gel or saline solution during a naturalistic recording can impede the flow of the experiment and can result in electrical bridging across electrodes (Alschuler et al., 2014; Gramann et al., 2014). High-density dry electrode systems that perform at the same level as the wet systems are yet to be developed to resolve this issue (Ladouce et al., 2017; Oliveira et al., 2016).

Another issue for naturalistic MoBI recordings is the lack of triggers to define stimulus onset. Body dynamics can be used to define stimulus onset during MoBI experiments, including heel strikes for measurement of movement dynamics (Gwin et al., 2011; Ladouce et al., 2017) or delivery of an auditory stimulus while the subject navigates a natural environment (Reiser et al., 2019). Investigation of visual attention in natural environments necessitates the use of a secondary eye-tracking data stream to determine precisely when the participant's gaze first touches a stimulus, and this can be used as an onset trigger during everyday real-world cognition (Ladouce et al., 2017). However, eye-trackers rely on accurate gaze calibration, and this cannot be ascertained in natural environments without stable reference points, therefore it is essential for gaze to be accurately deciphered to allow for examination of evoked potentials (Nikolaev et al., 2016). Moreover, the addition of another data stream can be problematic as both data-sets need to be precisely synchronised in order for triggers to be precisely time-locked to the onset of the visual stimulus (Dimigen & Ehinger, 2019). Finally, due to the lack of control over visual presentation during free-viewing in natural environments, evoked potentials elicited from MoBI and eye-tracking data can temporally overlap and must be distinguished (Dimigen et al., 2011; Stephani et al., 2019).

2.2.4. Solutions for artefact identification and removal in mobile EEG

The separation of cerebral from extra-cerebral artefacts is one of the most pressing challenges for mobile EEG research. Consequently, a number of practical and data cleaning solutions have been proposed to prevent or detect and remove movement-related artefacts, which are described below.

Practical measures can be taken during mobile EEG recordings to reduce artefact contamination; for example, cable sway artefacts can be reduced by clipping electrode strands to the subject's clothes (Soto et al., 2018). Additionally, using digital filters can allow identification and removal of extra-cerebral EEG contaminants and line noise can be reduced by using a 50 Hz notch filter (Leske & Dalal, 2019).

A traditional technique used for artefact removal in EEG is the regression method (Jiang & Bian, 2019). The regression method assumes that activity at each EEG electrode reflects a mixture of neural and artefactual activity. Amplitude relations between the reference channel and each EEG electrode are defined by transmission factors and then estimated artefacts are subtracted from the data. A limitation of regressions is that they require one or more reference EOG and ECG channels for the removal of artefacts (Jiang et al., 2019).

PCA (Berg & Scherg, 1991) is a well-known blind source separation method that is widely used to separate artefacts from neural data (Jiang et al., 2019). The PCA technique involves converting the correlated variables that make up the EEG signal into uncorrelated values called principal components, which are ordered from most to least explained variance in the data. Artefacts explaining a large proportion of variance in the data such as eye-blinks can then be identified and removed from the data using an inverse operation (Berg & Scherg, 1991; Jiang & Bian, 2019). Although it has been suggested that PCA is more efficient in terms of computation than regression methods, PCA is limited in that similar artefacts are not separated (Casarotto et al., 2004; Jiang & Bian, 2019).

ICA (Bell & Sejnowski, 1995) is a blind source separation method that is a widely applied to the remove artefactual contaminants such as ECG, EMG, eye-movements and blinks from EEG data (Makeig et al., 2009). A minimum of 64 electrodes are recommended for optimal ICA decomposition (Klug & Gramann, 2020). ICA is often utilised for MoBI data obtained in naturalistic settings as it is useful for extracting artefacts associated with free movement of the body, head and neck muscles and the eyes (Delorme & Makeig, 2004; Makeig & Jung, 1996; Makeig et al., 2002; Nikolaev et al., 2016; Protzak & Gramann, 2018). In addition to detecting artefacts, ICA can also be used to detect independent spatially and temporally distinct source activities that contribute to the overall observed scalp signal (Makeig et al., 2009). However, spatial filtering techniques such as ICA are unable to detect non-typical artefacts, such as saccades from every angle of viewing excluding vertical and horizontal saccades, unless they are discretely marked out. Therefore, methods of detecting atypical artefact topographies prior to ICA decomposition are needed. A combination of practical measures and ICA and PCA methods were utilised in the current thesis to correct ocular artefacts, drawing on guided saccade recordings for discrete marking of eye-movement artefacts.

2.2.5. Advantages and limitations of mobile EEG

Mobile EEG offers excellent temporal resolution which affords investigation of neural dynamics in real time with millisecond precision without constraining movements, which could alter natural responses. Neural dynamics underpinning behaviour in naturalistic environments is often guided by visual attention (Nikolaev et al., 2014). For instance, visual exploration of the environment is multi- and trans-saccadic, and information is integrated across successive saccades and fixations to direct visual attention (Dimigen et al., 2011; Prime et al., 2011; Ray et al., 2011). EEG experiments which do not allow for free eye-movements omit context, which can alter neural activations (Ladouce et al., 2017; Neisser, 1976), and brain states are known to differ during movement. Therefore, it is essential to verify laboratory-based findings of the neural dynamics of cognition in natural environments in order to determine whether findings actually reflect natural cognition.

Mobile EEG has a number of technical limitations which must be considered; these include the lack of triggers necessitating eye-tracking which must be precisely synchronised to the EEG, the lack of stable reference points for accurate gaze detection (Nikolaev et al., 2016), the large number of artefacts associated with movement (Gwin et al., 2010; Jung et al., 2000) and the degradation of signal quality over time (Lau-Zhu et al., 2019). Although the spatial resolution of EEG is limited compared to neuroimaging methods such as fMRI, cortical sources can often be accurately estimated using source modelling techniques (Lystad & Pollard, 2009). Additionally, there is currently no standard procedures for MoBI data collection and artefact removal. To investigate the spatio-temporal dynamics of SV in naturalistic settings, the experimental chapters of this thesis utilised mobile EEG and developed experimental paradigms to overcome the technical limitations associated with mobile EEG recordings.

2.3. Eye-tracking

Investigation of visual behaviours predates the 19th century, with early experimenters using mirrors to examine eye-movements during reading. During exploration of a natural visual scene, participants make a number of rapid eye-movements called saccades which are interrupted by pauses called fixations (Salvucci & Goldberg, 2000). Javal (1879) and Lamare (1892) pioneered the eye-tracking technique and discovered the presence of saccades and fixations. The first modern day computer-based eye-tracker, the oculometer, was developed in the 1960s (Merchant, 1966). Portable head-mounted eye-tracking revolutionized the investigation of visual behaviour in 1994 by allowing for movement of the head (Mohamed et al., 2007), affording examination of more naturalistic visual behaviours in the real-world.

2.3.1. General principles of eye-tracking

Eye-tracking is a standard research method directly measuring visual attention. Continuous recording of eye-movements allows for precise estimation of the location of the participants gaze by measuring the position of their eyes relative to their surroundings, or to their head (Singh & Singh, 2012). High sampling rates of eye-trackers provide excellent temporal resolution, affording investigation of gaze behaviour in an environment over time (Nikolaev et al., 2016). Underlying cognitive processes are inferred through examination visual angle, duration, length and frequency of saccades and fixations (Raney et al., 2014). A saccade is characterised by higher thresholds of velocity and acceleration (Konig & Buffalo, 2014), whereas fixations have lower thresholds and are relatively static despite containing micro-saccades, tremor and drift (Duchowski, 2017). Fixations can last from tens of milliseconds to several seconds, and are thought to index visual attention as information is taken in by the fovea (Holmqvist et al., 2011).

In the human eye, the iris permits light to the retina by expanding and contracting the pupil and the lens focuses the image on the retina, within the fovea which is filled with photoreceptors. These cells transduce light into electrical impulses and relay this to the optic nerve, which translates the information to the visual cortex (Singh & Singh, 2012). A dominant method for gaze estimation in eye-tracking relies on identification of eye-movements through detecting the pupil relative to the surrounding iris, and the corneal reflection is sometimes used as an additional reference point (Holmqvist et al., 2011).

In recent years, a range of head mounted eye-trackers have become available, affording investigation of natural behaviours in conjunction with mobile EEG. Head mounted eye-trackers include the EyeLink II (SR Research, EyeLink, Ontario, Canada), which incorporates three cameras on a padded headband, two eye-cameras, and a head-tracking camera to track the subject's field of view. Furthermore, the Tobii Pro Glasses (Tobii Pro, AB (publ), Stockholm, Sweden) utilise four eye-cameras which incorporate dark pupil detection, a gyroscope, an accelerometer, and a scene camera for the subject's point of view, all within a lightweight pair of glasses, which wirelessly transmits the data. More recently, the Tobii Pro 3 glasses have been developed which integrate all eye-tracking components including 4 eye-cameras and a scene camera within the frame of the glasses, making them perfect for blending into natural environments. A cheaper alternative to the Tobii system is the wearable head-mounted Pupil Labs Binocular eye-tracking glasses (Pupil Labs, GmbH, Berlin, Germany), a lightweight, modular system that relies on infrared (IR) video-based oculography. These glasses incorporate two eye-movement recording cameras using dark pupil detection, and a forward-facing world-view camera to record the subject's field of view (Kassner et al., 2014). The Pupil Labs eye-tracking glasses were used to track the subject's gaze during free viewing of products in naturalistic environments in the experimental chapters of the current thesis.

2.3.2. Pupil detection

A leading technique for head mounted eye-trackers to detect the pupils is the dark pupil detection method, which was utilised by the head mounted eye-tracking hardware utilised in the experiments presented in the current thesis. The dark pupil detection method is an algorithm which converts the eye-recording to grayscale to increase contrast, enhancing estimation of the dark pupil region of interest, with the strongest response for the pupil according to the centre surround feature (Swirski et al., 2012). Subsequently, the contours of the eye are detected using the Canny edge detection algorithm (Canny, 1986). The darkest region within the eye is specified using the lowest spike in the pixel intensity histogram, which reflects the distribution of tonal range in the grey-level video. The remaining edges, outside of the darkest area, are filtered to exclude spectral reflections and the non-spectral reflected edges can be extracted into contours corresponding with the iris and connected components, whereby similar pixels are clustered. Sub-contours are isolated using curvature continuity criteria to define the common edge between iris and pupil. Potential pupil ellipses are then established through ellipse fitting using least square good-fit criteria, and an augmented combinatorial search is used to construct the final ellipses with supporting edges, encompassing the centre and surrounding of the pupil. The final ellipse's edges are assessed based on their length and circumference and must pass confidence thresholding in order to be reported as a detected pupil contour, otherwise, the ellipse must be redefined. Figure 6 shows an example of pupils detected using this method.

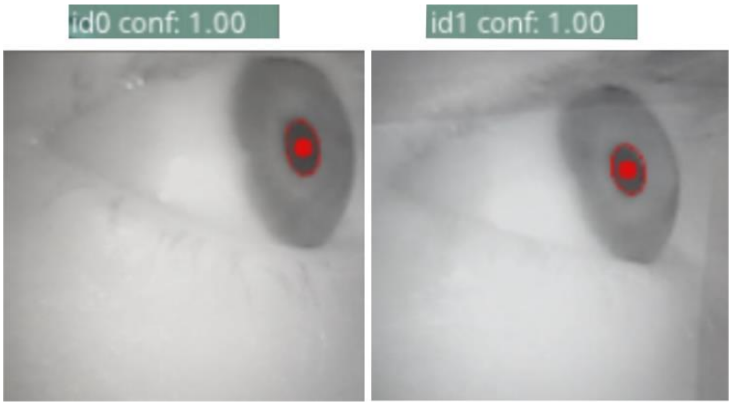

Figure 6. Calibrated left and right eye using the Pupil Labs Binocular eye-tracking glasses (Pupil Labs GmbH, Berlin, Germany). The pupils of both eyes were detected in the IR eye-cameras, indicated by the red ellipse, with the grey scale recording enhancing detection of the pupil. The pupils were detected with a high confidence threshold of 1.00 in both instances, indicating highly accurate pupil detection.

2.3.3. Eye-movements

Human eyes have a three-dimensional orientation inside the head facilitating horizontal, vertical and torsional eye-movements, and the orientation of the eyes determines the direction of the gaze (Holmqvist et al., 2011; Tweed & Vilis, 1990). The movement of the eyes can be broken down into three broad subdivisions; saccades, fixations and smooth pursuits. Saccades and fixations can be distinguished by their characteristics including velocity, acceleration, duration, and frequency. Saccades reflect frequent rapid movements of the eyes between stimuli in the environment, with enhanced velocity (30 – 100 °/s) and acceleration (4000 – 8000 °/s) thresholds (Holmqvist et al., 2011). Conversely, fixations have lower velocity and acceleration thresholds and must remain in a fixed position for a predetermined duration to be considered, ranging between 50 – 100 ms (Holmqvist et al., 2011).

Scan paths contain a sequence of saccades and fixations across a visual image. Within a scan path, the amplitude of the saccade can be measured as a vector between the origin fixation point A (F_1) and the end of the saccade; fixation point B (F_2), using the absolute direction φ and the relative direction φ'. The saccade angle θ can be calculated by computing the angle between the saccade axis and horizontal axis. These computations can be used to determine angle and amplitude for saccades of any orientation within a 360º circle; see Figure 7 for a visual schematic of saccade angles and direction computation.

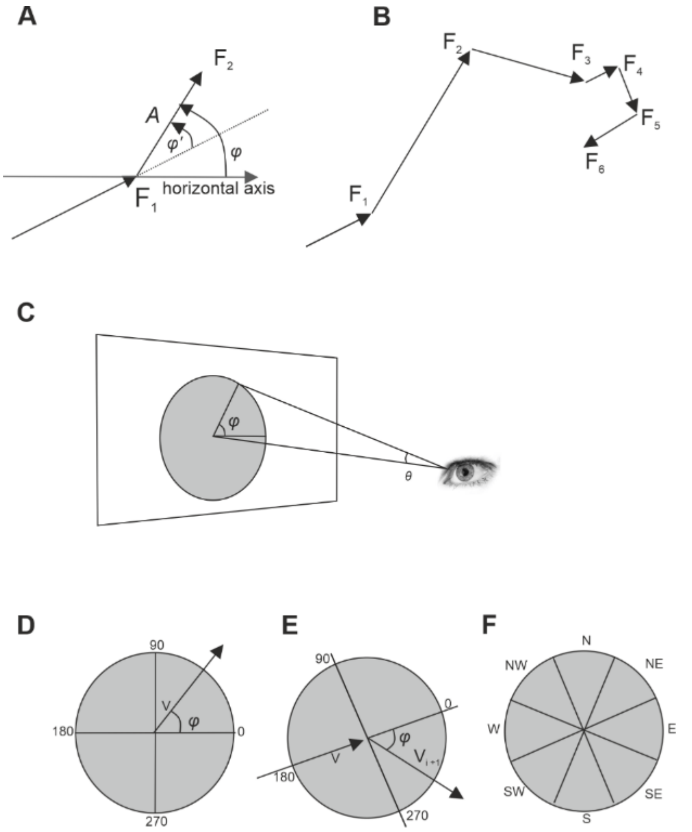

Figure 7. Saccade amplitude measurements adapted from (Holmqvist et al., 2011). (A) Saccade amplitude can be measured as a vector of fixation 1 (F_1) relative to fixation 2 (F_2), with the absolute direction φ and relative direction φ'. (B) A scan path containing a series of vectors, with the lines representing saccades and the arrows representing fixations (F_1 – F_6). (C) Saccade direction φ calculated by determining the angle between the saccade and horizontal axis, representing the saccade angle θ. (D) Absolute saccade direction (E) Relative saccade direction (C) Segmented saccade directions.

2.3.4. Gaze-tracking

To track a subject's gaze using a video-based binocular eye-tracker, 3-D gaze points must be estimated according to the relative positions of both eyes along the horizontal axis, according to principles of binocular geometry (Duchowski, 2017). Specifically, the pupils of both eyes are mapped and the vergence angle is calculated, which reflects the mid-point of the two eyes (Essig et al., 2006). The vergence angle is then geometrically computed in relation to the 3-D environment, providing a 3-D gaze position estimate which is extrapolated into the world-view video (Essig et al., 2006; Mlot et al., 2016).

The Pupil Labs binocular eye-tracker, utilised in the experimental chapters of the current thesis, relies on 3-D calibration to estimate gaze points, mapping the eye-position to the gaze direction, and a 9-point grid is commonly utilised for accurate gaze estimation (Cognolato et al., 2018; Hassoumi et al., 2019). For calibration, sequential fixations on screen calibration markers are required, or fixations on manual calibration markers moved sequentially in a 3-D environment.

2.3.5. Free viewing and removal of eye-movement-related EEG artefacts

Although traditional EEG has limited eye-movements to limit the number of artefacts contaminating the data, natural vision is highly trans-saccadic and 2–4 saccades are made per second (Dimigen, 2020). In recent years, The advent of head-mounted eye-trackers has afforded investigation of gaze behaviour and natural cognition during naturalistic free-viewing and whole-body movement (Niehorster et al., 2020) through co-registration of eye-movement and EEG recordings (Dimigen et al., 2011; Fischer et al., 2013; Nikolaev et al., 2011, 2013, 2016; Simola et al., 2015).

Head mounted eye-trackers incorporate a world-view camera, in addition to eye-cameras, to examine the subject’s point of view and examine visual responses in natural environments (Gidlöf et al., 2013, 2017). Increased sampling rates for head mounted eye-trackers has improved their temporal resolution (Cognolato et al., 2018). However, head mounted eye-trackers have been criticised for providing less precise gaze detection due to movement making the device become uncalibrated (Cognolato et al., 2018; Kolakowski & Pelz, 2005; Niehorster et al., 2020). Lighting conditions can also influence the ability of eye-trackers to detect the pupil by producing corneal reflections which is more likely to fluctuate in moving participants (Cognolato et al., 2018; Kolakowski & Pelz, 2005), and eye-glasses or contact lenses can exacerbate these effects (Gwon et al., 2014).

As saccade-related artefacts are highly prevalent in naturalistic recordings, it is essential to detect and remove artefacts associated with voltage distortions due to the following three types of ocular artefacts: movement of the eyeballs, movement of the eyelids and EMG activity due to contraction of the extraocular muscles at saccade onset (known as the saccadic spike potential) (Berg & Scherg, 1991; Keren et al., 2010; Picton et al., 2000; Plöchl et al., 2012; Thickbroom & Mastaglia, 1986). These artefacts preclude examination of neural events which have smaller amplitudes (Dimigen, 2020).

A number of ocular correction methods have been proposed in order to examine neural signals elicited during free viewing, including EEG on EOG regression, dipole modelling and beamforming, PCA, and ICA (Dimigen, 2020). Of these methods, ICA is the most commonly used method for removal of saccade and blink artefacts from free viewing EEG data (Delorme et al., 2007; Jung et al., 2000). ICs that are believed to reflect neural components are back projected to the electrode space, producing artefact free EEG data (Dimigen, 2020). Guided saccades can also be employed to objectively classify ICs as either artefacts or neural data (Plöchl et al., 2012) by detecting saccades of each angle (Berg & Scherg, 1991; Dimigen, 2019; Ille et al., 2002) and adaptive spatial filtering (ASF; Berg & Scherg, 1994; Ille et al., 2002) can then be used to remove the marked artefacts, although these methods have not yet been used in conjunction for ocular artefact correction.

2.3.6. Viewing 2-D versus 3-D products

Laboratory-based experiments assume that 2-D stimuli presented on a computer screen will elicit the same neural responses as 3-D versions of the stimuli that would be encountered in the real-world. However, this cannot be taken for granted. Translation from a 2-D image to a 3-D image poses perceptual challenges, as 2-D images tend to be smaller compared to real objects, with reduced resolution, altered colour and cues associated with depth such as motion, shadow and gradient are often absent or very different (Barr, 2010). Additionally, it has been shown that until the age of 3 years, children learn more from live demonstrations than they do from television, a phenomenon termed the video deficit, demonstrating the difficulty of transfer learning from 2-D to 3-D contexts (Barr, 2010). Further, Anderson & Jamniczky (2019) found that students who learned to recognise neuroanatomical structures using 3-D models showed greater object recognition and N250 amplitude compared to students who learned the structures using 2-D models. This demonstrates neural differences in perception and object recognition of 2-D and 3-D objects, which could be due to stereopsis in the 3-D condition facilitating object recognition (Anderson & Jamniczky, 2019).

The additional depth parameter in a naturalistic free-viewing situation affords examination of the stimulus from multiple viewpoints, and, as natural cognition is trans-saccadic, spatial relations and information obtained between these viewpoints is likely integrated over time to form a holistic representation. This is not accounted for by traditional laboratory-based fixed viewing research (Meilinger et al., 2011). Moreover, a moving subject might observe different luminance, contrast, shape, size, and position of the stimulus over time, and the stimulus might be viewed from atypical viewpoints causing difficulties in processing and identification, all of which needs to be consolidated by the brain. It may also require additional time, holding of information in working memory, additional visual information or further processing compared to static 2-D images (Biederman & Gerhardstein, 1993; Murphy et al., 2013). Taken together, evaluating 3-D relative to 2-D product representations could involve different neural processes and cognitive operations, which should be investigated in ecologically valid conditions.

2.4. Experimental techniques to measure SVs

SVs of choice options are often complex, multifaceted and context dependent. A holistic SV for an item might depend on a interaction between the products physical properties (e.g., size, shape, colour, function), the decision makers internal, emotional or motivational states (personal values, social values, anticipated feelings emotionally/physically towards the product, attitudes towards risk/ambiguity) and their external states (affordability, time delay, effort, risk, ambiguity, context) (Appelhans et al., 2019; Bagozzi et al., 2016; Bouzakraoui et al., 2017; Desrochers & Outreville, 2013; Nwankwo et al., 2014; Rangel et al., 2008). Consequently, it is essential to carefully consider experimental design to determine whether SVs are actually being examined and if SVs are reflective of those that would be produced in real-world conditions, as over-simplification may not produce data that is reflective of realistic SVs.

2.4.1. Forced bid paradigms

Traditionally, investigation of SV has relied on two alternative forced choice (2-AFC) paradigms whereby individuals make a binary decision between one product and one or more alternative products, and the selected product is considered to be the preferred option (Deneve, 2009). Alternatively, 2-AFC paradigms can involve asking participants to bid a set amount of money for one product over another (Plassmann et al., 2007, 2010). Although 2-AFC tasks afford enhanced control over experimental conditions, these paradigms are only able to provide a limited amount of information regarding SV, as the decision maker is unable to opt out of a purchase whereas during real-world decision making, individuals can always choose not to buy (Dhar & Simonson, 2003). Moreover, the decision-maker could just choose the least unpreferred option; therefore, the 2-AFC paradigm can generate artefactual ‘preference’ of a stimulus. Information about whether the product is preferred or unpreferred relative to an alternative in that specific context cannot necessarily provide understanding about the overall SV of the product in terms of high-value attribution or preference.

2.4.2. Auction tasks and WTP

Alternatively, free-bid paradigms such as auctions afford the participant the opportunity to submit their own monetary bid for a product, otherwise known as the willingness to pay (WTP) value. WTP refers to the maximum amount of resources that the consumer is willing to relinquish to obtain a good or service (Chib et al., 2009; Peters & Büchel, 2010; Plassmann et al., 2012).

Auction tasks are better suited to examining SV compared to forced bid tasks, as they require WTP value computation, and a bid of £0 can be submitted, giving the participant the opportunity to opt out (Plassmann et al., 2007). WTP values can be examined on a continuous scale, allowing the experimenter to rank SVs for products in a linear fashion. This allows for the determination of the most and least preferred items and can be used to examine whether brain areas correlate with the economic computation of WTP (Plassmann et al., 2007). Auction bids are also reflective of real-world SV attribution as they are incentive compatible, as participants are given an endowment to spend and actually receive products that they bid on and win (Keller, Segal & Wang, 1993; Lusk et al., 2004; Wertenbroch & Skiera, 2002), and submitting monetary bids and winning items is something that is prevalent in everyday life in online auction environments such as eBay (Grzesiuk & Cypryjański, 2017). Consequently, WTP values elicited via auction tasks are more likely to reflect real-world SVs (Keller et al., 1993).

There are a number of different auction paradigms available for the examination of WTP as a measure of SV. Open first-price ascending auction tasks, such as an English auction, involve participants submitting bids which increase until a single bidder remains, and the amount of money paid is equal to the final winning bid amount (Chow & Ooi, 2014). Alternatively, open first-price descending auction tasks, such as a Dutch auction, begins with a high maximum asking price which is then incrementally lowered until all bids are submitted, and the first bid, which is also the highest bid, wins the auction (Carare & Rothkopf, 2005). Open first price auctions are subject to strategies, due to the presence of opponents, which can alter detection of intrinsic SV. For instance, the winner's curse, the tendency for the winning bid to exceed the true SV of an item, and bid shading, a technique used to avoid overpaying for an item, both of which can obscure detection of the subject's true SV (Gligorijevic et al., 2020; Kagel et al., 1989). Therefore, the bidding behaviour in first-price auctions is not necessarily indicative of true SV. In contrast, second price sealed bid auctions such as the Vickrey auction (Vickrey, 1961) involves the participant submitting a bid of the amount that they would be WTP, without knowing the bids of competitors, and if they are the highest bidder, they pay the sum equal to the second highest bid (Ausubel & Milgrom, 2013).

One of the most influential auction tasks used in neuroeconomics is the Becker-DeGroot-Marschak auction task (BDM) (Becker et al., 1964), which is another example of a second-price sealed bid auction. During the BDM, a bid reflecting the participant’s WTP for a product is submitted and, the participant wins the auction if their bid is greater than or equal to a randomly generated number, paying the price equal to the random number. Importantly, the optimal bidding strategy of the second price sealed-bid auction is to bid one’s exact WTP value, as overbidding increases the chances of paying an amount higher than their WTP value and underbidding increases the risk of losing the auction. WTP values elicited from BDM auction tasks have been linked to real consumer choices (Roberts et al., 2018; Rozan et al., 2004; Tyson-Carr et al., 2018; 2020; Wertenbroch & Skiera, 2002) and are known to activate the brain valuation system (Chib et al., 2009; Plassmann et al., 2007; Plassmann et al., 2010; Tyson-Carr, et al, 2018; 2020).

In conclusion, free bid paradigms are more likely to provide an accurate measure of true WTP than forced bid paradigms, as they give participants the option to opt out of a purchase, allow ranking of SVs to ensure that items are actually highly valued, and they are incentive compatible, as participants bid real money and actually receive winning items. Of the free bid auctions, second price sealed-bid auctions are the most influential in neuroeconomics research, as the optimal bidding strategy is to bid one’s true SV, regardless of the strategies or behaviours of other bidders, therefore, they are thought to index true SV. Although the Vickrey auction and the BDM auction are theoretically comparable, behavioural data has shown that, during Vickrey auctions, the participant’s bidding behaviour diverges from the dominant strategy in the presence of rival bidders, altering the participant’s SV according to social dynamics (Toelch et al., 2014; van den Bos et al., 2008; Zeng et al., 2013). Therefore, the BDM auction is an optimal solution for measuring individual WTP outside of a social context (Flynn et al., 2016). As the current research is primarily interested in measuring true SV to products outside of social influence, the BDM auction was utilised in the experimental chapters of the current thesis.

3. RESEARCH PROBLEMS, HYPOTHESES AND THESIS OVERVIEW

3.1. Research problems

Recording value-based decisions in naturalistic environments is accompanied by a number of research problems, both technical and theoretical. Specifically, it is not known whether it is possible to examine EMRPs underpinning SVs of products in wirelessly recorded data, as it has not been examined in the neuroeconomic literature. Lack of EEG research investigating the spatio-temporal processes of valuation during free-movement in natural environments is primarily due to the presence of a large number of artefacts distorting the EEG data. In particular, during free eye-movements, saccade-related artefacts produce atypical topographies preventing their complete removal using techniques such as PCA or ICA. To examine the neural dynamics underlying naturalistic value-based decisions, it is essential to determine the best way of detecting and removing movement-related artefacts in naturalistic experiments involving wireless EEG and eye-tracking. Such methods are particularly needed when detailed information about the eyes is not available, and currently there is no standard approach to artefact removal within the field of MoBI.

The neuroeconomic literature detailing the temporal properties of the valuation process using EEG is scarce, although it has been suggested that SV can be computed rapidly by the brain (Goto et al., 2017; Ma et al., 2018; Telpaz et al., 2015; Tyson-Carr et al., 2018; Tyson-Carr et al., 2020). However, examination of the neural temporal dynamics of valuation in natural settings is non-existent, and it is unknown how the brain valuation system encodes products of different SVs in natural settings and how rapidly SVs are computed. An additional problem is that it is not known whether neural components for SVs will be encoded linearly within the same clusters, as suggested in fMRI experiments (Abitbol et al., 2015; Lebreton et al., 2009) or whether SV categories will be distinctly encoded in unique clusters within the BVS.

Attempts must be made to characterise the spatio-temporal properties of neural components underpinning SV for products in ecologically valid settings using wirelessly recorded EEG. Moreover, it is important to determine whether SV is linearly or uniquely encoded within the BVS.

Finally, it is assumed in the neuroeconomic literature that 2-D images of products are reflective of valuation responses to real products. This is problematic as 3-D products contain depth information affording examination from multiple viewpoints, which could require integration over time, additional processing and different neural dynamics (Meilinger et al., 2011; Murphy et al., 2013). Likewise, the presence of a product can produce attentional bias, modulating motivation-related brain areas and consumption behaviours (Blechert et al., 2016; Jędras et al., 2019;. Jones et al., 2012; Maas et al., 2012; Painter et al., 2002). Therefore, examination of neural responses during 3-D product valuation is necessary to determine the generalisability of findings derived from 2-D product images.

The current thesis investigated, for the first time, the spatio-temporal properties of the brain valuation process during free movement in naturalistic settings close to real life. The use of mobile EEG and eye-tracking methods allowed examination of the temporal dynamics of SV attribution to determine the latency of EMRP components encoding SV, and whether SV categories are encoded linearly or in distinct neural bands. Novel methods were developed to reduce the influence of artefactual noise, improving the quality of the mobile EEG data. The influence of 3-D products on the neural dynamics underpinning SV were explored. Utilising the high temporal resolution of EEG, data presented in the experimental chapters of the current thesis could facilitate deeper understanding of the spatio-temporal dynamics of the BVS and, for the first time, allow investigation of these dynamics in naturalistic environments, bridging a gap in the neuroeconomic literature. Such research could have broad implications as value-based decisions are continually made in daily life and are essential for surviving and thriving, with negative impacts on health and wellbeing during maladaptive valuation. Therefore, the current research could provide deeper insight into how SV is computed by the brain in naturalistic environments.

3.2. Hypotheses

Hypothesis 1: Components of EMRPs will distinguish between WTP values (SVs) for product images in a mock gallery.

Hypothesis 2: SVs of products will be linearly encoded by distinct components of EMRPs recorded using mobile EEG and eye-tracking.

Hypothesis 3: EMRP components of SVs will be determined early on during free viewing, reflecting the automaticity of the brain valuation process in naturalistic environments.

Hypothesis 4: Combining guided saccades and ASF will significantly reduce the presence of saccade-related artefacts in EEG data obtained from freely behaving participants in naturalistic environments, compared to standard eye-blink removal.

Hypothesis 5: Valuation decisions for 3-D products in a naturalistic shop will influence early neural valuation responses of EMRPs, reflecting enhanced complexity of stimuli.

3.3. Thesis chapter outline

Chapter 4 describes a combined EEG and eye-tracking experiment which determined whether it was possible to examine the early spatio-temporal neural dynamics underpinning SVs for products in a free viewing naturalistic setting (*Hypothesis 1*). It was anticipated that SVs would show linear encoding in distinct neural clusters during early intervals (*Hypothesis 2, 3*). The experiment examined EMRPs in a novel product gallery setting and used ICA back-projection to separate independent generators of activity, with source dipole modelling to investigate neural sources for ICs modulated by SV.

Chapter 5 is a continuation of the experiment described in chapter 4 and similarly aimed to determine if components of EMRP encoded SVs of products in the product gallery monotonically and linearly in early latencies (*Hypothesis 1, 2, 3*). The experiment extended the price range of products in an effort to examine neural responses to high-value items. Guided saccade recordings and ASF successfully removed residual saccade-related artefacts from the EEG data, outperforming standard eye-blink removal (*Hypothesis 4*). The study utilised an ICA cluster technique to determine distinct neural clusters reflecting SV conditions.

Chapter 6 involved the examination of the neural dynamics underlying SVs for real 3-D products in a custom-built mock shop using mobile EEG and eye-tracking. It was anticipated, in line with previous experiments, that independent components (ICs) of EMRP would encode SVs of products monotonically and linearly in early latencies (*Hypothesis 1, 2, 3*). Additionally, it was anticipated that the use of real 3-D products in a naturalistic shop would influence neural processing of SVs (*Hypothesis 5*).

Chapter 7 provides a general discussion of results obtained in all experimental chapters, with interpretation of their theoretical and practical significance in neuroeconomics, the limitations of the experiments, and discussion of directions for future avenues of research.

4. TRACKING THE ECONOMIC VALUE OF PRODUCTS IN NATURAL SETTINGS: A WIRELESS EEG STUDY

Tracking the Economic Value of Products in Natural Settings: A Wireless EEG Study

Hannah Roberts[1*], Vicente Soto[1], John Tyson-Carr[1],
Katerina Kokmotou[1,2], Stephanie Cook[1,3], Nicholas Fallon[1],
Timo Giesbrecht[4] and Andrej Stancak[1,2]

[1]Department of Psychological Sciences, Institute of Psychology, Health and Society, University of Liverpool, Liverpool, United Kingdom

[2]Institute for Risk and Uncertainty, University of Liverpool, Liverpool, United Kingdom

[3]Division of Psychology, De Montfort University, Leicester, United Kingdom

[4]Unilever Research & Development, Port Sunlight, United Kingdom

This experiment investigated the spatio-temporal dynamics underpinning the SVs of products in naturalistic settings using mobile EEG. This paper was published in Frontiers in Neuroscience (2018), doi:10.3389/fnins.2018.00910. The format of the text has been modified to match the style of this thesis.

The roles of the co-authors are summarised below:
Myself and Andrej Stancak, Nick Fallon and Timo Giesbrecht contributed to the development of the experimental design and planning of the current project. Myself, Vicente Soto and John Tyson-Carr contributed to the development of the stimuli and materials. Andrej Stancak and I contributed to the development of the behavioral rating task and carried out the data acquisition, pre-processing, synchronisation and analysis of the collected data as well as figure creation and production of the final written manuscript. Matlab scripts were created by Andrej Stancak. Vicente Soto, Katerina Kokmotou, John Tyson-Carr and Stephanie Cook assisted me with the data collection.

4.1. Abstract

Economic decision making refers to the process of individuals translating their preference into SV. Little is known about the dynamics of the neural processes that underpin this form of value-based decision making and no studies have investigated these processes outside of controlled laboratory settings. The current study investigated the spatio-temporal dynamics that accompany economic valuation of products using mobile EEG and eye-tracking techniques.

Participants viewed and rated images of household products in a gallery while EEG and eye-tracking data were collected wirelessly. A BDM auction task was subsequently used to quantify the individual's WTP for each product. WTP was used to classify products into low, low medium, high medium and high economic value conditions. EMRP were examined, and ICA was used to separate sources of activity from grand averaged EEG data.

Four ICs of EMRPs were modulated by WTP (i.e., SV) in the latency range of 150–250 ms. Of the four value-sensitive ICs, one IC displayed enhanced amplitude for all value conditions excluding low-value, and another IC presented enhanced amplitude for low-value products only. The remaining two value-sensitive ICs resolved inter-mediate levels of SV.

Our study quantified, for the first time, the neural processes involved in economic value-based decisions in a natural setting. Results suggest that multiple spatio-temporal brain activation patterns mediate the attention and aversion of products which could reflect an early valuation system. The EMRP parietal P200 component could reflect an attention allocation mechanism that separates the lowest-value products (IC7) from products of all other value (IC4), suggesting that low-value

items are categorized early on as being aversive. While none of the ICs showed linear amplitude changes that parallel SV's of products, results suggest that a combination of multiple components may sub-serve a fine-grained resolution of the SV of products.

4.2. Introduction

Rewarding and aversive stimuli that occur in natural environments prompt humans to make a large number of value-based decisions. Such decisions can be computed consciously, or can be reached without conscious awareness. Determining the SV of each parallel option is a key input for the decision process. Economic decisions occur when an individual evaluates how much a product is worth by computing subjective preferences reflecting their current needs and desires (Gluth et al., 2012; Polanía et al., 2014; Ruff & Fehr, 2014; Stott & Redish, 2015). According to the value maximization framework (Kahneman & Tversky, 1979; Samuelson, 1937), economic decisions involve the initial assignment of SVs to competing alternatives and the option with the highest SV is consequently selected (Bartra et al., 2013; Rangel et al., 2008; Wallis & Rich, 2011).

There is only a limited number of studies examining the temporal sequencing of economic value-based decisions in the brain using event related potential (ERP) methods, particularly for low-value products (Gajewski et al., 2016; Goto et al., 2017). Although limited, some studies have suggested that the N200 VEP represents an early selective attentional response to relevant stimuli and, hence, could be related to consumer preferences (Goto et al., 2017; Telpaz et al., 2015; Tyson-Carr et al., 2018). For example, Telpaz et al. (2015) employed a binary choice paradigm and found a smaller N200 for preferred products. Likewise, the P200, which is thought to index early selective attention, has also been implicated in economic decision making and buying decisions (Jones et al., 2012; Pozharliev et al., 2015; Tyson-Carr et al., 2018). Studies regarding later ERP components in relation to economic decisions, however, show conflicting results (Goto et al., 2017; Pozharliev et al., 2015; Telpaz et al., 2015). For instance, Pozharliev et al. (2015) found that the late positive potential (LPP) was modulated by product preferences for luxury items, but only when in the presence of other people. These components detailed above, including the N200 (Handy et al., 2010), P200 (Carretié et al., 2001b), and LPP (Schupp et al., 2000), have also been implicated in general hedonic processing. An important question for researchers is how making economic value-based decisions for low-value items differs from high-value items, and whether such decisions employ the same neural circuitry (Xie & Padoa-Schioppa, 2016) or multiple neural systems (Daw et al., 2005; Dickinson & Balleine, 2002; Rangel et al., 2008).

The SV of a good can be approximated by the amount of money an individual is willing to pay for an item (Chib et al., 2009; Peters & Büchel, 2010). WTP can be estimated using the BDM auction (Becker et al., 1964). The construction of the auction is such that a value smaller or larger than the actual value that a participant would be willing to pay would produce a disadvantageous outcome, whereas bidding their true WTP would maximise expected utility, and participants were made aware of this (Berry et al., 2012). The validity of the BDM has been supported by experiments demonstrating that it reliably activates brain areas that have been associated with value processing, such as the medial orbitofrontal cortex (Plassmann et al., 2007, 2010), the ventral striatum (De Martino et al., 2009) and the dorsomedial prefrontal cortex (Plassmann et al., 2007). The BDM auction paradigm is motivationally relevant as the subject receives a subset of items that have been purchased successfully, making it more likely that participants will provide a true economic value (Keller et al., 1993).

Recently, Tyson-Carr et al. (2018) used the BDM auction to examine the spatio-temporal dynamics of economic decisions for everyday household products in a laboratory-based setting. A negative component peaking at about 200 ms with a source in the right anterior insula was found to be stronger in low compared to high-value products, possibly due to an aversion to the risk of the financial loss associated with purchasing an unwanted item.

It has been argued that laboratory environments elicit unrealistic behavioral and neural responses and, as such, findings might not be generalizable to real-world scenarios (Brofenbrenner, 1977; Ladouce et al., 2017). In particular, the limiting environmental conditions could hamper important aspects of embodied human cognition that are essential to the decision-making process, such as the interactions between perception, cognition and action that occur in complex natural environments (Gramann et al., 2014; Ladouce et al., 2017). As such, to gain a more encompassing and realistic insight into economic value-based decisions for products, it is essential to examine these processes whilst participants navigate a real-world environment, moving toward analysing brain responses during a realistic shopping experience (Minguillon et al., 2017; Pradeep, 2010). Owing to recent advancements in mobile EEG technology and signal processing techniques, it is now possible to examine neural responses while participants move freely in the real-world (Banaei et al., 2017; Gwin et al., 2010; Jungnickel & Gramann, 2016). As a case in point, Soto et al. (2018) used mobile EEG and eye-tracking techniques to demonstrate the feasibility of using EMRPs to examine faces and objects within a valuation context in naturalistic conditions. The current study represents an initial attempt to examine economic value related ERPs in naturalistic settings where purchase decisions would be made, such as in a supermarket or shop.

The aim of the current experiment was to determine whether it is possible to resolve the spatio-temporal neural responses that encode the economic value of everyday household products during free viewing in a naturalistic, economically valid environment. A mobile EEG system was utilized to examine brain responses to products whilst participants viewed and selected the objects that they would be most or least likely to purchase in the gallery setting. Eye-tracking was used in tandem for real-world triggering and the procedure was based on a recent experiment by Soto et al. (2018). The BDM auction (Becker et al., 1964) was utilized to elicit WTP for products, which participants could freely inspect beforehand in a mock gallery.

4.3. Materials and Methods

4.3.1. Participants

Twenty-eight healthy participants (14 females) were recruited for the current experiment. Nine participants were removed from the final data analysis due to poor signal quality in EEG recordings (six participants) or insufficient eye-tracking data, such as a missing light emitting transistor–transistor logic (TTL) trigger in the world view camera (three participants). The amount of data loss in the current study can be attributed to the difficulties associated with acquisition of mobile EEG data in naturalistic conditions. For instance, some free movements in the real-world do not follow a stereotyped pattern and, as such, cannot be extracted using principal component analysis (PCA) or ICA methods (Jungnickel & Gramann, 2016). Data loss can also be attributed to difficulties associated with the collection of eye movement data. A TTL light emitting trigger box was used for synchronization of the data streams and, on three occasions, the light was not registered either due to misplacement of the light relative to the world view camera (two participants), or due to a computer buffering error (one subject). The final sample consisted of 19 participants (seven females) with an average age of 25 ± 5.02 (mean ± SD) years, three of which were left handed. All participants were provided with information about the nature of the experiment and gave written informed consent prior to the commencement of the experiment. Full ethical approval was obtained from the University of Liverpool Research Ethics Committee (reference number 1145), and all experimental procedures were conducted in accordance with the Declaration of Helsinki. Participants received a £10 reimbursement for their time and an average of £12.26 ± 1.96 (mean ± SD) was retained from the £16.00 endowment given during the BDM task, which was added to their final payment.

4.3.2. Product Images

The stimuli used in the current experiment consisted of 198 colour images of everyday household items from a shopping catalogue (2016, December 12). The images were split into three distinctive value categories; images of low-value products costing between £0.35 and £2.80, images of medium-value products costing between £3.00 and £5.50 and images of high-value products costing between £6.00 and £8.00, with a total of 66 images in each value category. All stimuli were pseudo-randomly distributed within their value conditions for all tasks. Due to the pseudo-random distribution of products around the fixation cross combined with the fact that value categories were subjectively defined, i.e., one product could be considered high-value for one subject and low-value for another subject, the researchers did not anticipate any order effects of value category, and this was not analysed in the current experiment. Furthermore, an effort was made to ensure that no two products of the same semantic category were displayed on the same board, i.e., it did not contain two toasters. Most participants tended to view the products beginning at the top middle image on a panel and sequentially viewing the products in a clockwise manner as this tends to be the easiest method in order to remember which products have already been viewed.

All images were presented on 22 A0 sized poster sheets which were mounted on to Styrofoam panels of equal size using adhesive tape (Figure 8A). Each panel displayed three images from each value category (low, medium and high) with a total of nine images per panel. All panels were mounted on to the walls of two hallways within a building at the University of Liverpool using adhesive Velcro, creating a product gallery setting (Figure 8B). All images (sized at around 15 cm × 20 cm) were arranged around a central fixation cross (14.3 cm × 14.3 cm, see Figure 8C). Across all panels, the accumulative value for all objects on each panel ranged between £32.30 and £42.24, with a mean price of £38.16 ± £0.53 (mean ± SD).

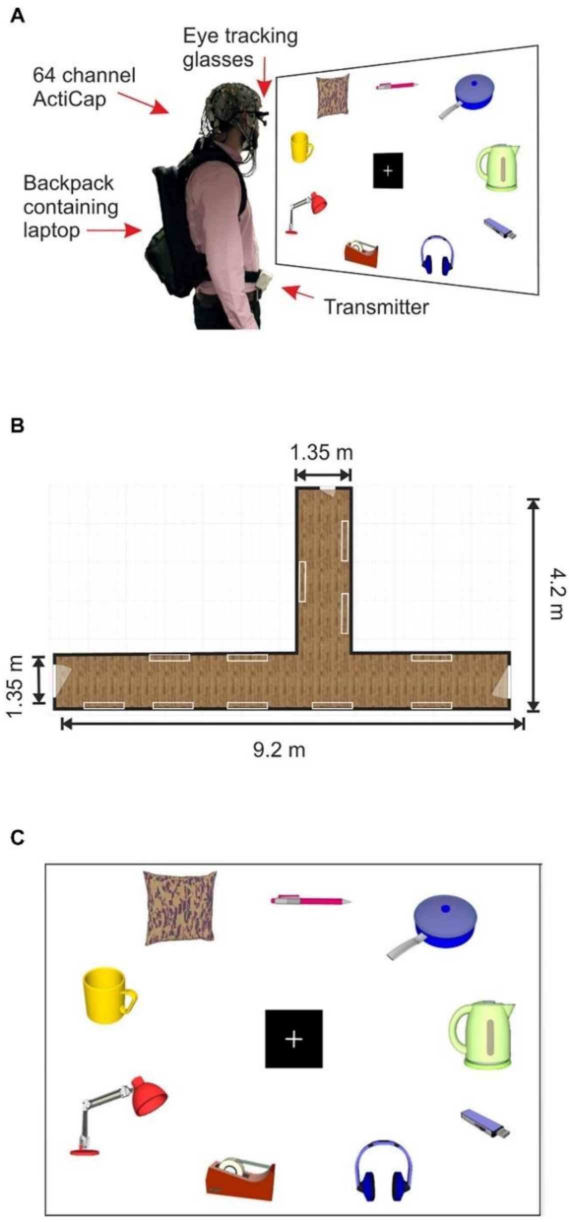

Figure 8. Mobile EEG set up and product gallery. (A) Example of a subject wearing the 64 channel actiCAP with active shielded electrodes attached to the Mobile EEG transmitter, located on the subject’s belt. The subject also wears PupiLabs eyetracking glasses which are plugged into a laptop located in a backpack. Subject looks at product panel. (B) Schematic representation of the corridor where the product gallery task took place. The white rectangles represent the locations of the product panels on the walls. (C) Schematic representation of a product panel located within the gallery. Product images in the figure were created using 3D Warehouse templates in SketchUp 2018. Each panel contained nine images of household products from a shopping catalog. The nine images were divided into three images from three different retail price categories, high (£6.00–£8.00), medium (£3.00–£5.50), and low (£0.35–£2.80).

4.3.3. Procedure

The experiment was split into two separate sessions due to the time intensive nature of the mobile EEG and eye-tracking set up. Session 1 included the product gallery task followed by the BDM auction task, and session 2 consisted of a behavioral rating task for hedonic aspects of the stimuli. In the first experimental session, participants arrived at a laboratory in a building at the University of Liverpool. Instructions were delivered and full informed consent was obtained. Participants had their heads measured and were then fitted with an EEG cap (actiCAP, Brain Products, GmbH). Electrolyte gel was applied to the scalp using a syringe and 64 electrodes were then attached to the cap, with care taken to ensure that electrode impedances were kept under 50 kΩ. Following impedance checks, participants were connected to the mobile EEG system and wireless signals were visually inspected during movement. Eye-tracking glasses (Pupil Binocular Eye Tracking Glasses, PupiLabs, Germany) were then fitted to the participant over the EEG cap and plugged into a lightweight Lenovo laptop using a universal serial bus connector. The subject's gaze was manually calibrated against a blank A0 sized panel using a 3D calibration routine with manual markers kept at a distance of 1 m.

The laptop was placed in a backpack which was worn by the participant during the mobile part of the experiment. The EEG electrode cables that ran from the EEG cap to the MOVE system transmitter (MOVE, Brain Products, GmbH, Mnich, Germany) on the subject's belt were clipped on to the backpack in order to reduce the likelihood of generating cable sway artifacts during gait (Gramann et al., 2010; Gwin et al., 2010, see Figure 8A for an example of the set up). The MOVE system receiver, amplifier and battery were plugged into a Toshiba laptop and all of the equipment was seated on a mobile trolley, which the experimenter pushed during the experiment. If the subject was moving too far out of range of the cart, the experimenter would push the cart closer to the transmitter in order to maintain optimal signal. As the subject was moving freely, it is possible that the distance between the subject and the receiver varied over the course of the experiment, however, the raw signal was consistently monitored throughout the experiment, and the distance between the transmitter and receiver never exceeded 7 m, after which the signal to noise ratio (SNR) is known to deteriorate (Reis et al., 2014).

Likewise, impedances were lowered to 50 kΩ at the beginning of the experiment and were checked in the break between the experimental blocks, as impedances can change during movement. If individual electrodes became noisy during the experiment, they were corrected using electrolyte gel while the subject made their ratings on an A4 sheet of paper, so as to distract them as little as possible during the task. Examination of whether there was any temporal modulation of the SNR over time during the experiment was also conducted by computing the broadband spectral power in the data at three time bins in block one and block two for all participants. No significant modulation of the broadband spectral power of the data was observed (all p-values > 0.05), which suggests that the signal quality was maintained throughout the experiment.

The product gallery task consisted of two experimental blocks and took approximately 30 min to complete. Following the product gallery task, the EEG equipment and eye-tracking glasses were removed and participants then took part in BDM auction task for the same 198 products in a laboratory space at the University of Liverpool. The task took approximately 35 min to complete. The second part of the experiment took place within 7 days of the first experimental session. Participants arrived in the same laboratory space at the University of Liverpool and took part in a behavioral rating task for the same 198 products. This task took approximately 35 min to complete. Afterward, participants received two random items that they had bid on and won in the BDM auction task, were asked to fill in a payment form and were debriefed and thanked for their time.

4.3.4. The Product Gallery Task

Following the mobile EEG and eye-tracking set up in the first session, participants took part in the product gallery task, which was conducted in two adjoining corridors at the University of Liverpool (see Figure 8B). At the beginning of both blocks of the product gallery task, a light emitting trigger box was used in order to synchronize EEG and eye-tracking data sets. In both blocks, participants were instructed to move in a natural manner through the gallery. Participants were informed that they could view the panels and the images on the panels in any order, provided that they viewed all of the images on one panel before continuing on to the next. Participants were also instructed to look at each object for a minimum of 3 s, and should always return their gaze to the fixation cross in the centre of the panel before moving on to look at another image. After viewing a complete panel, participants were required to indicate two objects that they would be most likely to buy and two objects that they would be least likely to buy on an A4 version of the panel using the pen provided. Importantly, to produce a more natural environment, the corridor was not isolated from the rest of the building and people were free to walk past at any point.

The decision to create a product gallery rather than use actual 3D products was to try and observe, for the first time, whether eye movement related potentials to EMRPs for products could be recorded outside of a laboratory-based environment at all before moving on to create a more ecologically valid setting in which 3D objects are evaluated. By using product images, it was possible to introduce some level of control into the experiment, while still maintaining a naturalistic gallery-like scenario. This allowed researchers to standardize the front facing view of the objects, the size of the objects, the lighting, and other aspects of the stimuli that could have influenced ERPs, to see whether it was possible to record ERPs at all in this naturalistic context.

4.3.5. The BDM Auction Task

Following the product gallery task, participants took part in a BDM auction task, which was displayed on a Dell monitor using a HP Compaq 8200 Elite computer. Presentation of the stimuli was controlled using Cogent 2000 (UCL, London, United Kingdom) running on MATLAB (version R2014a, The MathWorks, Inc., United States). The BDM task (Becker et al., 1964; Wilkinson & Klaes, 2012) was adapted from previous studies (Plassmann et al., 2007, 2010; Tyson-Carr et al., 2018). During the auction, 198 images of everyday household products from a shopping catalogue were presented once. Each trial in the auction task was comprised of a fixation cross (presented for 2 s), followed by an evaluation stage for the product (image presented for 3 s) and then a bidding stage (presented until button press) where participants were required to bid the amount they would be willing to pay for the product. Participants were required to bid between £0 and £8 on the products in increments of £0.50 and increments of £1 from £3.00 onward, producing a total of 11 bidding options.

During the feedback stage, participants were notified as to whether the item was ‘purchased’ or ‘not purchased.’ The purchasing outcome was dependent on the subject’s bid and its relationship with a randomly generated number. An item would be purchased if $b \geq r$, where b represents the subject’s bid and r represents the randomly generated number for each individual trial. Afterward, two ‘purchase’ auction trials were randomly selected, and for both items, the corresponding price of *r* was deducted from the subject's endowment of £16, which covered a maximum of £8 being spent on each trial. The subject received these winning items during the second experimental session. The task took approximately 35 minutes to complete.

4.3.6. Behavioral Rating Task

In the second experimental session, which took place within a week of the first experimental session, participants took part in a behavioral rating task in the same laboratory space at the University of Liverpool. Presentation of stimuli was again controlled using Cogent 2000 (UCL, London, United Kingdom) running on MATLAB (version R2014a). During the task, participants provided hedonic ratings for the same 198 product images using two sliding visual analog scales (VAS), which were sized at 10 cm and were anchored from 'not desirable' to 'very desirable' and from 'unpleasant' to 'pleasant'. Each trial consisted of a fixation cross (presented for 1 s), followed by an evaluation stage (presented for 2.5 s) and, finally, a rating screen (presented until button press). This task took approximately 35 minutes to complete.

4.3.7. EEG Recordings

EEG was continuously recorded over the whole scalp using a 64-channel wireless mobile EEG system (MOVE, Brain Products, GmbH, Münich, Germany). The wireless system included a lightweight signal transmitter which was carried by the subject on a Velcro belt tied around their waist, and a signal receiver, which was connected to the EEG amplifier and battery, see Figure 8A. Active Ag/AgCl electrodes were connected to the scalp via an elastic cap (actiCAP, Brain Products, GmbH) according to the 10-20 electrode system, using electrolyte gel to ensure electrode-to-skin impedances were consistently kept under 50 kΩ (SignaGel, Parker

Laboratories, Inc., Fairfield, NJ, United States). EEG recordings were sampled at a rate of 1,000 Hz, with electrode FPz used as the system ground and all electrodes were referenced to Fz. The EEG cap was placed in accordance with the midpoint of the anatomical landmarks of the nasion, the inion and the left and right pre-auricular points. EEG average reference was applied to all electrodes and signals were digitized to 1 kHz on a BrainAmp DC amplifier running on Brain Vision Recorder version 1.20.0601 for Windows on a Toshiba Satellite P875-149 laptop. A 50 Hz notch filter was utilized during the recording.

Given that the current study was exploratory in nature, high density recordings were necessary in order to investigate not only the temporal sequencing of economic decision making, but also to spatially estimate which brain regions were activated during decision making. Furthermore, high density EEG systems afford the use of advanced computational methods such as ICA to remove many artifacts that contaminate the data, as the more channels that are provided, the more effective ICA is at separating cerebral from non-cerebral artifacts (Gramann et al., 2010; Gwin, Gramann, et al., 2010; Lau et al., 2012; Palmer et al., 2008). A 64-electrode system represented a compromise between high density recordings in naturalistic environments, and more quick, convenient and wearer-friendly experimental set ups.

4.3.8. Eye-Tracking Recordings and Analysis

Eye-tracking recordings were taken on Pupil Binocular Eye Tracking Hardware using Pupil Capture software (version 0.9.6) running on Ubuntu SMP for Linux on a Lenovo Thinkpad x250 Ultrabook laptop (see Figure 8A). Both eye cameras and the world view video data streams maintained 800 × 600 resolution. The sampling rate for the world view camera was set at 60 Hz and the eye cameras were sampled at 120 Hz, however, the actual sampling rate of the world view camera was calculated offline to be 48.29 Hz (± 2.58) on average across all participants. The pupils of both eyes were detected using a plugin for Pupil Capture software that algorithmically separates the pupil from the cornea (center-surround detection algorithm, Świrski et al., 2012). A manual 3D calibration method was employed, whereby a grid of a minimum nine points was generated on a blank A0 sized panel in the world view camera of the subject. This protocol was repeated until gaze positions were ascertained to be accurate at all points where stimuli occurred on the panel. Mid-recording calibrations were conducted if pupil gaze was lost or misaligned during the product gallery recording.

The video streams were then exported and eye tracking data was subsequently processed using the Pupil Player Program (version 0.9.6). If the gaze fixation marker was off centre, fixation offsets were manually corrected using the Manual Gaze Correction plugin and fixation jitters were accounted for using in-house scripts in MATLAB version R2014a. Raw gaze positions were exported using the Raw Data Exporter plugin. Raw data exported files contained gaze positions, eye positions and level of confidence for each individual frame, as well as a corresponding time stamp based on the computer's real time clock. Eye-tracking videos were then visually inspected and the onset for a stimulus was defined as the first instance in which the gaze touched any part of the stimulus. The image reference number, value level and the onset frame was manually tabulated into an excel spreadsheet. Two participants' data were excluded from the sample due to loss of gaze calibration during the recordings. Analysis of gaze duration was not included as no information was registered for the last instance in which the participants gaze left the object. This was due to researchers only being interested in using gaze onset for real-world triggering.

Participants were asked to view each product for a minimum of 3–4 s, and could continue viewing the products for as long as they liked.

4.3.9. EEG and Eye-Tracking Data Synchronization

A trigger box with a light emitting diode was used to temporally synchronize the eye-tracking and EEG data streams. A pulse of light was delivered into the world view camera whilst a TTL pulse was inputted into the continuous EEG data and, from this, the frame in which the pulse of light was offset in the eye-tracking data and the last TTL trigger registered in the EEG data was recorded and used to zero both clocks. The temporal accuracy of the synchronization trigger was tested previously in a 15-min recording whereby 15 synchronizing light/TTL pulses were produced every minute and the temporal asynchrony between triggers in both data streams was 0.022 ± 0.020 ms (mean ± SD) within a 15-min period.

Using a custom MATLAB script, subject’s BDM ratings were split into quartiles based on monetary values assigned to the products, producing four SV levels: low-value, low medium value, high medium value, and high-value, and these were used to retrospectively redefine the value conditions. These subjective BDM values for each object were combined with the timestamp of the computer’s real time clock that corresponded to the tabulated frames where the eye first hit each object, and this was combined with a set file for each block in order to create an event file to import the triggers into the EEG data. In this way, value conditions were defined by each individual subjectively rather than by retail price.

4.3.10. Eye Movement Related Potentials and Handling Eye Movement Artefacts

EEG data was pre-processed using Brain Electrical Source Analysis (BESA) software version 6.1 (MEGIS Software GmbH, Munich, Germany). The data was referenced to a common average (Lehmann, 1987), and, following visual inspection, eye blink artifacts were identified by defining their topographies and removed using a principal component analysis pattern selection algorithm which identifies artifacts based on topographies of marked segments and excludes them from the data (Berg & Scherg, 1994). Muscle artefacts were manually selected and removed from the data. Event markers were inserted into the data by temporally synchronizing the EEG and eye-tracking data sets using custom Matlab scripts. The time period for baseline correction was from -300 ms to 0 ms, and the data was epoched from -300 pre-stimulus to 600 ms after the instance when the eye first hit the object (0 ms). The data was filtered from 1 to 35 Hz and all time-locked post-saccadic EMRPs from all participants across four value conditions (low-, low-medium, high-medium, and high-value) were analysed.

Due to the time locking of EMRPs to the offset of saccades, a number of saccade- related artefacts needed to be extracted from the data. Saccade related artifacts are generated by rotation of the corneoretinal dipole of the eye (Berg & Scherg, 1994; Dimigen et al., 2011), movement of the eyelid during blinking and vertical or horizontal saccades (Dimigen et al., 2011; Picton et al., 2000) and muscular activation at the beginning of a saccade, referred to as the saccadic spike potential (Dimigen et al., 2011; Nikolaev et al., 2016; Thickbroom & Mastaglia, 1986).

To separate further eye movement artifacts such as saccade-related potentials from genuine cortical activity, an infomax ICA analysis (Iriarte et al., 2003; Jung et al., 2000; Khushaba et al., 2013; Nikolaev et al., 2016) was performed which algorithmically separates the grand average signal into its maximally statistically independent constituents. An infomax ICA was conducted using concatenated grand averaged data from four different value conditions (2,400 time points). ICs weights were estimated, and, of these, ICs were selected based on spatial and temporal properties as well as responsiveness to value conditions. Subsequently, individual ICs were back projected onto single subject average data by loading the grand average ICA weights on single subject averages and exporting only the individual IC data of interest (Debener et al., 2010). This method allowed for the removal of ICs that represented residual saccadic artefacts from the grand averaged sensor signal by only back projecting the ICs of interest.

4.3.11. Source Dipole Modelling

To localize the generators of cortical potentials represented in ICs of interest, IC waveforms were analysed using source dipole analysis in BESA version 6.1 program. Using a sequential strategy (Hoechstetter et al., 2010; Stancak et al., 2002), equivalent current dipoles (ECDs) were fitted to describe the 3-dimensional source currents in the regions contributing predominantly to the data (Scherg & Von Cramon, 1986). ECDs were fitted one at a time to explain the latency components starting with the shortest latency. ECDs had free origins and orientations. The fitting procedure was stopped when the ECD explained the maximum amount of variance (at least 90%) or if the dipole was located outside of the head. A 4-shell ellipsoidal volume conductor model was used to create the source dipole model with the following conductivity levels assumed; head = 0.33 S/m, scalp = 0.33 S/m, bone = 0.00 S/m, and cerebral spinal fluid = 1.00 S/m.

4.3.12. Statistical Analyses

For behavioral ratings, separate one-way repeated measures ANOVAs (four levels) were employed to examine the relationship between value level (as defined by BDM rating) and BDM rating, retail price, desirability and pleasantness ratings. Greenhouse-Geisser corrections were used to overcome the violation of sphericity assumption when necessary. All significant effects were further analysed using *t*-tests and a critical threshold of $p < 0.005$ was utilized. All standard statistical tests were carried out in SPSS v. 24 (IBM Corp, 2016).

Independent component analysis waveforms for each individual IC were exported and one-way repeated measures ANOVAs were conducted using the EEGLab toolbox (Delorme & Makeig, 2004). The four SV levels (low-value, low-medium value, high-medium value, and high-value) were compared against IC amplitude across time windows where amplitude was maximal for each IC. *T*-tests were also used to compare all low versus all high-value conditions for each IC of interest. A 95% confidence level was always employed. To reduce the likelihood of generating false positives, *p*-values were corrected using 1,000 permutations (Maris & Oostenveld, 2007) and a critical threshold of $p < 0.005$ was utilized.

4.4. Results

4.4.1. Behavioral Results

Figure 9A–D show the mean values of WTP, retail price, desirability and pleasantness in four different levels of values ranging from low to high-value, respectively. All of these measures showed a statistically significant relationship with SV level according to one-way ANOVAs for repeated measures with four levels of values as the independent variable [BDM: $F(1,24) = 141.22$, $p < 0.001$; retail price: $F(2,43) = 72.61$, $p < 0.001$; desirability: $F(1,37) = 89.13$, $p < 0.001$; pleasantness: $F(2,38) = 75.53$, $p < 0.001$]. In all dependent measures, the *t*-tests showed statistically significant differences across all value levels ($p < 0.005$). Additionally, there was a highly significant linear trend component ($p < 0.001$ in all cases), confirming a linear increase in WTP, retail price and subjective ratings across all SV categories.

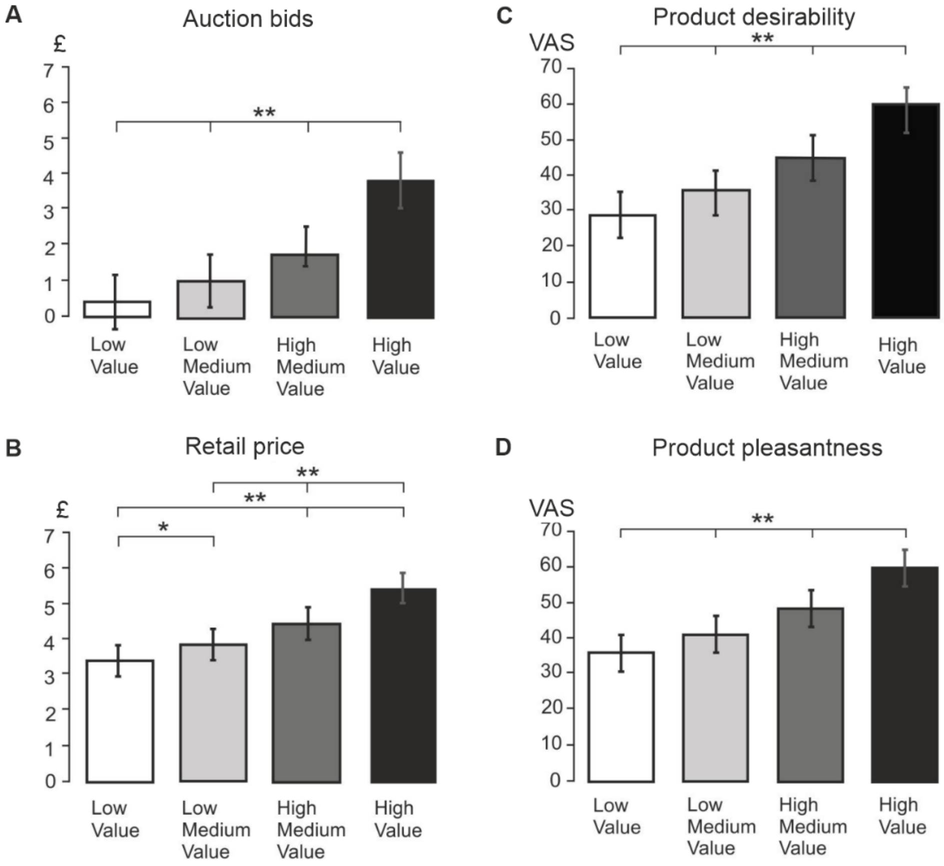

Figure 9. Average behavioral ratings. (A) Bar graph showing the mean BDM auction bids for four different value levels: low, low medium, high medium, and high-value. The value conditions are split by subject's auction rating, and the bar graph shows significant differences between all value conditions. A double asterisk (**) indicates presence of high statistical significance (p < 0.001), and a single asterisk indicates statistical significance (p < 0.05). This provides validation for the splitting product stimuli into four value categories based on BDM auction value. (B) Bar graph showing mean retail price across the four BDM auction value conditions. Highly significant differences were indicated with a double asterisk, and p < 0.05 was indicated with a single asterisk. The bar graph indicates that significant differences were found in retail price across all value levels (p < 0.05), suggesting that BDM auction value ratings mirror the actual retail price of the product. (C) Bar graph showing mean product desirability rating across four value conditions. From the graph it can be seen that mean desirability increased incrementally with BDM value (all p < 0.001). (D) Bar graph showing mean product pleasantness rating across all value levels. Again, this graph shows that mean pleasantness increases incrementally with BDM value (all p < 0.001).

4.4.2. Eye Movement Related Potentials

Figure 10A displays a grand average butterfly plot demonstrating EMRPs across all value conditions and all 19 participants. Figure 10B illustrates the topographic maps corresponding to time points of interest that are highlighted in Figure 10A. During the pre-stimulus interval prior to onset of fixation, the topographic map displays a large frontal positivity which is maximal in the region of the eyes at -18 ms across all conditions and participants. This potential component represented a corneoretinal artifact, and was associated with the offset of the saccadic eye movement when the subject directed their gaze toward a particular stimulus. At stimulus onset (0 ms), there was residual corneoretinal artifact associated with a saccadic eye movement. The lambda potential (Thickbroom et al., 1991; Yagi, 1979, 1981) (Figure 10A,B) peaked at 88 ms and demonstrated a large positivity across occipital electrodes similar to P100 component in a visual evoked potential. Figure 10A also demonstrates a positive peak around 168 ms, which was associated with positivity in parietal electrodes (Figure 10B). Another peak emerging at 227 ms demonstrated bilateral posterior positivity (Figure 10A, B).

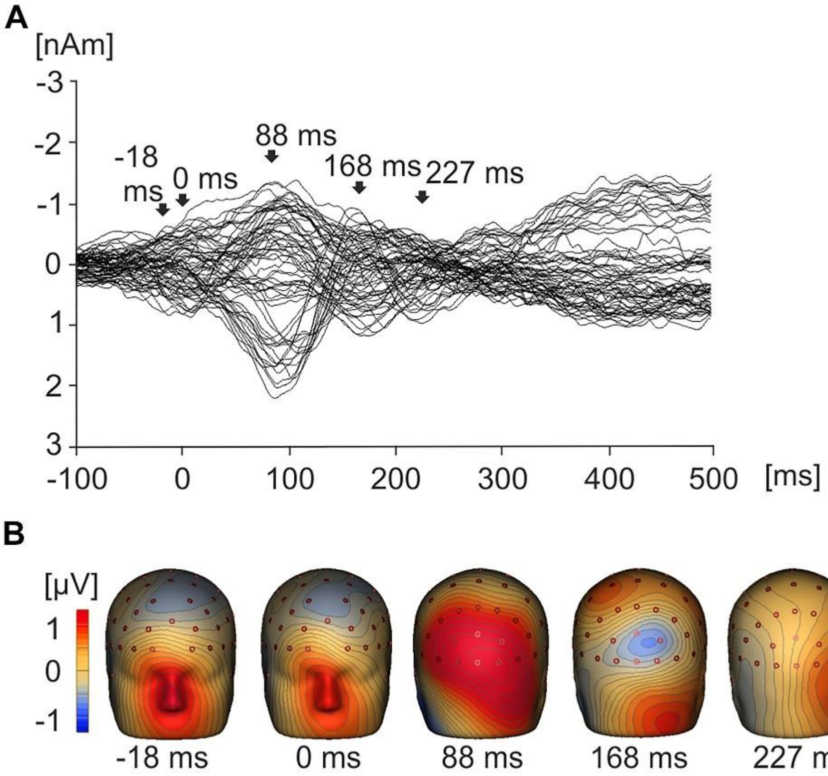

Figure 10. Grand average EMRPs waveforms and topographic maps. (A) Butterfly plot showing grand average EMRPs waveforms across all participants and all product value conditions with key points of interest highlighted with arrows. The butterfly plot demonstrates that eye movement activity is present in the baseline (–18 ms) and residual eye movement is present when the eye first touches the image (0 ms). The lambda component is highlighted (88 ms) and two later value related peaks are observed at 168 ms and 227 ms. (B) 3D whole head topographic maps displaying grand average EMRP cortical activation at key time points (–18 ms, 0 ms, 88 ms) and value related peaks (168 ms and 227 ms).

4.4.3. ICA Reconstruction of Eye Movement Related Potentials

Figure 11A shows the grand average IC activities for five separately back-projected IC components collapsed across four value conditions (low, low medium, high medium, and high-value products). Figure 11A also shows the topographic maps and source dipole solutions for each of the ICs. Figure 11B demonstrates how individual IC amplitude responds separately for each of the four value conditions.

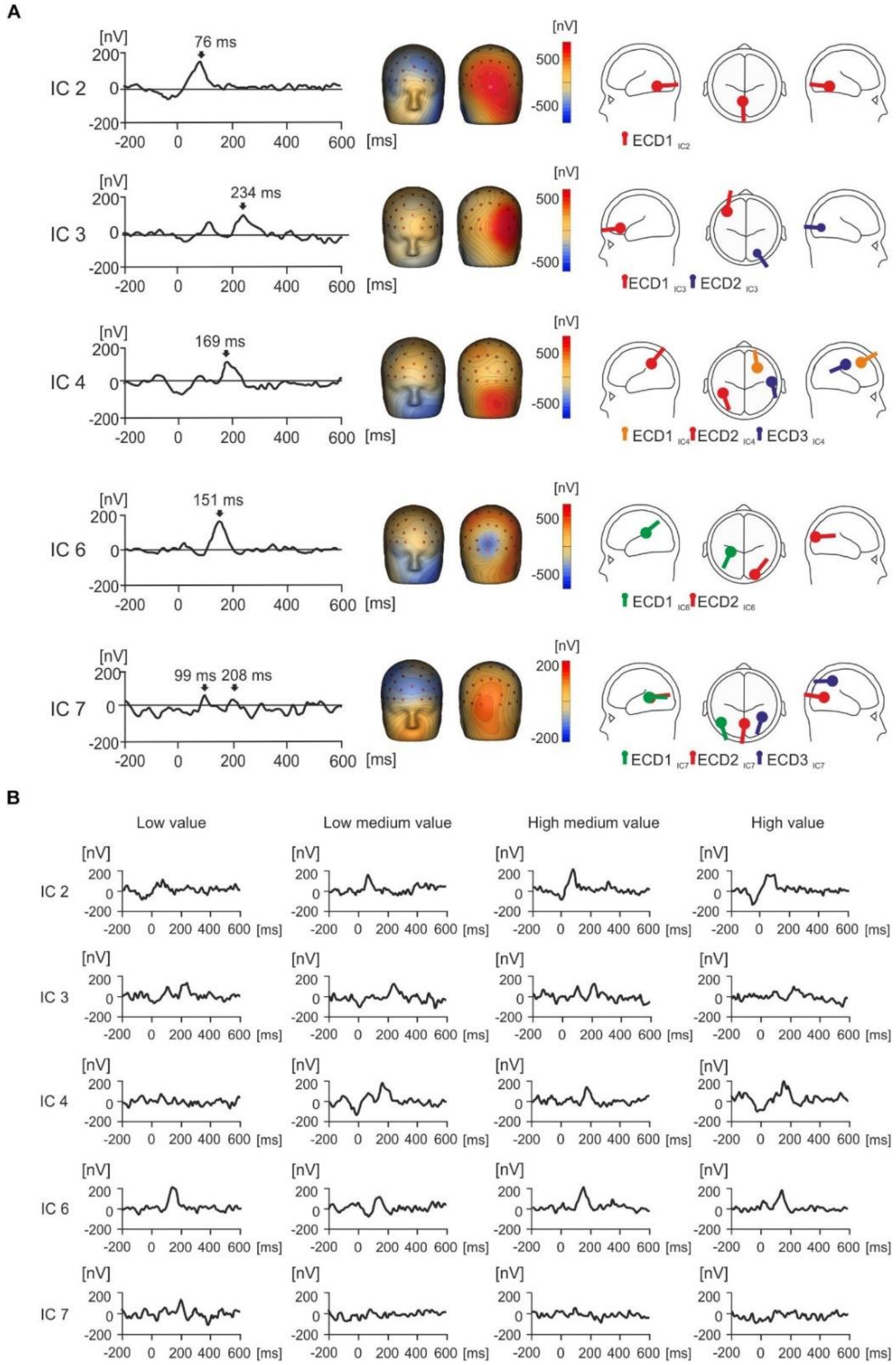

Figure 11. Grand average IC activity (nV) and value. (A) Grand average waveforms for each isolated IC of interest between –200 and 600 ms, with peak activity for each component indicated with an arrow. Source dipole modeling was used to estimate equivalent current dipoles (ECDs) in order to explain the cortical sources of activation for each IC. ECDs for each IC can be observed in a glass brain showing the location and orientation of estimated cortical activity, with no more than three sources utilized. (B) The grand average waveforms for each individual IC were split by condition in order to illustrate how each IC responds to value over time.

IC2 showed a strong positive peak at 76 ms, and the topographic maps presented a strong positive potential in the right occipital region of the scalp (Figure 11A). This spatio-temporal pattern was modeled with one ECD ($ECD1_{IC2}$) which was fitted in the visual association area (Brodmann area 18, approximate Talairach coordinates x = -4.5, y = -56.3, z = -10.4 mm). The peak in IC2 was seen in all four value conditions (Figure 11B).

IC3 displayed a positive potential maximum in the right occipito-temporal electrodes and a negative potential in the left frontal region of the scalp (Figure 11A). The time course of IC3 manifested a peak at 112 ms followed by a double peak around 210 ms and later around 250 ms. The spatial pattern of IC3 was modeled with two ECDs. $ECD1_{IC3}$ explained the most variance for left frontal negative activation in the dorsolateral prefrontal cortex (Brodmann area 46, approximate Talairach coordinates x = -41.7, y = 37.1, z = 5.4 mm). $ECD2_{IC3}$ accounted for the right occipital positivity and was placed in the visual association area (Brodmann area 19, approximate Talairach coordinates x = 24.9, y = -78.9, z = -4.4 mm). While the later latency peak at 250 ms was seen in all four value conditions, the earlier peak (212 ms) was prominent only in the low- and high-medium value conditions (Figure 11B).

IC4 showed a peak at 169 ms (Figure 11A). The spatio-temporal maps of IC4 showed two large positive and negative component maxima in frontal and occipital regions of the scalp, respectively, and further positive maxima in centroparietal electrodes. This complex spatio-temporal configuration required a model with three ECDs (Figure 11A). $ECD1_{IC4}$ explained the large negative potential maxima in the left frontal region and was located in the frontal eye field area of the cortex (Brodmann area 8, approximate Talairach coordinates x = 28.8, y = 20.6, z = 44.7 mm), which was maximal around 169 ms. $ECD2_{IC4}$ was fitted into the left parietal area (Brodmann area

39, approximate Talairach coordinates *x* = -45.9, *y* = -50, *z* = 33.4 mm), to explain the temporal positivity. $ECD3_{IC4}$ was fitted to the right primary somatosensory cortex (approximate Talairach coordinates *x* = 56.3, *y* = -16.7, *z* = 35.8 mm) and explained right localized parietal negativity and right occipital positivity at 169 ms. The IC4 component peak at about 169 ms was seen in all value conditions except the low-value condition (Figure 11B).

IC6 demonstrated a positive peak occurring at 151 ms (Figure 11A). The topographic map manifested a frontal negative potential, a parietal positivity, and a localized negative potential in the midline occipital electrodes. Two ECDs explained this topographic map. $ECD1_{IC6,}$ located in the parietal cortex (Brodmann area 40, approximate Talairach coordinates *x* = -28.4, *y* = -32.7, *z* = 21.5 mm) accounted for frontal negativity. $ECD2_{IC6}$ pointed to the negative potential in the midline occipital electrodes (Brodmann area 18, approximate Talairach coordinates *x* = 22.5, *y* = -97.0, *z* = 9.4 mm) and was located in the right visual association area. The peak at about 150 ms was seen in all four value conditions (Figure 11B).

Figure 11A displays a peak for IC7 at 99 ms, and a second smaller peak at 208 ms, with large frontal negativity and occipital positivity. Three ECDs were used to explain this activation, and this can be seen in Figure 11A. $ECD1_{IC7}$ explained most variance in the frontal cortex (Brodmann area 19, approximate Talairach coordinates *x* = -48.7, *y* = -65.9, *z* = 6.7 mm), which peaked at 208 ms and accounted for negativity in the frontal cortex. $ECD2_{IC7}$ explained most variance in the left occipital region (Brodmann area 18, approximate Talairach coordinates *x* = -0.3, *y* = -71.2, *z* = 7.3 mm), in the left primary visual area, peaking at 208 ms and explaining the occipital positivity. $ECD3_{IC7}$ explained a source in the parietal cortex (right Brodmann area 39, approximate Talairach coordinates *x* = 39.4, *y* = -55.8, *z* = 44.9

mm), in the angular gyrus, and this accounted for right frontal negativity peaking at 208 ms. In Figure 11B, IC7 displays a peak for low-value objects at 208 ms that does not seem to appear for other value conditions.

Notably, the use of ICA afforded the separation of components that had a cerebral origin and responded to product values from the potentials caused by oculomotor activity such as saccades, spike potentials and residual eye blinks (Berg & Scherg, 1991; Dimigen et al., 2011; Nikolaev et al., 2016; Picton et al., 2000; Thickbroom & Mastaglia, 1986). Examples of the artefact-related ICs are shown in Figure 12A, B. For instance, IC11 showed strong positive activation around the eyes which peaked at 6 ms indicating that this IC represents artefactual saccadic activity. Likewise, IC16 showed a positive potential maximum that was biased to the right eye with a peak at 5 ms. This suggests that the subject was making a right sided saccade when their gaze touched the first image.

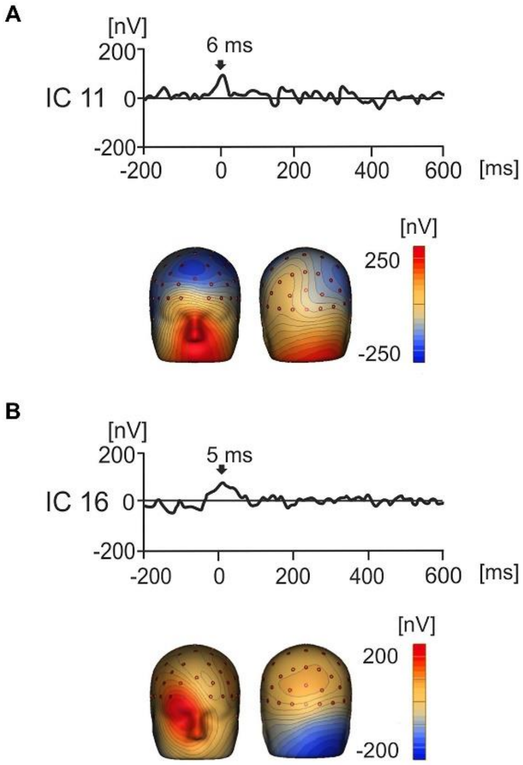

Figure 12. Grand average IC waveforms and corresponding 3D whole head topographic maps (nV) for two ICs that represent eye movement related artifacts. (A) IC11 showed peak activity around image onset (6 ms), with a positive maxima around the eyes, suggesting that this component represented left biased saccadic eye movement related activity. (B) IC16 showed peak activation around product image onset (5 ms) and positivity maximal around the right eye, suggesting that that this component represents right-biased saccadic eye movement related activity.

4.4.4. The Effect of Value on ICs

Figure 13A–D show, for each individual IC, statistically significant effects of values with all value conditions superimposed and bar graphs with mean voltage amplitude differences at key time points of interest for each IC, with standard error bars. IC3, IC4, IC6, and IC7 showed statistically significant effects of value categories according to a one-way ANOVA for repeated measures which was conducted for five components, including IC2, across all time points ranging from -200 ms to 600 ms.

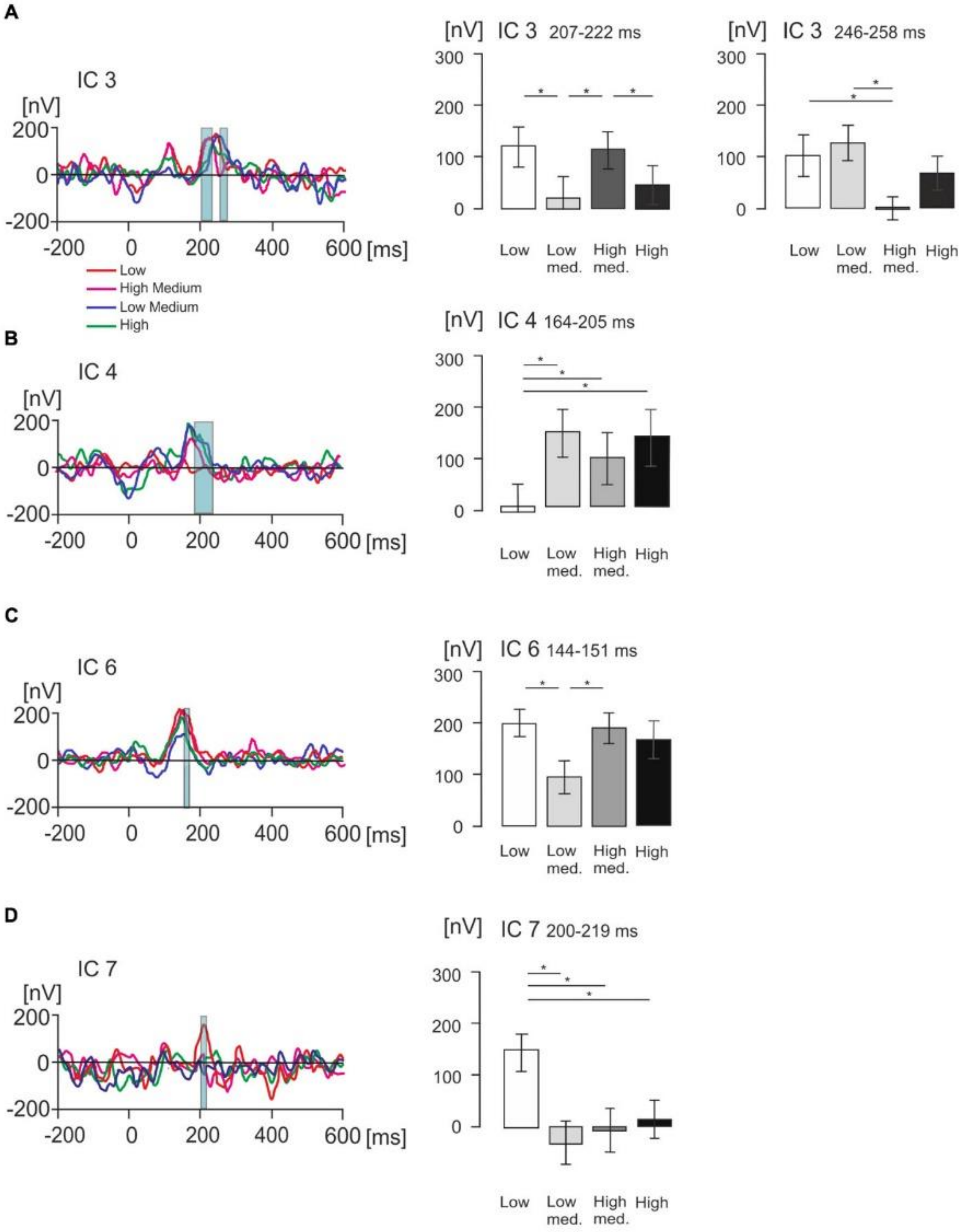

Figure 13. Statistical differences in product value for ICs of interest measured in nanovolts (nV). (A–D) Figures illustrating grand average EMRP activity split across four value conditions, indicated by different colored lines, for four isolated ICs of interest including IC3, IC4, IC6 and IC7 respectively. The corresponding bar graphs illustrate differences in mean amplitude across the four SV conditions for each isolated IC of interest. Significant differences between mean amplitude across conditions are indicated with a single asterisk for differences significant at $p < 0.05$.

In IC3, a statistically significant effect of value was found in two latency intervals, 207–222 ms and 246–258 ms. In the time window 207–222 ms [$F(2, 42) = 7.22$, $p < 0.005$, Figure 13A], the effect of product value was largely driven by the low-medium value products demonstrating a significantly lower amplitude compared to low- ($p = 0.014$) and high-medium value products ($p = 0.006$). The high-medium value also demonstrated a significantly higher IC3 amplitude than the high-value category ($p = 0.033$). When all low- and all high-value conditions were compiled, there were no statistically significant differences ($p > 0.05$).

In the latency interval 246–258 ms, the effect of product values [$F(2, 51) = 6.67$, $p = 0.001$] was related to the high-medium products producing lower IC3 amplitude compared to low-value ($p = 0.013$) and low-medium product amplitude ($p = 0.007$). When all low- and all high-value conditions were compiled and compared using a *t*-test, we found low-value products produced higher IC3 amplitude (116 ± 26 nV, mean ± SEM) compared to high-value products (33 ± 21 nV, mean ± SEM), and this difference was statistically significant [$t(36) = 4.02$, $p < 0.001$].

In IC4 (Figure 13B), a statistically significant effect of product values was found in the latency interval 164–205 ms [$F(2, 42) = 7.36$, $p < 0.005$], with low-value products producing significantly smaller amplitude compared to low-medium value ($p = 0.002$), high-medium value ($p = 0.03$), and high-value products ($p = 0.04$). When low- and high-value levels were compiled, products showed no statistically significant differences ($p > 0.05$).

In IC6 (Figure 13C), the product values differed significantly in the latency interval 144–151 ms [$F(2, 41) = 5.61$, $p = 0.005$] with low-value products producing significantly higher IC6 amplitude compared to low-medium value products ($p =$

0.005), and high-medium value producing significantly higher IC6 amplitude compared to low-medium products ($p = 0.023$). When low and high-values were compiled, the difference between low- and high-value was not statistically significant ($p > 0.05$).

Finally, IC7 showed no statistically significant effect on the peak at 99 ms, but did show a statistically significant effect of product values in the latency interval 200–219 ms [$F(2, 45) = 6.95$, $p = 0.001$, Figure 13D]. This effect was driven by the low-value category producing significantly higher IC7 amplitude compared to low-medium ($p = 0.009$), high-medium ($p = 0.017$) and high-value conditions ($p = 0.010$). When all low-and all high-values were compiled, the difference was not statistically significant ($p > 0.05$).

4.5. Discussion

The present study explored the cortical representations of economic decisions for products using EMRPs extracted from mobile EEG. ICA revealed a typical lambda component as well as four components that were modulated by subjective economic value in the latency range of 150 – 200 ms. The most important finding in the current study was that two ICs demonstrated contrasting responses to low-value products, with IC4 modulating amplitude for all except the lowest value products, and IC7 exhibiting enhanced amplitude for lowest value products.

Viewing high and intermediate value items was associated with comparatively strong IC4 activity peaking at 169 ms. This enhanced responsiveness of IC4 to all value conditions excluding low suggests that there is early enhanced attentional processing for higher-valued items and this could point toward a relatively automatic valuation system that preferentially attends to more highly-valued items (Anderson et al., 2011; Glimcher & Fehr, 2014). Support for this interpretation comes from research demonstrating that a shorter latency and larger amplitude of the P200 component was associated with early preferential attention (Hanatani et al., 2005). In a recent study, Tyson-Carr et al. (2018) found that the P200 component was modulated by valuation context during product preference decisions. The authors observed enhanced P200 activation when participants considered product desirability, which they suggested was related to attention allocation during valuation decisions. These results align with the present experiment in that more highly valued, desirable stimuli received enhanced attention, making it more likely that they would be readily purchased at a later stage. Likewise, the P200 has also been associated with preferential processing of primary reinforcers such as sugary foods (Schienele et al., 2017). Our data suggests that the cortical response captured by IC4 represents an automatic attention allocation mechanism that responds preferentially to higher-valued stimuli in order to facilitate purchasing for higher valued items and to avoid aversive low-value stimuli, irrespective of product category. An ECD for IC4 was estimated in the left parietal area (BA39). The parietal cortex has been shown to become activated during explicit comparisons (Cappelletti et al., 2010; Hsu & Goh, 2016; Menon et al., 2000) and correlated with evidence seeking during reward related decisions (Furl & Averbeck, 2011). An ECD for IC4 was also observed in the right primary somatosensory cortex, which has shown modulation following rewards in a somatosensory task (Pessoa & Engelmann, 2010). These results lend some support to the interpretation that IC4 represents an early neural attention allocation mechanism that selectively responds to more highly valued stimuli and is insensitive to the stimuli that are the least positively valued, even in the case of everyday household products.

In contrast to IC4, IC7 responded to low-value items around 200 ms. This early enhanced processing for the low-value objects can be understood in terms of very low-value products representing an aversive stimulus, due to the potential for the loss of monetary resources. In support of this interpretation, the P200 ERP component has been found to be modulated by emotional valence of a stimulus (Ashley et al., 2004; Carretié et al., 2001a; Huang & Luo, 2006), and to moderate attention allocation (Carretié et al., 2001b) for products of different valence (Carretié et al., 2001a; Polezzi et al., 2008). Moreover, some studies suggest that the P200 ERP component is reflective of a subjectively negative assessment (Polezzi et al., 2008). For instance, Carretié et al. (2001b) found a higher P200 amplitude and shorter latency when viewing negative stimuli, which they attributed to enhanced attention for aversive stimuli. Source dipole modeling for IC7 revealed an ECD in the visual association area, which has been shown to be modulated by the motivational relevance of a stimulus (Krawczyk et al., 2007). Another ECD was located in the angular gyrus, which is associated with numerical problem solving, (Seghier, 2013), attention allocation for salient stimuli (Gottlieb, 2007), response inhibition (Gottlieb, 2007; Nee et al., 2007; Seghier, 2013) and stimulus value (Lin et al., 2012). Angular gyrus activation has also been observed in gambling tasks, with more activation for potential losses (Minati et al., 2012). Therefore, it is likely that the angular gyrus is involved in enhancing attention toward low-value stimuli to inhibit buying and avoid monetary loss. Taken together, we suggest that IC4 and IC7 reflect attention-related and aversive responses which are likely part of an early valuation system that serves to enhance attention for intermediate and high-value stimuli to facilitate purchasing and to enhance attention for aversive low-value stimuli in order to facilitate avoidance (Libera & Chelazzi, 2009). In this way, basic economic decision making appears to occur quickly in order to isolate the lowest value products and to ensure monetary resources are being economically optimized. The authors recognize, however, that IC7 represents a very small component that peaks close to baseline, therefore, any conclusions should be viewed with caution.

Two other ICs, IC3, and IC6, preferentially responded to medium-value products, although these responses are more difficult to interpret. IC6 peaked at 151 ms and exhibited higher amplitude for low and high medium-value products. The P150 ERP component has been associated with a basic rapid visual categorization process and it might be that it forms part of a 'tagging' mechanism that marks items out for later enhanced processing downstream (Cesarei et al., 2015; Kirchner & Thorpe, 2006; Nikolaev et al., 2013). In support of this interpretation, an ECD was located in the left supramarginal gyrus, which has been implicated in semantic categorization of visual stimuli (Pexman et al., 2007), and economic decisions for products (Deppe et al., 2005). Another dipole was observed in the visual association area, which has been shown to be modulated by the motivational relevance of a stimulus (Krawczyk et al., 2007).

IC3 showed statistically significant increases in activity for medium-value categories in two latency windows within the range of the P200 ERP component. Further data and replications are needed to fully understand the role of IC3 in product evaluations in natural settings. However, the finding of a source contributing to IC3 in the dorsolateral prefrontal cortex suggests that this component was related to value-based decision-making as important components of decision making such as WTP, moderation of risk, and top down attention have been shown to be mediated by this brain region (Bartra et al., 2013; Hubert & Kenning, 2008; Mahesan et al., 2016; Morris et al., 2014; Plassmann et al., 2007).

Our data suggests that attention or aversion reflecting SV is attributed to products during free viewing in quasi-naturalistic settings as early as 200 ms. Further support for this comes from studies of single neurons in monkey’s orbitofrontal cortex, which have been shown to respond to values and risks as early as 180 ms (Critchley & Rolls, 1996; Padoa-Schioppa & Assad, 2006; Schultz et al., 1993). The data also suggest that this early automatic valuation is mediated by a set of cortical activation patterns, none of which encodes values in a linear fashion. Rather, our results prompt the hypothesis that certain cortical regions or sub regions of larger brain areas are tuned to respond predominantly to low -or high- value items. Value-tuned brain modules that are responsible for spotting low- or high-value items in our environment would allow rapid categorization and prompt behavioral avoidance or approach responses.

The fast bottom-up responses for low and higher value products and the potentially more deliberative top-down responses for more ‘difficult’ medium-value decisions can be better understood from the perspective of the Fuzzy Trace Theory (Brainerd & Reyna, 1990). The theory postulates that decisions in the real-world are calculated based on two processes that are computed in parallel; verbatim representations, which involve automatically matching characteristics to representations stored in memory, and more meaningful top-down gist representations (Corbin et al., 2015). In the current study, it is possible that high and low-value items elicit an automatic verbatim representation as they have been experienced before, whereas medium-value products require more top-down deliberation and elicit a semantic ‘gist’ representation. As such, the Fuzzy Trace Theory provides explanation for the similar latencies of the ICs as they are processed in parallel and clarifies the recruitment of top-down brain areas for medium-value decisions. This draws similarities to the neuroeconomic concept that multiple brain systems are involved in the computation of value (Dickinson & Balleine, 2002; Rangel et al., 2008). Daw et al. (2005) propose that different brain systems might be involved when choosing between options with different values under varying levels of uncertainty. These systems include habitual processing, which represents fast responses that are learned through trial and error, and goal-directed responses, which involve the assignment of value through outcome assessment and reward calculation for multiple options. In the current study it could be the case that the habitual processing system was employed for valuation of products that participants had more experience of choosing between, i.e., high and low-value products. Conversely, when the product is not categorized as either high or low-value, the goal-directed system dominates as further assessments are needed in order to determine the products' worth. The results of the current study are also highly relevant to the field of neuromarketing as it was shown that, within the first 200 ms of viewing a product, the brain already computes and assigns a value (Jones et al., 2012; Pozharliev et al., 2015; Tyson-Carr et al., 2018). As such, it appears that first impressions are very important when deciding whether to purchase a product and previous experience and expertise can influence purchase decisions.

There are, however, several limitations associated with the current study. One limitation of this experiment is that we were unable to detect EMRPs occurring later than 300 ms post stimulus. Previous research has highlighted the role of the P300 (San Martín, 2012; Yeung & Sanfey, 2004) in outcome evaluation during economic decisions. In traditional laboratory-based experiments, participants are presented with a fixation cross followed by a stimulus in the same predefined position in order to avoid saccade related artefacts (Dimigen et al., 2011). In contrast, free-viewing in the real-world is both a multi-and-*trans*-saccadic process in which the visual stream is constantly being updated and integrates new sensory information into continuous perceptual and cognitive processes (Dimigen et al., 2011). As a result, the new sensory information does not show a fixed phase relative to the time-locked event and distortion of the signal occurs later in the EMRP (i.e., after 300 ms; Dimigen et al., 2011). This is an ongoing issue for experiments that combine free eye movements with EEG, as it is difficult to ensure that continuous visual updating does not distort the EMRP without compromising the ecological validity of the experiment. As a result, the current findings should be viewed as preliminary, and more research is needed to determine how the brain computes valuation decisions later in the decision-making process. Another limitation of the current study is that source dipole modelling was used to estimate sources for EMRP activity. It must be emphasized that any conclusions drawn from source dipole modelling in mobile EEG should always be viewed with caution and any interpretations are tentative. As such, no statistics were performed on the dipole analysis, which was conducted purely for exploratory purposes. This is because of the difficulties associated with source localization in EEG data (Luck, 2005), which are exacerbated in mobile EEG data (Grech et al., 2008).

Moreover, to avoid explicitly asking participants to provide an economic value for a product, participants were asked to rate whether they would purchase products during the gallery task and were later required to bid on the items, and these bids were used to retrospectively define the value conditions. However, it cannot be ruled out that participants considered other factors such as desirability and pleasantness to inform their decision in the gallery. These factors could theoretically influence attention or aversion, as our results show that desirability and pleasantness ratings echoed the economic value of the stimulus. Future studies should endeavour to isolate value related from non-value related attentional processes, although this is very difficult to achieve. Likewise, attention, aversion and early economic valuation decisions should be further explored using fMRI and fMRI informed source analysis techniques in EEG. Finally, it is possible that the limited price range could have influenced economic value responses as the current experiment failed to show a component that responded exclusively to the highest value condition. This could be because objects within the £8 price bracket are only considered to be high-value within the context of products on offer. Future experiments may benefit from expanding the price range to better examine how the temporal sequencing of economic value attribution occurs in the brain.

Finally, findings from the current study can be compared with results obtained from a standard laboratory recording. The present study follows a laboratory-based experiment from our research group by Tyson-Carr et al. (2018), who found, using the same BDM auction paradigm, that the N200 resolved the valuation of everyday household products, with a bias toward low-value objects. The authors suggested that the modulation of the N200 for low-value objects hints toward an automatic valuation system, which is similar to what was observed in the current study. Therefore, as the current study provides further support for automatic valuation of products even in naturalistic environments, this adds validity to the data. This is an extremely important and novel contribution as the current experiment was able to demonstrate the feasibility of examining EMRPs for products in naturalistic environments.

4.6. Conclusion

In conclusion, the current experiment demonstrated that, to some extent, the neural spatio-temporal dynamics that underpin economic decisions for household products can be resolved in a naturalistic setting. Findings suggest that the EMRP parietal P200 component reflects an attention allocation mechanism that responds extremely quickly to isolate the lowest (IC7) value stimuli from all other value stimuli (IC4), as these represent important decisions in terms of maximizing economic resources. Other components responded to medium-value products and may indicate a fine grating of more difficult decisions (IC3, IC6). Overall, while none of the ICs displayed linear amplitude changes that parallel the SVs of products, results suggest that a combination of multiple ICs may sub-serve a fine-grained resolution of the subjective economic values of products. In order to fully disentangle the spatio-temporal neural processes that underpin economic decisions for products in the real world and to better understand how medium and high-value products are represented, more research is needed with a broader range of stimuli.

5. INVESTIGATING NEURAL RESPONSES UNDERLYING PRODUCT VALUATION IN THE REAL-WORLD USING WIRELESS ELECTROENCEPHALOGRAPHY AND EYE-TRACKING

Investigating Neural Responses Underlying Product Valuation in The Real-World Using Wireless Electroencephalography and Eye-Tracking

Roberts, Hannah[1*], Tyson-Carr, John[1], Soto, Vicente[4], Kokmotou, Katerina[1,3], Byrne, Adam[1,2], Fallon, Nick[1], Giesbrecht, Timo[3], Stancak, Andrej[1,2]

[1]Department of Psychological Sciences, Institute of Psychology Health and Society, Faculty of Health and Life Sciences, University of Liverpool, Liverpool, United Kingdom

[2]Institute for Risk and Uncertainty, University of Liverpool, Liverpool, United Kingdom

[3]Unilever Research & Development, Port Sunlight, United Kingdom

[4] Department of Psychology, Viña del Mar University, Chile

This experiment examined subjective valuation of products during free-viewing in naturalistic settings, with expansion of retail price ranges and guided saccade recordings for removal of saccade-related artefacts.

This manuscript is currently in preparation for submission.

The roles of the co-authors are summarised below:

Myself and Andrej Stancak, Nick Fallon and Timo Giesbrecht contributed to the development of the experimental design and planning of this work. Myself and John Tyson-Carr contributed to the development of the stimuli and materials. Andrej Stancak and I contributed to the development of the behavioral rating task and carried out the data acquisition, pre-processing, synchronisation and analysis of the collected data as well as figure creation and production of the final written manuscript. Matlab scripts were created by myself, Andrej Stancak and John Tyson-Carr. Vicente Soto, Katerina Kokmotou, John Tyson-Carr and Adam Bryne assisted me with the data collection.

5.1. Abstract

Previous laboratory-based EEG studies have shown that SV of objects within the visual field can be computed within hundreds of milliseconds. Our recent study (Roberts et al., 2018) used wireless EEG recordings and eye-tracking to identify components of EMRPs resolving SVs of household and office items viewed on a tour through a mock gallery. The P200 component of EMRPs has been shown to resolve low- versus high-value items. The present study investigated if EMRPs during product viewing would encode their SVs linearly by expanding the range of retail values of displayed products and by implementing a guided-saccade method for removal of saccade-related potentials that contaminate EMRPs and worsen the signal-to-noise ratio.

Participants viewed 216 product images in a gallery whilst a 64-channel wireless EEG and eye-tracking data were recorded. Afterwards, an auction task was used to elicit WTP to establish the SV of items. SVs were used to retrospectively categorise products into four distinct SV categories. ASF was used to remove saccade-related potentials extracted from guided saccade recordings. EMRPs were analysed using IC analysis and a clustering analysis of group data.

The guided-saccade method removed saccade-related artefacts more efficiently than a standard pattern-matching algorithm fitted to eyeblink artefacts. Four ICs peaking in the latency window 50‑230 ms resolved the SV of items. One IC operating in the latency period of the lambda potential showed a linearly decreasing component activity paralleling increasing SV with the strongest IC activity seen during viewing of the low-value items. The rest of ICs responded preferentially to one

of the medium-value categories. The components resolving SVs early on (50‑60 ms) differentiated the low-value category from other categories.

Results suggest that the cortical activation components elicited during free-viewing of household and office items in quasi-naturalistic settings are tuned to specific values bands, with the lowest-value items producing early activations. SV of items formed automatically during the initial period of viewing is based on a coarse grid of values, with low-values being attributed early on during free-viewing of items.

5.2. Introduction

The real-world contains large amounts of complex visual information competing for our attention, so it is essential to selectively allocate attentional resources towards salient information that supports the attainment of current goals (Oberauer, 2019). Despite the belief that decision making is an entirely conscious process, many of the decision making processes that are responsible for execution of repetitive procedures are fast, automatic and unconscious, preventing the conscious mind from information overload (Lebreton et al., 2009; Milosavljevic et al., 2011; Soon et al., 2008; Telpaz et al., 2015). According to the common neural currency hypothesis (Levy & Glimcher, 2012), irrespective of demand, values are continuously and automatically computed and assigned to objects in the environment (Bartra et al., 2013; Lebreton et al., 2009; Levy & Glimcher, 2012; Tyson-Carr et al., 2018; Westbrook et al., 2019). In support of the automaticity of the brain valuation process, single neuron recordings from monkey prefrontal cortex have shown that valuation occurs early in the brain between 100‑200 ms (Padoa-Schioppa, 2013). The ventromedial prefrontal cortex has shown encoding of SV of objects such as paintings houses or music in a linear fashion in humans (Lebreton et al., 2009) and in primates (Abitbol et al., 2015; Lebreton et al., 2009).

In humans, event-related potentials (ERPs) facilitate investigation of how value-based decisions evolve in the brain over time (Milosavljevic, Koch, & Rangel, 2011; Roberts et al., 2018; Telpaz, Webb, & Levy, 2015; Tyson-Carr et al., 2018; 2020). Electroencephalographic (EEG) research in laboratory settings has indicated that early ERP components such as the N200 (Telpaz, Webb & Levy, 2015; Tyson-Carr et al., 2018; 2020; Goto et al 2017) and the P200 (Ma et al., 2018) are modulated for products of different SV, particularly for the more extreme categories of least and most valued products, supporting the presence of an early attention-based neural valuation system.

Because humans are active agents who navigate the environment according to their current needs and goals (Makeig et al., 2009), it could be hypothesised that the purpose of this early valuation process is to filter relevant from irrelevant stimuli, promoting automatic approach and avoidance responses, facilitating this navigation (Krieglmeyer et al., 2010, 2013). However, it is not known how the valuation process works in naturalistic settings during free-viewing. Naturalistic settings provide a different framing to objects occurring in the visual field due to the presence of a natural context influencing neural activations in humans (Ladouce et al., 2017; Neisser, 1976). Exploration of a visual scene (e.g., during shopping) involves multi- and trans-saccadic operations in the brain to integrate information obtained in series of successive eye-fixations and to anticipate the visual features before the next saccade (Melcher & Colby, 2008). Upright posture in freely moving individuals compared to the sitting posture utilised in laboratory settings has been shown to affect brain activity and cognition (Thibault et al., 2014, 2015). Presenting one stimulus at a time removes the opportunity for detecting trans-saccadic operations, including integration of information accumulated from the environment across saccades to guide attention (Dimigen et al., 2011; Prime et al., 2011; Ray et al., 2011) and interactions with short term memory (Hollingworth et al., 2008). Such operations are important for decision making in natural environments when multiple stimuli are present.

Technological constraints have prevented the examination of valuation decisions within naturalistic settings in the past. However, recent advances in technological aspects of EEG recordings and data analysis have opened up possibilities for exploring brain activations in freely behaving individuals. MoBI is a novel non-invasive brain imaging approach to investigate brain activations occurring in freely behaving individuals (Gramann et al., 2011; Makeig et al., 2009). MoBI incorporates wireless EEG recordings and a multi-modal approach to data analysis which combines EEG recordings with recordings of muscle activity, spatial head coordinates, and eye movements (Ojeda et al., 2014). A MoBI approach has been implemented in a range of natural settings and activities including walking (Severens et al., 2012; Wagner et al., 2012), cycling (Zink et al., 2016), or piloting an airplane while airborne (Callan et al., 2015).

We have implemented a MoBI approach to study the encoding of SVs in early electrocortical responses associated with viewing household and office items of different SVs displayed in a mock gallery (Roberts et al., 2018). The preliminary study employed wireless EEG and a lightweight eye-tracking device to record eye-movements. After synchronising EEG and eye-tracking data streams and using the first instant of eye-fixation on an item image in the visual field of the participant, averaged EMRPs were computed. WTP was elicited for every item using Becker-DeGroot-Marschack (BDM) auction (Becker et al., 1964). Results revealed a lambda potential component in EMRP which is an equivalent of the P100 visual evoked potential (Thickbroom et al., 1991; Yagi, 1979a, 1981a) and EMRP components in the latency of 200 ms. differentiated the lowest-value products from all mid- and high-value items, suggesting that early cortical activation might automatically resolve values in a binary and coarse manner.

However, the coarse and binary resolution of values in EMRPs observed by Roberts et al. (2018) might have reflected the limited range of values in the study, which could have prevented the detection of a component responding exclusively to high-value, as products with a maximum retail value of £8 may not be attributed a high SV. The limited range of SVs may have reduced possibilities to identify the cortical activation components that would encode SV linearly. Therefore, the present study aimed to explore encoding of SVs in EMRPs using a larger range of values, with the highest retail price reaching £12.

Another factor that may have limited the possibilities of resolving linear encoding of SVs in our previous study (Roberts et al., 2018) may be the presence of residual saccade-related potentials that would increase the noise levels in EMRP data and increase the risk of Type I error. Notably, saccade-related potentials originating from the corneoretinal potential of the eye (Berg & Scherg, 1991b; Dimigen et al., 2011), movements of the eye lid (Picton et al., 2000) and contractions of eye muscles (Dimigen et al., 2011; Nikolaev et al., 2016; Thickbroom & Mastaglia, 1986) also affect scalp potentials in remote parietal or occipital electrodes (Forgacs et al., 2008).

During free-viewing, saccade-related artefacts are of particular concern due to their increased prevalence (Cao et al., 2020; Dimigen, 2018; Dimigen et al., 2011; Ille, Berg & Scherg, 2002) and methods have been developed to reduce saccade-related artefacts (Nikolaev et al., 2016; Plöchl et al., 2012; Roberts et al., 2018; Soto et al., 2018; Tyson-Carr et al., 2020). Soto et al. (2018) approached removal of saccade-related potentials by placing regional sources with three orthogonal equivalent source dipoles into the eye orbits. Roberts et al. (2018) employed a pattern-matching algorithm and PCA (Berg & Scherg, 1994) to identify and remove eyeblink artefacts. To further remove saccade-related artefacts, we employed an infomax ICA to decompose grand averaged data and subsequently back projected selected IC weights onto single-subject averaged data by exporting only the IC of interest (Debener et al., 2010). To further improve on removal of saccade-related potentials, guided-saccade recordings can be employed, which was initially suggested by Berg and Scherg and later adopted by others (Berg & Scherg, 1991; Dimigen, 2019; Ille et al., 2002). In this way, saccades of various viewing angles can be produced prior to the recording allowing for precise detection and extraction of saccade-related artefacts by applying the ASF method (Berg & Scherg, 1994; Ille et al., 2002). ASF models and subtracts the saccade-related artefacts from the EEG data using a PCA spatial filter. Guided-saccade recordings combined with ASF offer an alternative saccade removal solution for naturalistic recordings. Alternatives for saccade-related artefact removal are necessary when detailed information about saccade amplitudes and angles is not available, preventing implementation of linear deconvolution methods such as Unfold Toolbox (Ehinger et al., 2018).

The current study aimed to examine the automatic valuation process in naturalistic settings elicited during free-viewing of products to investigate whether components of EMRP encoded SVs of household and office items monotonically and linearly. The primary objective of the present study was to address the limitations of our preliminary study (Roberts et al., 2018) by exploring the cortical activation patterns underlying product valuation with an extended range of retail values. The current study achieved this by increasing the number of products and the monetary retail value threshold of the products. WTP values of items were evaluated using a BDM auction task, similar to Roberts et al. (2018).

A secondary objective of the study was to implement guided-saccade recordings and ASF to remove saccade-related artefacts from wirelessly recorded EMRPs and to evaluate the effectiveness of this procedure by examining amplitude reduction of EMRP in frontal electrodes in the vicinity of the eye orbits. It was hypothesised that by incorporating a larger range of values, one or more independent components would show monotonically rising or decreasing activation paralleling SVs. Furthermore, it was hypothesised that low-value products would show neural prioritisation reflected in a shorter latency of early EMRP components (Roberts et al., 2018; Tyson-Carr et al., 2018). Finally, it was hypothesised that the combined guided-saccade recordings and ASF would outperform the standard eyeblink artefact removal method implemented in Roberts et al. (2018).

5.3. Materials and methods

5.3.1. Participants

Twenty-three participants (13 females) were recruited for the current experiment. Three participants were excluded from the final analysis due to inability to export the eye-tracking data (1 subject), insufficient eye-tracking calibration resulting in a low number of trials (1 subject) or high residual variance in the EEG data at the ICA level (1 subject > 40% RV). A final sample of twenty participants was retained (11 female), with an average age of 27 ± 5.9 years (mean ± SD), two of which were left-handed.

All participants received information about the experimental procedure prior to the commencement of the study.

5.3.2. Ethical standards

Full informed consent was obtained before the study began and ethical approval was awarded from the Health and Life Sciences Research Ethics Committee (Psychology, Health and Society) reference number 1145 (extended). All experimental proceedings were conducted in accordance with the Declaration of Helsinki. Participants were remunerated £10 for their participation. The remaining balance from their endowment received during a BDM auction task was added to their final payment (after deducting the price equal to the random number assigned to the winning products), with an average of £16.52 ± 2.42 (mean ± SD) retained. Participants also received two household products worth up to £12 each.

5.3.3. Product images

Two hundred and sixteen colour images of everyday household products taken from a shopping catalogue were utilized in the current experiment. Three retail price categories ranging between £0.50 and £12.00 were developed. Low-value products were priced between £0.50 – £4.00 (2.32 ± 1.16), medium-value products were priced between £4.50 – £8.00 (£6.31 ± 1.17) and high- value products priced between £8.40 – £12.00 (10.46 ± 1.12), with 72 product images in each category. The product images were roughly sized at 20 × 20 cm and were presented on an A0 sized panel arranged around a central fixation cross (14.3 cm × 14.3 cm). All product images were pseudo-randomly distributed around the central fixation cross, with care taken to ensure than no two products of the same type (i.e., two kettles) were included on the same panel.

All A0 sheets containing the stimuli and fixation crosses were mounted onto Styrofoam panels, with adhesive Velcro to secure them to the wall (see Figure 14A). All 12 panels were double sided with stimuli for block two on the reverse side. Panels were mounted onto the walls of two adjoining corridors in the Eleanor Rathbone Building at the University of Liverpool, creating a product gallery (Figure 14B). The retail value of products per panel ranged between £47 – £64, with an average value per panel of £56.93 ± £4.49 and an aggregate retail value across all panels of £1366.40.

5.3.4. Procedure

Participants took part in two experimental sessions over two days, with session two taking place within one week. Session one involved the mobile EEG and eye-tracking set up, the product viewing task and the computerized BDM auction task. Session two involved a computerized hedonic rating task.

During the first experimental session, participants arrived at a laboratory space in the Eleanor Rathbone Building at the University of Liverpool. Participants were greeted, the experimental procedures were outlined, and fully informed consent was given. Participants had their heads measured and were fitted with a 64 channel actiCap (Brain Products, GmbH), which was placed according to the centre point between the anatomical landmarks of the nasion, the inion and the right and left pre-auricular points. Electrolyte gel was applied using a blunt syringe and 64 active shielded electrodes were connected, in accordance with the international 10 – 20 system. Once impendences were lowered to below 50 KΩ, the subject was connected to the wireless MOVE system (Figure 14A).

Pupilabs binocular eye-tracking glasses (Pupil Binocular Eye Tracking Glasses, PupiLabs, Germany) were applied and plugged into a lightweight Lenovo laptop. Once the eyes were calibrated using the 3D calibration routine on a blank A0 panel with manual markers kept at a distance of 1 meter, the recording was started. Participants were asked to make a number of saccades on a circular template in order to map saccade-related artefacts (Figure 14C). Afterwards, the laptop was placed in a backpack which was carried by the participant during the task, with the electrodes that run from the EEG cap to the transmitter were clipped onto the backpack in order to avoid cable sway artefacts (Gramann et al., 2010; Gwin et al., 2010; Roberts et al., 2018; Soto et al., 2018).

Before the product viewing task began, a light-emitting transistor-transistor-logic (TTL) pulse synchronized the eye-tracking and EEG data sets, indicating the beginning of the experiment. Participants navigated a gallery-like setting containing 216 images of products over 2 blocks. Following the product viewing task, the equipment was disconnected and participants took part in a computerized BDM auction experiment to elicit subjective economic WTP values for each of the 216 products. In the second experimental session, participants completed a hedonic rating task, rating the 216 stimuli for desirability and pleasantness. Afterwards, they received a random two products that they bid on and won during the BDM auction task and were debriefed and thanked for their participation.

5.3.5. Product Viewing Task

When the mobile EEG and eye-tracking systems were running, participants walked through a product gallery, viewing each product on a panel to determine which two products on a panel that they would be most and least likely to purchase. Central fixation crosses were viewed in between image evaluation, serving as a neutral baseline and allowing gaze correction. The product viewing task included two experimental blocks with 12 panels per block displaying 9 images per panel (108 images per block). On average, participants took 15 minutes per block to view and rate the images. The corridor was not closed off, maintaining a naturalistic environment (Figures 14A–B).

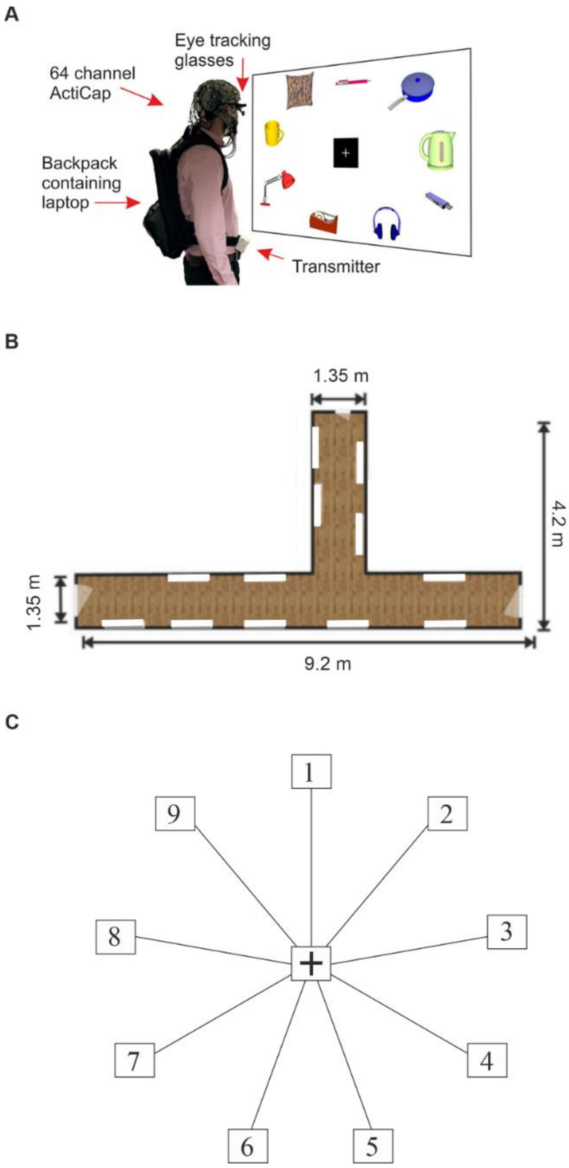

Figure 14. Stimuli and set up for Mobile EEG product viewing task. (A) Example of the mobile EEG and eye-tracking set up in the product gallery setting. The participant wears a 64 channel actiCAP with active-shielded electrodes attached to the move system transmitter, which is attached to the participant’s belt. The subject wears PupiLabs eye-tracking glasses which are plugged into a laptop contained in a backpack that is worn during the task. Participants view a product panel during the task

containing 9 household products and a central fixation cross to check gaze accuracy. (B) Template of the mock gallery in which the products were viewed and rated while EEG and eye-tracking recordings were taken. (C). Guided saccade template. Participants made a saccade from the centre fixation cross to a number and back to the cross three times sequentially from 1-9, mirroring the angle and distance that each product would be viewed.

5.3.6. BDM Auction task

Once the product viewing task was completed, participants took part in a computerized BDM auction task in a laboratory. Stimulus presentation was controlled using Cogent 2000 (UCL, London, United Kingdom) running on Matlab (version R2014a, The MathWorks, Inc, United States) on a Dell monitor on a HP Compaq 8200 computer. Participants were endowed with £24, which was refreshed for each trial, and were asked to bid between 0 – £12 the amount that they would be willing to pay for each of the 216 products, with 14 bidding options available in increments of £0.50 from £0.00-£0.50, and in increments of £1 from £1-£12. Feedback was given regarding whether a bid resulted in a purchase. Importantly, the auction task required participants to bid their true WTP value, as there was no optimal 'strategy' for bidding. Importantly, participants actually received two products that they were bidding on, therefore, the task was incentive compatible and more likely to reflect true SV. The task took approximately 35 minutes to complete. The BDM auction task was used in a previous experiment in our laboratory (see Roberts et al., 2018 for a full outline of the task). Individual WTP values for each product were retrospectively used to subjectively categorize each product that the participant viewed in the gallery task, creating four categories for EMRPs; low, low medium, high medium and high. The task took approximately 35 minutes.

5.3.7. Hedonic rating task

In the second experimental session, within one week of the first experimental session, participants took part in a computerized hedonic rating task in the same laboratory space. Stimuli were again presented using cogent 2000 running on MATLAB (version R2014a). Participants viewed the same 216 stimuli once and rated them for both desirability and pleasantness. The task took approximately 30 minutes to complete.

5.3.8. Electrophysiological recordings

EEG was recorded continuously over the whole scalp using a 64-channel wireless mobile EEG system (MOVE system, Brain Products, GmbH, Munich, Germany). In addition to the amplifier and battery, the wireless EEG system included a signal transmitter which connected to electrodes and was attached to a Velcro belt and a signal receiver. 64 active-shielded Ag/AgCl electrodes were applied to the scalp using an Elastic cap (ActiCap, Brain Products, Munich, Germany), in accordance with the international 10 – 20 system. The centre of the cap was placed in line with the centre of the nasion, the inion and the right and left pre-auricular landmarks. Electrolyte gel was applied to each hole before the sensors were connected, maintaining signals under 50 KΩ (SuperVisc Gel, Brain products). EEG was sampled at 1,000 Hz, electrode FPz was utilized as the system ground, and Fz was used as a reference for all electrodes. The signal was digitized to 1 kHz on an ActiChamp amplifier (Brain Vision Recorder v 1.20.0601) on a Toshiba Satellite (P875-149) laptop. A 50 Hz notch filter was also used during the recording. PupiLabs Binocular Eye Tracking glasses tracked visual behaviour and were connected to a Lenovo Thinkpad x250 Ultrabook laptop. The eye-tracking data was continuously recorded via the pupil capture software (PupiLabs, version 1.4.1) on Ubuntu SMP which was carried in a backpack during the recording.

The pupils of both eyes were detected using the pupil gaze centre-surround algorithm (Świrski et al., 2012) and a 3D calibration was used against a blank A0 panel. The resolution of the world camera was set to 1280 × 720 and was sampled at 60 frames per second, however, the actual sampling rate of the world view camera was calculated to be 46.55 (±12) frames per second on average across all participants. The resolution of the right eye was 192 × 192 and the frame rate was 200 samples per second. The left eye maintained a resolution of 380 × 240 with a frame rate of 120 samples per second. The eye-tracking data was imported into Pupil Player version 1.7.42 and if the gaze was considered to be off centre (i.e. when viewing the central fixation cross), the gaze marker was manually corrected using the manual gaze correction plugin. Fixation jitters were corrected using in-house scripts in MATLAB (R2017a). Raw data were exported using the Raw Data Exporter plugin. Gaze onset was exclusively used for triggering stimulus onset in the real-world. EEG and eye-tracking data sets were synchronized using a light emitting TTL trigger box by aligning the offset of a button press (the last TTL) with the light offset of the LED in the world view camera, indicating time zero (see Roberts et al. (2018) for full details).

5.3.9. Eye-Movement-Related Potentials guided saccade recordings and ASF

Once the triggers were created and imported, EEG data was processed using Brain Electrical Source Analysis (BESA) software version 6.1 (MEGIS Software, GmbH, Munich, Germany). A common average reference was employed, and muscle artefacts were removed upon visual inspection.

Because eye-movement-related potentials (EMRPs) were time time-locked to the offset of the saccade, when the gaze first hit an image, a number of saccade-related artefacts were present in the data. To reduce saccade-related artefacts in the EEG data, guided saccade recordings were taken prior to commencement of the experiment reflecting each angle of viewing from the central fixation cross to each image in the product gallery. Participants viewed an A4 panel displaying a circular template with nine 15 cm lines spaced 40 degrees apart that converged in the centre (Figure 14C). At the end of the lines were nine boxes labelled from 1 to 9 and participants were asked to make a saccade from the centre of the circle to box one, make a saccade back to the centre, and to repeat this process for all numbered boxes at least three times. Saccade angles were calculated by measuring the angle that the object would be viewed given the maximum distance that the subject could stand away from the panel (94 cm) in the corridor and the distance from the floor to the lowest image (38 cm). The effectiveness of this saccade-removal method was calculated for all participants.

Because each saccade angle was linked to an onset trigger in guided saccade recordings, typical saccade-related artefact topographies for each angle of viewing could be identified in the continuous EEG data, which were subsequently removed using ASF (Ille et al., 2002) in Brain Electrical Source Analysis (BESA) software version 6.1 (MEGIS Software GmbH, Munich, Germany). Specifically, ASF modelled each saccade-related artefact defined by visual inspection of topographies, using the amplitude criterion exceeding normal range (such as eye blinks, eye movements), and correlation criterion indicating similarity between the marked segment and topographies at certain time points throughout the recording. Next, a PCA (Berg & Scherg, 1994) decomposed the subset of matched components to model the activity and explain the variance and the component with the highest *p* value explaining the least variance (e.g., below 5 to 10% of data variance) is then subtracted from the EEG data (Ille et al., 2002).

The effectiveness of saccade-related artefact removal technique was examined by comparing amplitude for eye electrodes FP1 and FP2 during saccades made before stimulus onset (-7 ms). EMRP data for 20 participants with saccade-related artefacts removed using guided saccades and ASF were compared with EMRP data in the same participants with only eye blinks removed using ASF and with uncorrected EMRPs.

Once the raw data was clean of muscle, eye blink and saccade-related artefacts, the EMRP data was exported to EEGLAB (Derlorme & Makeig, 2004) running in MATLAB R2017a (MathWorks, Inc., United States), and input into the EEGLAB STUDY structure to allow clustering of ICs across participants. The data was epoched from -200 to 600ms, baseline corrected -200 to -100 and filtered from 1–30 Hz. Set files were merged across experimental blocks to create four set files for the four value conditions for each subject.

5.3.10. ICA decomposition, equivalent current dipole fitting and component clustering

The block-concatenated single-subject epochs were subjected to an infomax independent component analysis (ICA; Delorme & Makeig, 2004; Makeig et al., 1996) using the ‘run.ica’ function in the EEGLAB toolbox (Bell & Sejnowski, 1995) individually for each subject in order to decompose the grand averaged EEG signal into its maximally temporal independent and spatially fixed component processes or ICs (Makeig et al., 1996). ICA was performed on 20 individual data sets for all conditions from -200 to 600 ms.

Using the ICA weights for each subject, for each independent component map an equivalent current dipole was automatically computed using the spherical head model within the DIPFIT2 toolbox (Delorme et al., 2011; Maris & Oostenveld, 2007) running in EEGLAB. The amount of residual variance for the dipoles was set to 30%. The study design comprised one independent variable having four levels (low-, low-medium-, high-medium-, high-value).

Clustering methods are employed to identify and categorise components of EEG data into similar and dissimilar component clusters (Ding, & Xiaofeng, 2004). The dimensionality of the data was reduced using a PCA method so patterns of clusters could be detected more readily (Ding & He, 2004). A K-means clustering solution was then be applied in the lower-dimensional subspace (Ding & Xiaofeng, 2004; Zha, Ding, Gu, He, & Simon, 2001). Clustering of independent components was performed on ICA decomposed grand averaged EMRP data for 20 participants using the PCA method in EEGLAB (Delorme & Makeig, 2004a). The data were pre-clustered across participants using event-related potentials, scalp maps and equivalent current dipole locations for each subject, condition and cluster to determine the disparity between each IC, using the default weightings. In line with the EEGLAB protocol, a PCA reduced the dimensionality of these measures down to the first 10 principal components.

A k-means clustering algorithm was then employed in EEGLAB with the number of clusters set to 8. The number of components was estimated in pilot analyses by observing the residual variance and strengths of extracted components. ICs located outside of the head were considered not reflective of brain activation and any components with a distance of more than 3 SDs from the mean of any cluster centroid in the joint measure space were automatically assigned to an outlier cluster and were excluded from further analysis. The parent cluster had 165 ICs and clusters were only subjected to further analysis if they had a minimum of 10 ICs and occurred in at least nine of the participants.

In order to identify significant clusters and latencies in a more objective way, for each cluster in the solution, 95% confidence intervals for the mean IC cluster activity were calculated across the whole epoch; -200 to 600 ms. Only clusters in which the confidence intervals deviated from baseline were subjected to further statistical analysis.

5.3.11. Statistical analyses

Four one-way repeated measures ANOVAs were conducted in order to analyse the effect of four value categories on retail price, desirability, pleasantness and willingness to pay. Greenhouse-Geisser corrections were used to overcome a violation of the sphericity assumption due to larger than two levels in the independent variable. Significant differences outlined in the ANOVA were subjected to pairwise t-tests and a critical threshold of $p <. 05$ was maintained. To examine the effectiveness of guided saccade and ASF for removal of saccade-related artefacts, one-way repeated measures ANOVAs were computed for FP1 and FP2 respectively, comparing amplitude in electrodes in the eye orbit for saccade corrected, blink corrected and uncorrected data. Greenhouse-Geisser corrections were used when sphericity was violated and $p < .05$ was utilized.

To analyse the effects of value on EMRPs, one-way ANOVAs for repeated measures were carried out to compare SV category (low, low-medium, high-medium, high) for each mean IC cluster activity over the latency interval 50 – 450 ms using the ‘statcond’ function in EEGLAB (Derlorme & Makeig, 2004). In order to reduce the likelihood of generating false positives, *p* values were corrected using 5000 permutations (Maris & Oostenveld, 2007). Significant main effects regarding a cluster at a certain latency interval were further investigated using post hoc paired t-tests. A critical threshold of p <.05 was always adhered to.

5.4. Results

5.4.1. Behavioural results

Figure 15A – D show that, for all behavioural measures, a significant relationship between SV level (low, low-medium, high-medium and high) was observed in the following variables; WTP: F (1, 27) = 186.95, p < .001; desirability: F (1, 40) = 79.62, p < .001; pleasantness F (1, 39) = 64.42, p <. 001 and retail price F (1, 32) = 56.81, p < .001. There was also a highly statistically significant linear relationship between SV and all dependent measures (p < .001 in all instances). Post hoc t-tests revealed significant differences between all conditions for all dependent measures (p < .005) except for retail price, as low- and low-medium-value conditions did not significantly differ (p = .134).

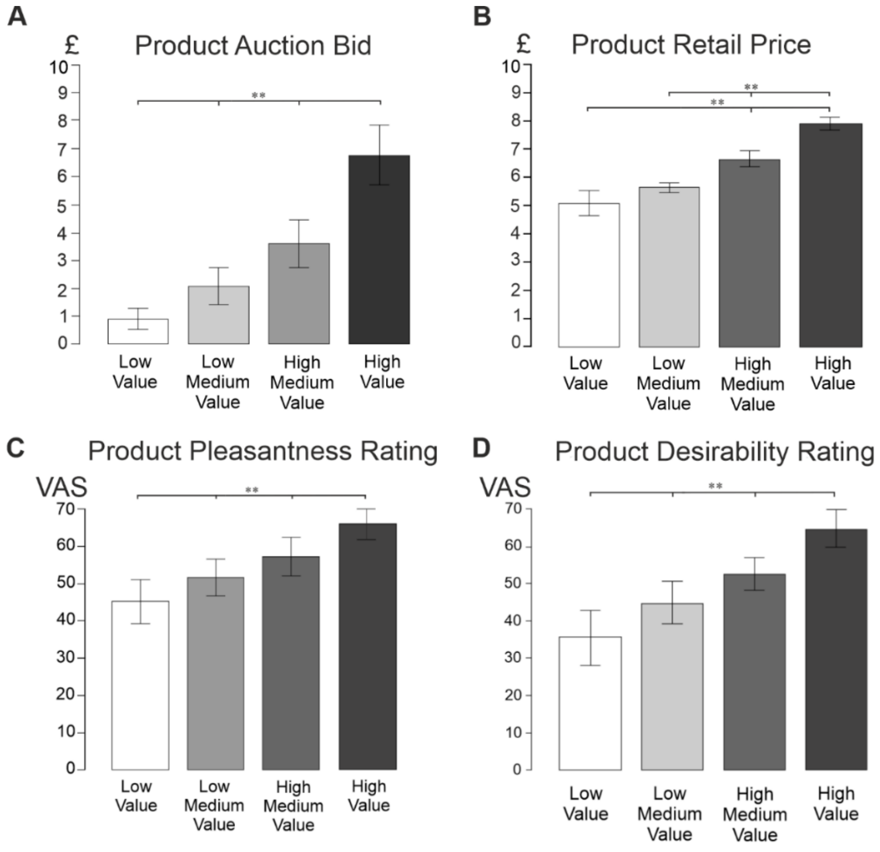

Figure 15. Bar graphs showing mean behavioural ratings for 20 participants. (A) Mean auction bids split into quartiles creating the four SV conditions; low, low-medium, high-medium and high. There were highly statistically significant differences across all SV conditions (B), in retail price for all SV conditions except between low- and low-medium-value and in pleasantness ratings (D) and in desirability ratings across all SV conditions, showing a linear increase with SV in all cases ***p* <. 001.

5.4.2. Saccade-related artefact removal

Figure 16(A) demonstrates a progressively decreased amplitude of potentials in FP1 (right) and FP2 (left) amplitude from non-eye-artefact corrected data (uncorrected) to eye-blink artefact corrected (blink corrected) and saccade-related artefact corrected (saccade corrected) methods at -7 ms. Statistical analysis revealed that electrode FP1 was significantly modulated by correction method F (2, 78) = 27.80, p < .001, with significantly reduced FP1 amplitude for saccade corrected data (4.51 ± 2.22) compared to uncorrected (17.48 ± 11.64; $p < .001$) and eye-blink corrected (11.00 ± 9.02; $p < .001$), and reduced amplitude for eye-blink corrected data compared to uncorrected ($p = .006$, Figure 16B). A similar effect was seen in FP2 electrode ($F(2, 78) = 40.08$, $p < .001$) with significantly reduced amplitude for saccade corrected data (4.93 ± 2.19) compared to uncorrected (17.80 ± 10.19; $p < .001$) and eye-blink corrected (10.44 ± 7.90; $p < .001$), and reduced amplitude for eye-bink corrected compared to uncorrected ($p < .001$, Figure 16C).

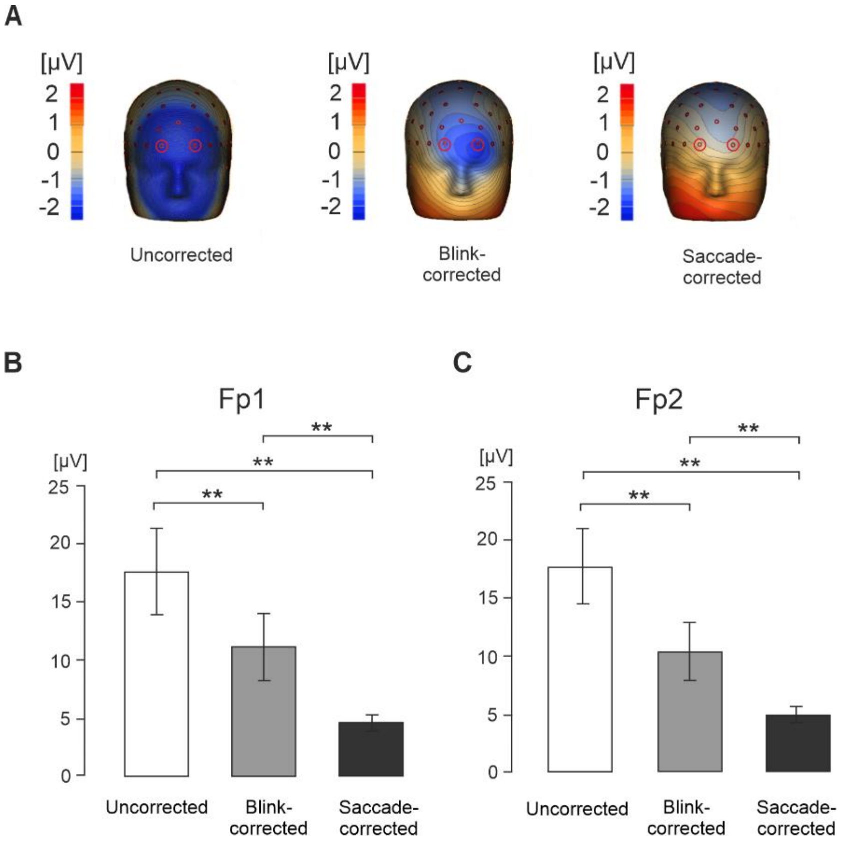

Figure 16. Comparison of grand averages for guided saccade and ASF cleaned data (saccade-related artefact corrected), blink ASF-cleaned data (eye blink artefact corrected) and uncorrected data in electrodes around the eye orbit. (A) Grand averaged topographic maps show visual monotonic reduction of amplitude at eye electrodes FP1 (right circle) and FP2 (left circle) from uncorrected to saccade corrected methods. (B-C). Bar graphs showing statistically reduced amplitude at FP1 and FP2 eye electrodes, respectively for saccade-corrected compared to uncorrected and blink corrected, and for blink-corrected compared to uncorrected. $^{**}p < .001$.

5.4.3. Eye-movement-related potentials

Figure 17 shows the grand averaged EMRPs across conditions for 20 participants in form of a butterfly plot, with corresponding topographic maps for key time points that show deflections from baseline. Small baseline noise is present, however, across all participants as a saccade was made towards a stimulus (-7 ms) and at stimulus onset (0 ms), a lack of activation around eye electrodes was observed indicating attenuation of saccade-related artefacts in EMRP data. The lambda potential can be observed at 88 ms and manifests as a large positivity at occipital electrodes (Thickbroom et al., 1991; Yagi, 1979a, 1979b, 1981a). The lambda potential represents a visual response to a stimulus and is the free eye movement equivalent of the visually evoked P100 component (Kazai & Yagi, 2003; Roberts et al., 2018; Soto et al., 2018). At 145 ms, a peak can also be observed displaying both parietal positivity and occipital negativity.

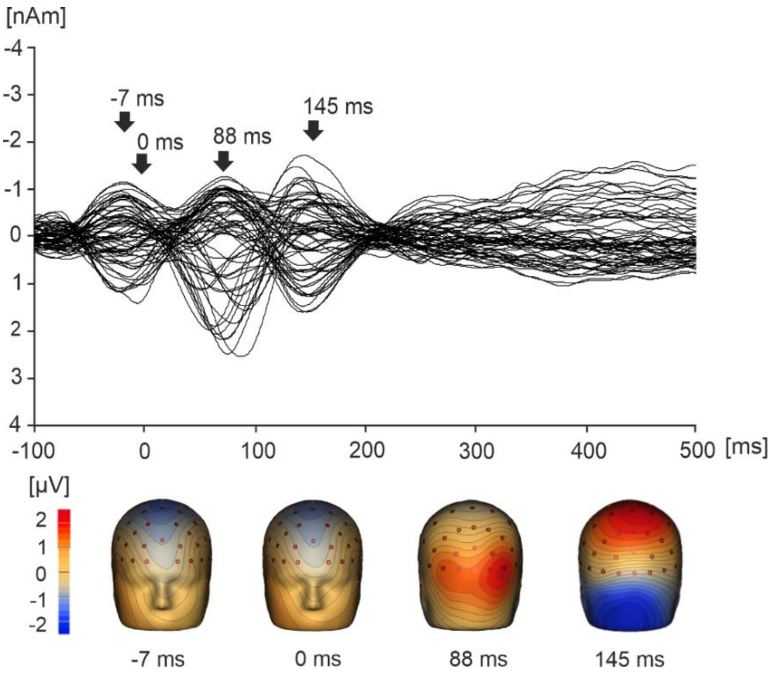

Figure 17. Butterfly plot and topographic maps of EMRPs at selected latency points. Butterfly plot displays grand averaged EMRP activation across all participants and across low, low- medium, high-medium and high SV conditions between -100 and 500

ms. Topographic maps show attenuation of saccade-related artefacts in the saccade period between -7 and 0 ms. The lambda potential component is present at 88 ms, and the corresponding occipital positivity can be seen in the topographic map. A value-related peak is observed at 145 ms and displays parietal positivity and occipital negative potential.

5.4.4. ICA clustering of EMRPs with source dipole reconstruction

Four IC clusters showed significant differences in cluster amplitude across value conditions between 50 – 230 ms. Cluster 3 (Figure 18A) displayed a positive potential in right occipital electrodes and negativity in central midline electrodes and peaking at 81 ms. An equivalent current dipole (ECD) was fitted to the mean cluster centroid. The ECD representing Cluster 3 was located in the right visual association area (Brodmann area 18, approximate Talairach coordinates x = 11, y = -66, z = 3) and explained 87.54% of variance.

Cluster 5 featured a negative potential in the right occipital-parietal electrodes and a positive potential in the right occipital electrodes with a peak at 79 ms (Figure 18B). An ECD was fitted to the left visual association area (Brodmann area 19; x = -1, y = -90, z = -12) and explained 81.42% of variance.

Cluster 6 was represented by a large positive potential in central midline electrodes peaking at 144 ms. An ECD was fitted to the ventral posterior cingulate area (right Brodmann area 23, x = 1, y = -38, z = 37, Figure 18C).

Cluster 9 was featured by a negative potential in the medial central-parietal region of the scalp and a positive potential in occipital electrodes, with a strong positive deflection occurring at 78 ms. An equivalent current dipole was fitted to the left primary visual cortex (Brodmann area 17, x = -1, y = -71, z = 12, Figure 18D).

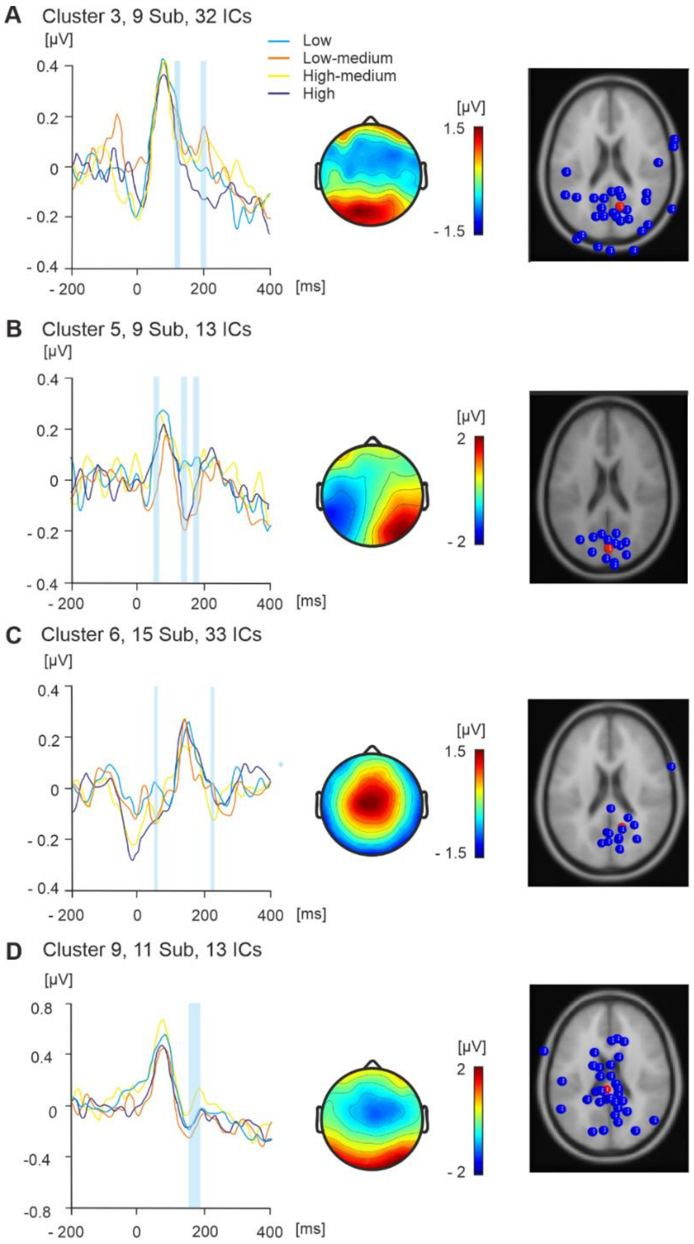

Figure 18. Averaged IC cluster amplitude between -200 and 400 ms for independent clusters across four SV condition and source dipole reconstruction from EMRPs. (A) Averaged cluster 3 amplitude comprising 9 participants and 32 ICs. A positive potential peaked at 81 ms and the averaged source dipole was localized to the visual association area. (B) Averaged Cluster 5 amplitude comprising 9 participants and 13 ICs, displaying a strong positive peak at 79 ms. Averaged source dipole was localized to the left visual association area. (C) Averaged Cluster 6 amplitude comprising 15 participants and 33 ICs, with a positive peak at 144 ms, and source dipole localized to the ventral posterior cingulate area. (D) Averaged Cluster 9 amplitude consisting of 11 participants and 13 ICs, with a positive peak at 78 ms. An equivalent current dipole was fitted to the left primary visual cortex.

5.4.5. The effect of SV on IC clusters

In Cluster 3, the component activity differed significantly across four value categories in the latency interval 116 – 127 ms (F(3, 24) = 3.88, *p* = .023) with a stronger component amplitude for low- compared to high-medium (*p* = .025) and high-value items (*p* = .032). Moreover, between 193 and 204 ms (F(3, 24) = 2.56, *p* = .03), low-medium-value products showed higher cluster 3 amplitude compared to high (*p* = .031), and high-medium-value products showed higher cluster 3 amplitude compared to high-value products (*p* = .033, Figure 19A).

Figure 19B shows statistically significant effects of value categories in Cluster 5 between 50 and 63 ms (F(3, 24) = 3.268, *p* = .035), with low-value products displaying larger amplitude compared to low-medium products (*p* = .034). Between 132 – 148 ms (F(3, 24) = 3.116, *p* = .029), low-value products showed larger amplitude compared to low medium (*p* = .024) and high (*p* = .029). Likewise, between 170 and 183 ms, low-value products showed significantly larger amplitude compared to low-medium (*p* = .003) and high-medium items (*p* = .045) (F(3, 24) = 4.74, *p* = .010).

Figure 19C highlights a statistically significant main effect of SV categories for Cluster 6 between 55 – 58 ms (F(3, 42) = 2.85, *p* = .045) with low-value products showing larger amplitude compared to high-medium (*p* = .002), and high-value products (*p* = .044). Between 226 – 230 ms, a statistically significant effect of four value categories was also observed (F(3, 42) = 2.974, *p* = .042), with high-medium-value products showing reduced amplitude compared to low (*p* = .015), low-medium (*p* = 0.031) and high-value products (*p* = .039).

Finally, a statistically significant effect of value categories was seen in Cluster 9 between 157 – 184 ms (F(3, 30) = 5.05, *p* = .006), with a larger component amplitude in high-medium-value products to low- (*p* = .011), low-medium- (*p* = .007) and high-value products (*p* = .011) (Figure 19D).

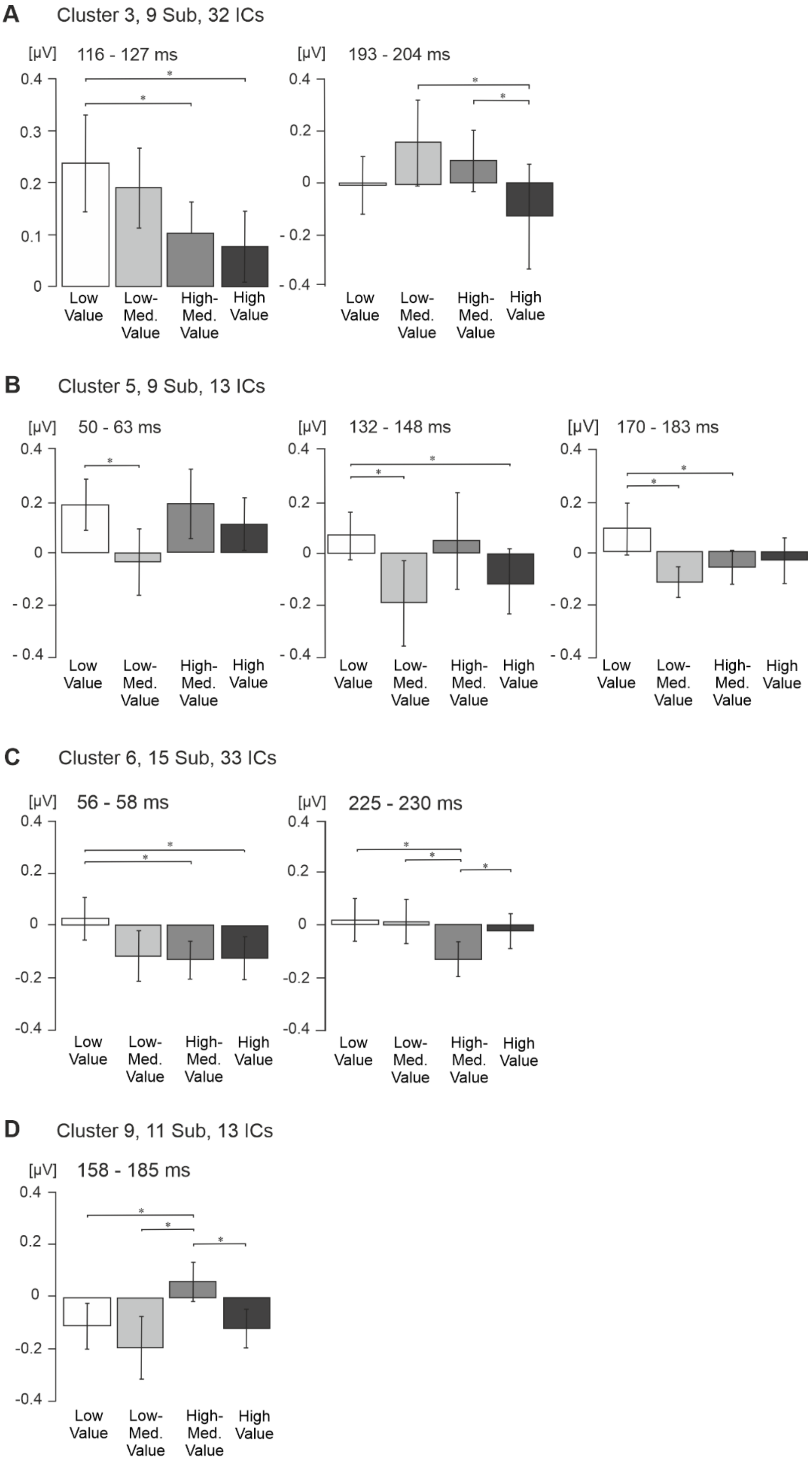

Figure 19. The effect of SV on IC cluster amplitude. (A) Cluster 3 amplitude shows a statistically significant relationship with SV between 116 – 127 ms, with low-value

significantly differing from both high-value conditions. Between 193 – 204 ms, high-value significantly differed from both medium-value products. (B) Cluster 5 amplitude shows a statistically significant difference between SV, with low-value differing from low-medium-value between 50 – 63 ms, low-value differing from low-medium and high-value between 132 – 148 ms, and low-value differing from both medium-values between 170 – 183 ms. (C) Cluster 6 amplitude shows a statistically significant difference between low and both high-value conditions between 56 –58 ms, followed by a difference between high-medium and all value conditions between 225 – 230 ms. (D) Cluster 9 amplitude shows a statistically significant effect of SV, with high-medium-value differing from all others between 158 – 185 ms.

5.4.6. IC cluster amplitude and WTP

To check whether WTP had a linear association with amplitudes of ICs, simple linear regressions were conducted individually for each cluster and latency interval of interest, with mean WTP (SV) as a predictor and cluster amplitude as a dependent variable. Only Cluster 3 showed a comparatively modest but statistically significant linear relationship with WTP in the latency epoch of 116‑127 ms. A mean adjusted R^2 of 0.46 ± 0.32 was found across participants. A one sample *t*-test of the beta-coefficients representing a linear association between WTP and IC amplitude confirmed that beta coefficients were different from zero ($t(8) = -3.24$, $p = .01$). Thus, amplitude of Cluster 3 was inversely related to WTP between 116‑127 ms, with the highest amplitude of Cluster 3 for low-value products. While the linear association between IC amplitude and WTP in Cluster 3 was statistically significant, the pair-wise contrasts in IC3 (Figure 19A) were statistically significant only between low- and high-medium and high-value items but not among any other categories suggesting that this component still offers only a limited resolution of SV.

5.5. Discussion

The current study examined wirelessly recorded EMRPs in freely moving participants during automatic valuation of household and office items in a mock gallery. SVs of all items were evaluated using a BDM auction. Compared to our previous study (Roberts et al., 2018), items displayed included higher retail values of up to £12. Furthermore, an improved method of saccade-related artefact removal based on guided saccade recordings and ASF was implemented to probe a linear association between amplitudes of EMRPs and SV, which was previously reported in fMRI data (Abitbol et al., 2015; Lebreton et al., 2009).

Results showed that implementation of guided saccade recordings and ASF significantly attenuated the saccade-related artefacts occurring during the saccade period. Three out of four ICs that demonstrated a statistically significant effect of value categories singled out the low-value category as showing the strongest component activity. Stronger IC activity in the low-value category compared to other value categories was observed in the early latency intervals, starting as early as 50 ms post stimulus. The low-medium and high-medium products showed the strongest IC activities in the latency epochs >150 ms in three out of four ICs. Only one IC showed a statistically significant linear association with SV and this linear association was largely due to the contrast between low- and high-medium and high-value categories.

The present study replicated the findings of our previous study (Roberts et al., 2018) by revealing that the early cortical activations manifested in EMRPs resolve SVs of products on a course grid by contrasting low-value items against items with higher SV. Furthermore, the low-value items elicit an early cortical response starting as early as 50 – 60 ms after the end of a saccade.

Clusters 3, 5 and 6 presented enhanced activation for low-value, compared to low- medium and high-value products, within the latency of the lambda component. Moreover, activation favouring low-value products occurred early on during the lambda component between 50 – 60 ms in Cluster 5. A fast and binary assignment of SVs reflected in early cortical responses, can be essential for survival, for instance, when deciding which food to eat and which to avoid (Polanía et al., 2014). Therefore, the observed early neural responses could reflect an adaptive dichotomous representation of low- and high-value within a domain-general system, facilitating approach and avoidance behaviours (Bartra et al., 2013; Westbrook et al., 2019). In line with a common neural system facilitating approach and avoidance, research has shown an overlap between neural circuits for processing of a wide range of appetitive and aversive stimuli (Delgado, 2007; Levy & Glimcher, 2012; Pessiglione & Delgado, Mauricio, 2015; Tyson-Carr et al., 2018). Furthermore, when considering low-value choices, potentially rewarding stimuli can be treated as aversive if they do not match expectations (Shenhav et al., 2018) generating avoidance motivation, feelings of anxiety (Shenhav et al., 2018) and activation of anxiety-related brain areas (Blair et al., 2006). Therefore, low-value items could have elicited an aversive response as participants were instructed that they would actually be receiving two of the items and the early activation might reflect an avoidance mechanism towards unattractive prospects to protect against potential financial loss. Notably, a previous ERP study conducted in a laboratory setting showed a larger amplitude of N200 component after presenting low-value compared to medium- or high-value products (Tyson-Carr et al., 2018).

A strong representation of low-value category in EMRPs is evidenced by the short latencies in which effects of low-value items have manifested. The earliest latency interval featured enhanced activation for the low-value category between 50–63 ms in Cluster 5. In contrast, low-medium and high-medium-value categories were only resolved in the latency intervals >150 ms in Clusters 3, 6 and 9. Enhanced early activation for the low-value category could reflect a loss-aversion response to low-value stimuli, in line with previous research (Roberts et al., 2018; Tyson-Carr et al., 2018; 2020). Enhanced motivational salience, arousal and neural activation for losses compared to relative gains (Baumeister et al., 2001; Rozin & Royzman, 2001; Sokol-Hessner et al., 2009; Stancak et al., 2015) and a comparable negativity bias have been consistently reported in value processing, reflected in a reduced latency and enhanced amplitude of early ERPs such as the P100 (Cacioppo & Berntson, 1994; Vaish et al., 2008; Williams et al., 2006; Yuan et al., 2015), P200 (Carretié et al., 2001b; Huang & Luo, 2006; Roberts et al., 2018; Schuermann et al., 2012) and N200 (Lithari et al., 2009; Tyson-Carr et al., 2018; 2020) in response to negatively-valenced stimuli (Baumeister et al., 2001; Forbes & Leitner, 2014; Hofmann et al., 2009; Leleu et al., 2015; Williams et al., 2006). The reduced latency of the component responding to the low-value category, between 50–63 ms, can be explained in terms of the free-viewing paradigm. Inclusion of eye-movements can facilitate processing of unpleasant information, suggesting facilitated attentional capture during free-viewing due to parafoveal processes, as covert attention can be allocated to a stimulus prior to the eyes reaching it during the saccade period (Simola et al., 2013). Low-value products were also contrasted against the higher-value categories in early latency periods for Clusters 3, 5 and 6. Modulation for positively-valenced stimuli have also been reported within P100 (Smith et al., 2003), P200 (Ma et al., 2018) and N200 (Goto et al., 2017; Kiss et al., 2009; Telpaz et al., 2015), supporting the interpretation that distinctive cortical components reflect binary categorisation of high- and low-value categories within an early automatic valuation system. Medium-value products were discriminated in Clusters 3, 5, 6 and 9 in later latency intervals exceeding 158 ms, therefore, intermediate-value products could require further processing before value categorisation (Philiastides & Heekeren, 2009; Roberts et al., 2018), indicating that the early binary mechanism does not allow for rapid categorisation of intermediate values. Research supports this interpretation by highlighting the role of the P200 in outcome unpredictability during uncertain decisions (Polezzi et al., 2008; Beate Schuermann et al., 2012; Xu et al., 2011) and ‘anchors’ determined by the binary mechanism could be used to facilitate further value estimation leading to categorisation of these uncertain items (Mussweiler & Strack, 2000).

Cluster 5 showed a statistically significant negative linear relationship between SV and component activity. While this finding would match previous reports of a linear association between SV, defined by pleasantness rating, and brain activation (Abitbol et al., 2015; Lebreton et al., 2009), the present finding is limited by the lack of statistically significant contrasts among neighbouring value categories, defined by WTP, with contrasts only observed between low- and high-medium and high-value items. Inspection of the scatter plots representing associations between SV and fMRI-BOLD activity in the ventromedial prefrontal cortex in Figure 5 of Lebreton et al. (2009) study suggests only modest differences between medium-value categories. It is therefore possible, that the linear association between SV and Cluster 5 activity builds primarily on a steep difference between low- and high-value items.

Clusters 3, 5 and 6 resolved low-value, versus high-value in the latency of the lambda EMRP, whereas Clusters 3 and 9 showed increased activity exclusively for viewing low-medium-value and high-medium-value items, from 158 ms onwards. The current results support the interpretation that distinct EMRP components resolve specific bands of values during early valuation (Roberts et al., 2018; Tyson-Carr et al., 2020). The possibility of multiple cortical activation patterns each encoding a distinct value category is consistent with a wealth of brain imaging data which supports the presence of unique patterns of voxels tuned to specific qualities of odours (Howard et al., 2009), visual objects (Haxby et al., 2000; 2001), emotions (Kragel & LaBar, 2016) or abstract stimuli such as scenes (Diana et al., 2008) or numbers (Bulthé et al., 2014).

The combined implementation of guided-saccade recordings and ASF, first proposed by Berg and Scherg (1991), allowed for removal of the saccade-related artefacts generated in naturalistic free-viewing conditions. Therefore, it is unlikely that a linear association between EMRP component amplitudes and SV were smeared by the presence of saccade-related artefacts in the data. The viable alternative method for saccade removal utilised in the current study is important for MoBI research with co-registered eye-tracking as detailed saccade-related information such as saccade angle amplitude and duration, required for sophisticated linear deconvolution techniques such as Unfold Toolbox (Ehinger et al., 2018), is unavailable in recordings taken in freely behaving individuals. Therefore, MoBI research could benefit from implementing a combination of guided-saccade recordings (Berg & Scherg, 1991) and ASF (Ille et al., 2002) in the examination of neural responses in more naturalistic settings.

The current study, building upon preliminary work by Roberts et al (2018), examined EMRPs in a product gallery to increase experimental control while maintaining a naturalistic scenario, affording examination of EMRPs for medium- and high-value products. However, 2-D product images might be processed differently to more complex 3-D images, as they can be observed from many different viewpoints and visual features and spatial relations must be integrated over time by the brain to form a holistic representation of an object (Bülthoff et al., 1995; Orlov & Zohary, 2018). Future research should endeavour to develop a mock-shop environment displaying 3-D products to determine whether distinct neural categorisation for low and high compared to medium-value products can also be resolved. However, the lack of experimental control over product size, luminance, contrast (Dimigen et al., 2011; Nikolaev et al., 2016), and multiple 3-D items in the visual field (Martin Eimer & Grubert, 2014; Tjan & Legge, 1998) must be accounted for, as these can influence early evoked potentials. Additionally, future studies should examine the influence of socioeconomic status on bidding behaviour, as data from the marketing sector suggests a positive relationship between purchasing and socioeconomic status (Slama & Tashchian, 1985).

5.6. Conclusion

To conclude, economic valuation of objects in the visual field rests on a coarse grid of SVs which primarily differentiates low-value items from items with higher SV. The low-value items evoked a cortical response early on during an EMRP. Furthermore, data suggest that multiple cortical activation components and latency intervals are tuned to specific bands of SVs. A linear association between SV and cortical activity was found in one EMRP component without resolving the differences between adjacent value categories. Our study contributes to the understanding of early, automatic valuation processing in naturalistic settings and demonstrates a viable method for controlling saccade-related artefacts in wirelessly recorded EEG data in humans engaged in free-viewing of visual scenes.

6. EXAMINING REAL-WORLD PRODUCT VALUATION IN A MOCK SHOP LABORATORY USING MOBILE ELECTROENCEPHALOGRAPHY AND EYE-TRACKING

Examining real-world product valuation in a mock shop laboratory using mobile electroencephalography and eye-tracking

Roberts, H[1*]., Tyson-Carr, J[1]., Newton-Fenner, A[1,2]., Byrne, A[1,2]., Fallon, N.[1], Giesbrecht, T.[3], Stancak, A[1,2].

[1]Department of Psychological Sciences, Institute of Psychology Health and Society, Faculty of Health and Life Sciences, University of Liverpool, Liverpool, United Kingdom

[2]Institute for Risk and Uncertainty, University of Liverpool, Liverpool, United Kingdom

[3]Unilever Research & Development, Port Sunlight, United Kingdom

This experiment examined the spatio-temporal neural correlates of SVs for real 3-D products displayed on shelves in a mock-shop environment.

This manuscript is currently in preparation for submission.

The roles of the co-authors are summarised below:

Myself and Andrej Stancak, Nick Fallon and Timo Giesbrecht contributed to the development of the experimental design and planning of this work. Myself and John Tyson-Carr contributed to the development of the stimuli and materials. Andrej Stancak and I contributed to the development of the behavioral rating task and carried out the data acquisition, pre-processing, synchronisation and analysis of the collected data, figure creation and production of the final written manuscript. Matlab scripts were created by myself, Andrej Stancak and John Tyson-Carr. John Tyson-Carr, Alice Newton-Fenner and Adam Bryne assisted me with the data collection.

6.1. Abstract

Stationary laboratory EEG studies have revealed encoding of product SV within hundreds of milliseconds, and wireless EEG studies have demonstrated binary encoding of low- and higher SV within distinct clusters of lambda and P200 EMRP components during economic decisions for 2-D product images. Real 3-D products have different physical and motivational properties to 2-D product representations, which could alter SV and underlying components. The current study investigated, for the first time, whether binary or linear encoding of SV would be observed for real 3-D products in a novel mock shop.

EEG and eye-tracking data was obtained from participants viewing 216 3-D products displayed in a mock shop, whilst deciding which products to purchase at the end of the session. Subsequently, a BDM auction was used to determine WTP for products to ascertain product SV. EMRPs were analysed using ICA clustering analysis of group data.

IC analysis of EMRPs revealed four IC clusters modulated by SV in the latency window of 72–359 ms. Low- and high-value products were discriminated binarily between 72–139 ms, and a positive linear association with SV and cluster amplitude was observed between 129–139 ms. Intermediately-valued products were resolved between 170–359 ms, with high-medium discriminated last. A positive linear relationship between cluster amplitude and SV was observed between 323–359 ms.

Results indicate that EMRPs rapidly discriminate different bands of SVs for 3-D products, with facilitated binary encoding of low- and high-value products and later encoding of intermediate-value products. Initial attribution of SV to real 3-D products

is accomplished on a coarse grid, with different cortical activation patterns responding to bands of SVs monotonically and linearly.

6.2. Introduction

Purchasing encompasses a dynamic process of forming a preference for one or a number of products, comparing relative costs and benefits within and across products to form SVs, ultimately resulting in a binary choice; to purchase or not to purchase (Beresford & Sloper, 2008; Chawla & Miyapuram, 2018; Padoa-Schioppa, 2011). In natural contexts such as a shop, valuation decisions might be modulated by visual attention (Tovar et al., 2019) as items are not presented in isolation and multiple stimuli compete for attention in complex real-world environments (Scalf et al., 2013). To prevent cognitive overload, computation and assignment of SVs is often conducted automatically, unconsciously and continuously (Anderson, 2013; Lebreton et al., 2009; Tyson-Carr et al., 2018; 2020). Although laboratory research has highlighted that automatic value-based decisions could occur as early as 150 ms following stimulus presentation, the precise temporal sequencing of early SV assignment is not well understood due to lack of research (Harris et al., 2011; Larsen & O'Doherty, 2014; Tyson-Carr et al., 2018; 2020; Tzovara et al., 2015). Moreover, it has been debated whether SVs are represented linearly within single cortical components (Abitbol et al., 2015; Lebreton et al., 2009) or whether multiple unique cortical clusters encode each SV (Tyson-Carr et al., 2020).

Previous stationary lab-based EEG studies incorporating product images displayed on a computer screen have provided evidence for the existence of unique cortical activation patterns that selectively and automatically respond to products of different SV during early product valuation, within the latency of the N200 (Tyson-

Carr 2018; Tyson-Carr 2020) and P200 VEPs (Goto et al., 2017; Ma et al., 2018; Telpaz et al., 2015;). However, stationary laboratory environments bypass a plethora of information which can be essential in influencing the neural dynamics that underpin valuation processes (Ladouce et al., 2017; Neisser, 1976).

Processes which may affect valuation of products in more naturalistic settings include the trans-saccadic integration of information across successive eye fixations (Melcher & Colby, 2008; Prime et al., 2011), visual anticipation and prediction (Dias et al., 2013) and the influence of short-term memory (Hollingworth, et al., 2007). Furthermore, in the real-world, early automatic modulation of attention for products of different SV could be used to facilitate approach-avoidance responses for these items during purchasing (Krieglmeyer et al., 2010, 2013). Despite the importance of examining the neural dynamics of SV within their natural context, the majority of neuroeconomic research has prevented movements and environmental stimulation when examining the neural dynamics of valuation decisions (Rangel et al., 2008; Sanfey et al., 2006; Tremblay, 2018) due to technical and methodological limitations preventing detection of underlying neural dynamics (Makeig et al., 2009; Reis et al., 2014). During stationary laboratory EEG recordings, movement of the head and neck is traditionally prohibited in an attempt to reduce distortion of underlying neural components caused by movement artefacts (Gwin et al., 2010; Symeonidou et al., 2018) including movement of the eyes (Cao et al., 2020) and the muscles (Jung et al., 2000). Thus, stationary EEG introduces considerable limitations and restraints to the understanding of early SV attribution in everyday environments and examination of SV in naturalistic settings in which the subject is free to move is essential to validate and expand upon the laboratory-based findings.

Capitalising on recent methdological and technical advancements in MoBI and eye-tracking research (Dimigen, 2014; Fischer et al., 2013; Gramann et al., 2010; Gramann et al., 2011; Gwin et al., 2010; Liao et al., 2012; Makeig et al., 2009; Nikolaev et al., 2014, 2016; Ojeda et al., 2014), recent research has shown, using wireless EEG recordings in quasi-natural settings, a set of independently tuned brain activation components for unique bands of SVs elicited by household products images in a mock gallery (Roberts et al., 2018; Roberts et al., in preparation). In particular, Roberts et al. (2018) showed an EMRP component at 200 ms responding to low-value compared to all other products. Using an increased value range in the subsequent study (Roberts et al., in preparation), independent cortical clusters highlighted low- and higher-value products within the lambda component (EMRP equivalent of P100 VEP), and medium-value products showed activation clusters within 200 ms latency (See Study 2). Therefore, recent studies examining SVs of product images under naturalistic conditions suggested early encoding of SV in multiple distinct cortical clusters of EMRPs, similar to laboratory-based VEP findings. SV may be represented earlier in more realistic settings as indicated by modulation of low- and higher SV in the lambda component latency.

Viewing and categorising 3-D products invokes different neural processes compared to viewing and categorising 2-D product photographs. For instance, the addition of depth affords examination from multiple viewpoints, therefore, a moving subject might observe different luminance, contrast, shape, size, and position of the stimulus (Murphy et al., 2013). Spatial relations between these viewpoints need to be integrated over time to form a holistic visual representation (Meilinger et al., 2011). 3-D products viewed from atypical angles can require additional visual information, processing, and time for identification (Biederman & Gerhardstein, 1993).

Furthermore, a previous study has shown that multisensory evaluation defines product perception, both consciously and subconsciously (Krishna, 2012). The presence of a physical product affords consumers the opportunity to validate as they can touch, feel and smell it (Haridasan & Fernando, 2018; Peck & Wiggins, 2006). Therefore, the sensory and perceptual experience of a 3-D product could be significantly more complex and different from the interactions with 2-D images representing the same items, which could influence valuation processes, and this has previously not been considered.

The sensory and perceptual aspects of 3-D products, compared to 2-D images, could signal their imminent availability which could influence their motivational salience, behavioural responses and associated neural dynamics. Environmental cues signalling product availability can increase attentional bias for related product cues (Jędras et al., 2019; Jones et al., 2012). Enhanced visibility and close within-reach proximity to food products can promote consumption (Maas et al., 2012; Painter et al., 2002), increasing their palatability and activation of motivation-related reward circuits (Blechert et al., 2016). Due to the imminent availability of a product, reduced effort is needed to obtain it, and inclusion of real 3-D products could culminate in a more convenient shopping experience compared to an online sale which includes 2-D product representations (Haridasan & Fernando, 2018; Noble et al., 2005; Pauwels & Neslin, 2015). The changes in product salience and motivated behaviours related to product availability and accessibility demonstrate the importance of these factors in product valuation. Thus, the importance of using real 3-D products in the investigation of early SV attribution and associated neural responses must be considered.

Despite the important differences between 3-D products and their 2-D representations, to date, no studies have investigated the neural dynamics of early SV of realistic 3-D products. The present study aimed to expand initial findings (Roberts et al., 2018; Roberts et al., in preparation; Tyson-Carr et al., 2018, 2020), examining the neural underpinnings of early automatic product valuation for real 3-D products in a naturalistic shopping environment. Previously, product luminance, size and spacing were standardised to determine the feasibility of detecting EMRPs to products in naturalistic settings (Roberts et al., 2018; Roberts et al., in preparation).

In the current study, control over the environment was maintained by reducing the influence of low-level visual features such as luminance, contrast, distancing and position, whilst allowing the subject to freely roam and view the products from any angle, affording maintenance of a controlled environment to elicit evoked potentials whilst still facilitating a naturalistic shop context. As the previous study in this series partially supported the presence of linear encoding of value for 2-D product images (Roberts et al., in preparation), the study also aimed to determine whether cortical activation components could encode SV in a linear manner for real products. It was hypothesised that, in line with previous experiments (Roberts et al., 2018; Roberts et al., in preparation; Tyson-Carr et al., 2018), multiple distinct components would be detected in EMRPs monotonically and linearly for low-, high- and medium-value items and low-value products would show neural prioritisation reflected in reduced EMRP latency.

6.3. Methods and materials

6.3.1. Participants

Thirty-seven participants (24 females) were recruited for the current experiment. Participants were excluded due to bidding too low (4 participants. In these participants the mean difference between the two low-price groups of items was only £0.51), insufficient eye-tracking calibration (1 subject), a glitch in the Pupil Labs recorder resulting in no world view video export (1 subject), noise in the EEG data (1 subject) and residual variance in EEG at the ICA level exceeding 40% (3 participants). A final sample of 27 participants (17 female) was retained, with a mean age of 29 ± 6.25 years and one left handed participant.

6.3.2. Ethical standards

Full informed consent was obtained prior to commencement of the study. Ethical approval was awarded by the Health and Life Sciences Research Ethics Committee (Psychology, Health and Society; reference number 4693). The study was conducted in accordance with proceedings outlined in the Declaration of Helsinki. participants were remunerated £25.27 ± 5.70 (mean ± SD) and received a minimum of two products of their choice worth an average of £21.85 ± 5.73.

6.3.3. Materials and procedures

A mock shop was constructed in two adjoining rooms in the Brain and Behaviour Lab at the University of Liverpool. To optimise the number of products that could be displayed, thus increasing the number of trials for the EEG analysis, 18 shelves were constructed and divided into two using Styrofoam panel boards, resulting in 36 shelves (see Figure 20A).

Figure 20.(A) Schematic representation of the mock shop, with 36 shelves across six aisles displaying products. (B) An example of an aisle in the mock shop experiment with floor markers for participant position measurement, fixation crosses for gaze calibration and cardboard stands to ensure front facing view of the product.

The room length was 1021 cm and the room width was 407 cm. The shelves were purchased from a DIY retailer and were sized at 182 cm × 78.50 cm × 40 cm. The shelves were spaced 11 cm apart within their aisles. All aisles maintained a viewing distance of 116 cm as this was the minimum distance that the world camera could view every single product on the shelf. The minimum distance was marked out with adhesive tape indicating generally where participants should stand when viewing a shelf (Figure 20B). Eight images of geometric fractals, taken from Google images, were mounted on the walls at the start of every aisle and in the walk ways. Participants were instructed to observe the fractals while equipment was being readjusted at the beginning of the experiment and in between aisles to prevent boredom during inactive periods and to serve as a neutral baseline.

6.3.4. Products

Two hundred and sixteen everyday household products from online retailers (Tesco, Argos, The Range, Wilko) were displayed in the current study. Products were equally divided (n = 72) into three retail price categories of low (£0.50 – £4; £2.32 ± £1.20), medium (£4.50 – £8; 6.77 ± 1.21) and high (£8.50 – £12; 10.27 ± 1.17). One product from each retail category was pseudo-randomly positioned on each of the top two shelves, with six products in total displayed on each unit. The retail value of products displayed on each shelving unit ranged between £30.99 and £45.49 (£38.30 ± 3.23) and a cumulative value across all shelves of £1378.90. Products were spaced as evenly as possible, preventing product overlap.

In order to reduce the impact of low-level visual features of displayed objects, measures were taken to space products evenly according to the lighting in the room (with pseudo-random positioning of one product from each retail category on each shelf). To increase visual contrast for dark products, white paper was attached to the bottom of the product and white card was mounted behind the products to increase visual contrast and to produce a neutral background for all items. Products were arranged so that they maintained a front-facing view for the participant and, where necessary, stands were used to maintain this position (Figure 20B). To avoid product overlap, only medium- and small-sized products were displayed on shelves and products were spaced as evenly apart as possible.

Front-facing colour images of the 216 products (white background, 400 × 400 pixels, 300 dpi) were displayed in the mock shop were taken from online shopping catalogues and used in the Becker-DeGroot-Marschak (BDM) auction paradigm and hedonic rating tasks.

6.3.5. Procedure

The experiment consisted of two testing sessions conducted on two separate occasions within 7 days. The first session involved mobile EEG and eye-tracking setup and the shopping experiment. The second session involved two computerized tasks; a BDM auction task and a desirability/pleasantness rating task.

Participants were briefed at least one day prior to arrival and the consent form was signed before the experiment commenced. The participant's head was measured and they were fitted with an EEG cap and electrodes and electrolyte gel was applied. Subsequently, participants were connected to the wireless EEG system and eye-tracking glasses were fitted and calibrated. A short EEG recording was acquired to register guided-saccades for different directions (Figure 21). Once completed, the laptop recording the eye movements was placed into a backpack on the participants back and the electrodes were secured to the backpack to reduce cable sway artefacts (Gramann et al., 2010; Gwin et al., 2010; Roberts et al., 2018).

For the first part of the shop task, participants were asked to view a geometric fractal mounted on the wall of the first aisle of the mock shop. The eye-tracking, EEG and camcorder recordings were initiated and a synchronization flash was produced, indicating the start of the experiment. Participants then navigated the shop setting, viewing each of the products at least once across two experimental blocks. In the second block, participants made their purchases. Afterwards, the equipment was removed and the next session was scheduled.

The second experimental session involved a computerized BDM auction experiment for the products previously seen in the mock shop and participants subsequently completed a computerized pleasantness/desirability rating task for the same products. Finally, participants were debriefed, thanked for their participation and received the products that they purchased and their winning BDM item within one week.

6.3.6. Shopping task

The shopping task consisted of two experimental blocks. The first experimental block was a window-shopping task during which participants were asked to think about what products they would like to purchase in block two with a £20 endowment. There was a caveat in that they had to purchase at least one product and could spend as much of the money as they wanted or retain the remaining endowment. Participants were instructed to stand as far back from the shelf as possible, to look at the central fixation cross, to observe a product for at least 4 seconds and to return their gaze to the fixation cross before observing the next product on the shelf. Participants were told that they could view the products on the shelf in any order that they desired and as many times as they liked, but they had to look at each product on the shelving unit at least once before moving on. Participants observed all products following a predetermined path around the room. First participants observed aisle 1 (shelves 1 – 4), followed by aisle 2 (shelves 5 – 9) and aisle 3 which was double sided (viewing shelves 10–13 and then turning and viewing shelves 14 – 17). Next, participants viewed products on aisle 4 (also double sided and viewed shelves 18 – 22 before turning and viewing shelves (23 – 27), aisle 5 (shelves 28 – 32) and aisle 6 (shelves 33–36; Figure 20A).

In the second (purchase) block, participants were encouraged to shop as naturally as possible, including picking the products up and asking questions. Participants were informed that they only needed to observe the products that they were interested in. Participants made their purchases during this block by asking the experimenter about the retail prices of the products that they wanted to purchase and calculating how much of their £20 endowment they wanted to spend on the products. Block two was recorded for purposes beyond the current experiment and consequently no data from block two is recorded in the current study.

6.3.7. Becker-DeGroot-Marschak auction task

The computerized BDM auction task took place during the second experimental session, developed and described in more detail in Roberts et al (2018). In short, the task elicited subject’s willingness to pay (WTP) values for each of the 216 products. Participants placed bids reflecting how much they were willing to pay for each product between £0 and £12. If the participant’s bid was greater than or equal to a random number, the bid resulted in a purchase. Of the purchased trials, a random product was selected for the participant to take home and the price equal to the random number was deducted from their £12 endowment. The task took approximately 35 minutes.

6.3.8. Hedonic rating task

After the BDM auction task, participants took part in a computerized hedonic rating task, described in full in previous work (Roberts et al., 2018). In brief, participants rated 216 products for desirability and pleasantness on two sliding VAS scales anchored from ‘desirable’ to ‘undesirable’ and from ‘pleasant’ to ‘unpleasant’. The task took approximately 35 minutes.

6.3.9. EEG recordings

EEG was recorded continuously over the whole scalp using a 64-channel ActiCHamp EEG and wireless MOVE system (Brain Products, GmbH, Münich, Germany). The MOVE system included a lightweight signal transmitter mounted on a Velcro belt worn by the participant and a receiver, which was plugged into an amplifier and battery located on a mobile trolley. The trolley was manoeuvred by the experimenter in order to maintain a distance of no more than 7 m from the transmitter (after which the signal is known to deteriorate). 64 active shielded Ag/AgCl electrodes were applied to the scalp using an elastic cap (ActiCap, Brain Products GmbH, Munich, Germany), in accordance with the international 10–20 system. The centre of the cap was placed in line with the mid-point of the anatomical landmarks of the nasion, the inion and the right and left pre-auricular points. Electrolyte gel was applied to each hole to ensure that every sensor maintained a good connection with the scalp and impedances were kept under 50 KΩ (Super Visc, Brain Products, GmbH, Münich, Germany). EEG was sampled at 1,000 Hz, electrode FPz was utilized as the system ground and Fz was used as a reference for all electrodes. EEG average reference was applied to all electrodes after the recording and the signal was digitized to 1 kHz on an ActiChamp amplifier running on Brain Vision Recorder (version 1.20.0601) for Windows on a Toshiba Satellite P875-149 laptop. A 50 Hz notch filter was also used during the recording. An Ansteker HD 1080P camcorder (Shenzhen BaoBei Yuan Technology Co., Ltd, China) recorded the participant’s location in the room.

6.3.10. Eye-tracking recordings

Binocular Eye Tracking glasses (Pupil Labs, GmbH, Berlin, Germany) were utilized in the current experiment. The glasses were connected to a lightweight Lenovo Ultrabook laptop using a micro USB cable and data was recorded via the Pupil Capture software (Pupil Labs, version 1.12.17) running on Ubuntu SMP for Linux, which was carried by participants in a backpack. The pupils of both eyes were detected using the pupil gaze centre-surround algorithm for Pupil Capture (Swirski et al., 2012). A 3-D calibration was utilized to calibrate the eyes to the shelf using a 9-point grid. The calibration was checked via the live video feed at the beginning of the experiment and in between experimental blocks to ensure sufficient gaze accuracy. The resolution of the world camera was set to 1280 ×720 and was sampled at 60 frames per second, however, the actual sampling rate of the world view camera was calculated to be 49 ± 8 frames per second across all participants. The resolution of the left and right eye was 200 ×200 and the frame rate was 200 samples per second.

The eye-tracking data was imported into Pupil Player (Pupil Labs, version 1.12.17). Fixation jitters were corrected using in-house scripts in MATLAB (R2017a, The MathWorks, Inc., United States). The raw data were exported using the Raw Data Exporter plugin. Gaze onset was exclusively used for triggering stimulus onset from freely behaving individuals in naturalistic environment.

6.3.11. Synchronization of data streams

Data were recorded in three streams: a camcorder, EEG, and eye-tracking. To synchronise these data streams, a synchronization mark was delivered into all three data streams marking the beginning of the recordings, the start of a new shelf in block one and the beginning of each new aisle in block two. Each synchronisation mark was a combination of a TTL pulse and a Canon Speedlite 430 EX III-RT Flash pulse, which was initiated by pressing a membrane switch keypad attached to the button. When the switch was pressed, this initiated a flash from the flashgun and also delivered a TTL pulse into the EEG amplifier using a custom-built Arduino. The powerful flash was used as this allowed delivery of synchronization flashes from across the room rather than directly in front of the world view camera as in previous studies (Roberts et al., 2018), allowing for multiple synchronizations, enhancing the accuracy of data stream temporal alignment without compromising the flow of the experiment. The offset of the light in the world view of the eye tracker was aligned to the last TTL trigger by setting both data streams to zero in a custom MATLAB script. The temporal asynchrony between data streams was checked in a 25-minute recording of EEG and eye-tracking data in which the flash was triggered every minute. There was a 50 ms lag between the button press and flash discharge, which was corrected in a custom MATLAB script during EEG data processing.

The alignment of EEG and eye-tracking data was tested in a pilot experiment by comparing time intervals between successive synchronization pulses in both data streams. While the mean difference in timing of successive pulses was zero, there was a standard deviation of 16.61 ms suggesting minor variability in time-locking of the EEG and the eye-tracking data. The variability was possibly related to the accuracy of detection of flash onsets in eye-tracking data which was limited by the eye-tracker's sampling rate of 60 Hz, yielding a 16.61 ms time grid.

The frames in which the subject's gaze first touched any part of a product were tabulated in Pupil Player program and combined with the timestamp of the computer's real-time clock and a set file. Each product fell into one of four value categories which were determined according to individual WTP values; low, low-medium, high-medium, and high.

6.3.12. EEG data pre-processing.

The initial pre-processing of EEG data was carried out using BESA software (version 6.1). A common average reference was employed, and gross movement and muscle artefacts were removed upon visual inspection. Before analysing EEG data from the shopping task, guided saccade recordings were examined. A PCA pattern matching algorithm was used to detect saccades of each of the nine angles in the guided saccade EEG recording. All instances of saccades that matched the marked segments in the continuous data were removed (Berg & Scherg, 1994). The artefact pattern file was then imported into the continuous EEG data recorded during the shopping task and all saccade patterns were removed using PCA. Figure 21 shows typical saccade patterns for selected directions of gaze.

Cleaned EEG data was exported to EEGLAB (Derlorme & Makeig, 2004) running in MATLAB. Data were filtered from 1 Hz to 25 Hz during export. The artefact-free event files were used to create four EEGLAB files for each subject reflecting each SV condition. The data was epoched from -200 to 600ms, baseline corrected -200 to -100 and filtered from 1–25 Hz.

6.3.13. Guided-saccade recordings

EMRPs were time-locked to the offset of the saccade and, consequently when the gaze first hit an image, a number of saccade-related artefacts were present in the data. The artefacts can be produced by either the movement of the eyelid muscles during eye movements, the rotation of the corneoretinal dipole of the eye, or the saccadic spike potential which refers to the contraction of extra-ocular muscles during saccade onset (Carl et al., 2012; Nikolaev et al., 2018). All such processes can distort the ability to identify the underlying neural signal.

Roberts et al. (in preparation) utilised a combination of guided-saccade recordings (Berg & Scherg, 1991) to identify saccade-related artefacts and ASF to remove the saccade-related artefacts from the data (Berg & Scherg, 1994; Ille et al., 2002) and this protocol was followed in the current experiment. Participants were asked to stand behind a marked line which was 116 cm away from an A0 sized portrait-oriented panel. The panel housed a circular template with a central fixation cross. Extending from the centre of the cross were 15 cm lines spaced 40 degrees apart ending in numbered boxes labelled 1 – 9. The template was designed to mimic every saccade direction that could occur when viewing products on a shelf. Once the guided saccade recording was initiated, a flash synchronised with a TTL pulse delivered to the EEG amplifier indicated the first saccade angle and participants made 5 consecutive saccades from the central fixation cross to number 1 and back. The same procedure was repeated for all numbers from 1 – 9 clockwise. The procedure allowed recording and quantification of a typical saccade topography for each angle of product viewing to be identified in the continuous EEG data, which were subsequently removed using Adaptive Spatial Filtering in BESA (Version 6.1) (Figure 21). These artefact topographies were then be imported and removed from the EEG recording obtained during the shop task.

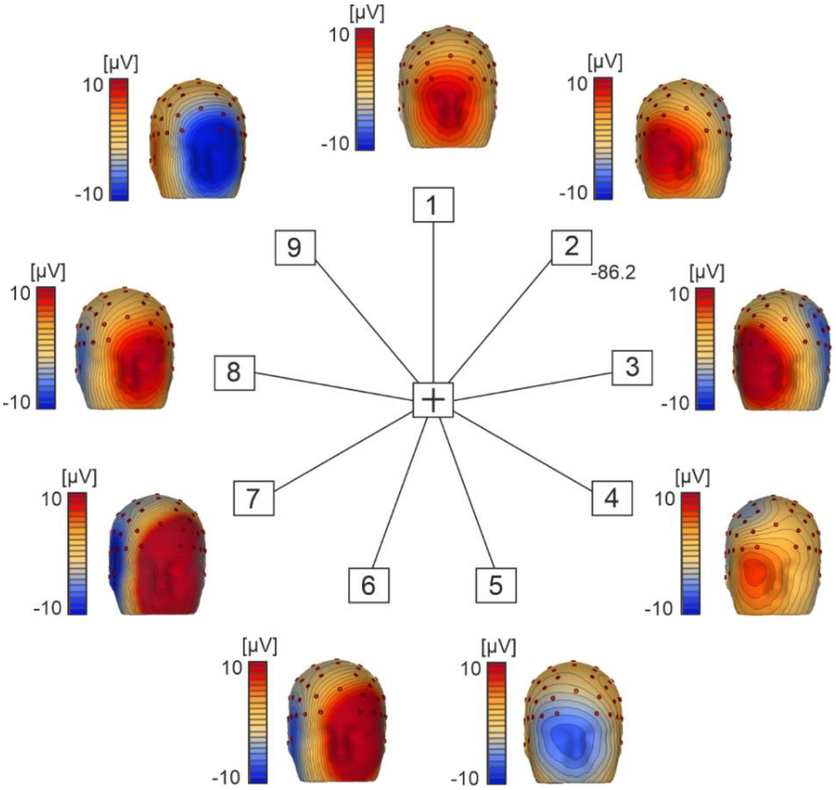

Figure 21. Template used for guided-saccade recordings**.** Topographic maps show saccade-related potential configurations for different gaze directions, including when subject made a saccade to number 1, 40º to the right to number 2 and 40º to the left to number 9.

6.3.14. ICA decomposition and equivalent current dipole fitting

Four EEGLAB files for every subject, representing four value categories, were merged and the concatenated epochs were subjected to an Infomax ICA (Bell & Sejnowski, 1995). For each independent component map in each subject, an equivalent current dipole was automatically computed using the spherical head model within the DIPFIT2 toolbox (Delorme et al., 2011; Maris & Oostenveld, 2007) running in EEGLAB.

Group analysis of individual ICA data was carried out as a Study project in EEGLAB. The amount of residual variance for the dipoles was set to 35%. The study design comprised one factor with four conditions standing for four value categories. Clustering of independent components was performed on ICA decomposed grand averaged EMRP data for 27 participants using the PCA EEGLAB routine. The data was pre-clustered using event related potentials, scalp maps and equivalent current dipole locations for each subject, condition and cluster to determine the disparity between each IC, using the default weightings. A PCA reduced the dimensionality of these measures down to the first 10 principal components.

A *k*-means clustering algorithm was employed in EEGLAB with the number of clusters set to 7. ICs located outside of the head were considered not reflective of brain activation and any components with a distance of more than 3 SDs from the mean of any cluster centroid were automatically assigned to an outlier cluster and were excluded from further analysis. The parent cluster had 87 ICs and were only subjected to further analysis if they had a minimum of 10 ICs and occurred in at least eight participants**.** To identify significant clusters and latencies in a more objective way, 95% confidence intervals for the mean IC cluster activity were calculated across the whole epoch between -200 to 600 ms for each cluster. Only clusters in which the confidence intervals deviated from baseline were subjected to further statistical analysis.

6.3.15. Statistical analysis

One-way ANOVA for repeated measures was conducted to examine the effect of value categories on retail price, desirability, pleasantness and WTP. To check whether socioeconomic status altered bidding behaviours, which was highlighted as a limitation of previous research (Roberts et al., in preparation), an index of multiple deprivation (IMD) was calculated for each participant (The English Index of Multiple

Deprivation, 2015). Participants were divided into two groups based on their IMD decile. Participants in group 1 had an IMD decile of 5 or less (where decile 1 is amongst the most deprived areas in England, 19 participants) and participants in group 2 had an IMD decile between 6 and 10 (least economically deprived; 8 participants). To examine the effects of socioeconomic status on BDM bid, a 2 × 4 ANOVA for repeated measures was conducted comparing the effects of socioeconomic status (IMD low vs. high) and value category (low-, low-medium-, high-medium-, high-value) on BDM auction bid. Greenhouse-Geisser corrections were utilised whenever sphericity was violated. Significant differences outlined in the ANOVA were subjected to pairwise *t*-tests and a critical threshold of $p < .05$ was upheld.

One-way ANOVAs for repeated measures were used to compare mean amplitude in eye electrodes Fp1 and Fp2 for uncorrected, blink corrected and saccade corrected methods to determine whether effective saccade-related artefact removal seen in Study 2 could be replicated. To reduce the likelihood of false positive generation, *p* values were corrected with 1000 permutations. $p < .005$ was always upheld.

To investigate the effects of value categories on EMRPs, one-way ANOVAs for repeated measures were carried out to compare value category (low, low-medium, high-medium, high) for each mean IC cluster amplitude over the latency interval 50–450 ms using the *statcond* function in EEGLAB (Derlorme & Makeig, 2004). To reduce the likelihood of generating false positives, *p* values were corrected using 5000 permutations (Maris & Oostenveld, 2007). Significant main effects were further investigated using post hoc paired *t*-tests for individual clusters. A critical threshold of $p < .05$ was always adhered to.

6.4. Results

6.4.1. Product values and ratings

Product retail prices, WTP, pleasantness and desirability ratings were analysed to check if value categories yielded linearly increasing trends from low to high-value categories. Figure 22A-D show significant effects of product categories (low, low-medium, high-medium, high) in retail price ($F(1, 49) = 235.2$, $p < .001$); willingness to pay ($F(1, 31) = 331.3$, $p < .001$); product pleasantness ($F(1, 40) = 122.3$, $p < .001$) and product desirability ($F(1, 41) = 117.6$, $p < .001$). *T*-tests showed significant differences between all value categories in all dependent measures ($p < .001$).

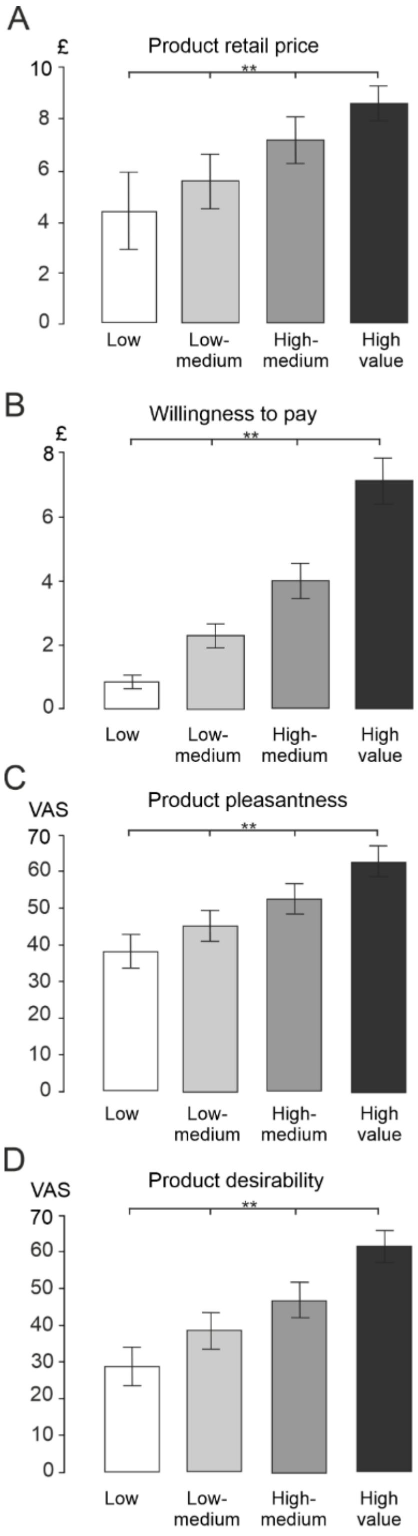

Figure 22. Mean values and standard deviations of retail price (A), willingness to pay (B) product pleasantness rating (C) and product desirability rating (D) across four value categories of products. Significant differences between SV conditions *p* < .001 are indicated with a double asterisk.

There was no significant main effect of socioeconomic status (IMD) on WTP values (*p* = .451) and no interaction effect between value categories and socioeconomic status (*p* = .316). Therefore, the socioeconomic status was not considered in further analyses.

6.4.2. Saccade-related artefact removal

Figure 23A demonstrates reduction of potential activation in eye electrodes FP1 (right) and FP2 (left) from non-eye-artefact corrected data (uncorrected) to eye blink artefact corrected (blink corrected) and saccade-related artefact corrected (saccade corrected) methods at -7 ms. Statistical analysis revealed that electrode FP1 was significantly modulated by correction method *F*(1.485, 28.217) = 16.072, *p* < .001 (Figure 23B). Saccade corrected data (5.50 ± 1.84 µV) showed significantly reduced amplitude compared to uncorrected (10.84 ± 5.36 µV; *p* < .001) and eye blink corrected methods (8.89 ± 3.54 µV; *p* < .001), however, eye blink corrected data did not significantly differ in amplitude compared to uncorrected data (*p* = .157). FP2 electrode also displayed significant amplitude modulation according to correction method *F*(1.944, 36.937) = 55.327, *p* < .001, with significantly reduced amplitude for saccade corrected data (4.91 ± 1.61) compared to uncorrected (13.65 ± 4.82; *p* < .001) and blink corrected (8.39 ± 4.18; *p* = .001), and reduced amplitude for bink corrected compared to uncorrected (*p* < .001, Figure 23C).

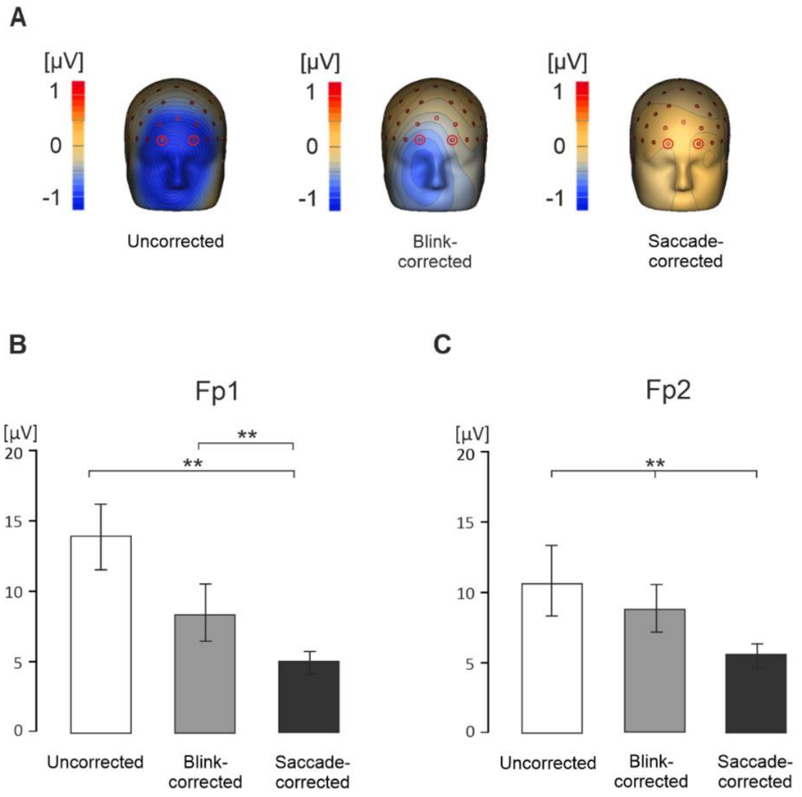

Figure 23. (A) Topographic maps showing attenuation of saccadic artefacts at frontal and occipital electrodes for the saccade corrected compared to uncorrected and blink corrected methods at -7 ms. Statistically significant amplitude modulation was observed in electrodes Fp1 (B) and Fp2 (C) according to correction methods. $**p <$ .001.

6.4.3. *Eye movement related potentials*

Figure 24A displays, in form of a butterfly plot, grand averaged EMRP signals in all 63 electrodes collapsed across four value categories. Key latency points of interest are indicated with arrows showing deflections from baseline and these are also displayed in topographic maps (Figure 24B). The first time point reflects the offset of a saccade at 0 ms and shows no residual eye movement activity around the eyes or in the occipital cortex, suggesting that the method for isolating and removing saccades was effective. The next time point indicated at 130 ms was featured by a positive potential in occipital electrodes which corresponded to the lambda potential (Roberts et al., 2018; Thickbroom et al., 1991; Yagi, 1979a, 1981a). At 152 ms, the positive potential shifted to more occipital regions, with negativity in parietal electrodes. At 276 ms, the EMRP showed a strong positive potential at vertex electrodes Cz, and FCz. The peak latency and the topographic configuration of this latency component resemble a P300 component seen in event-related potentials (Jiang et al., 2017; Polich et al., 1997; Strüber & Polich, 2002; Wang et al., 1999).

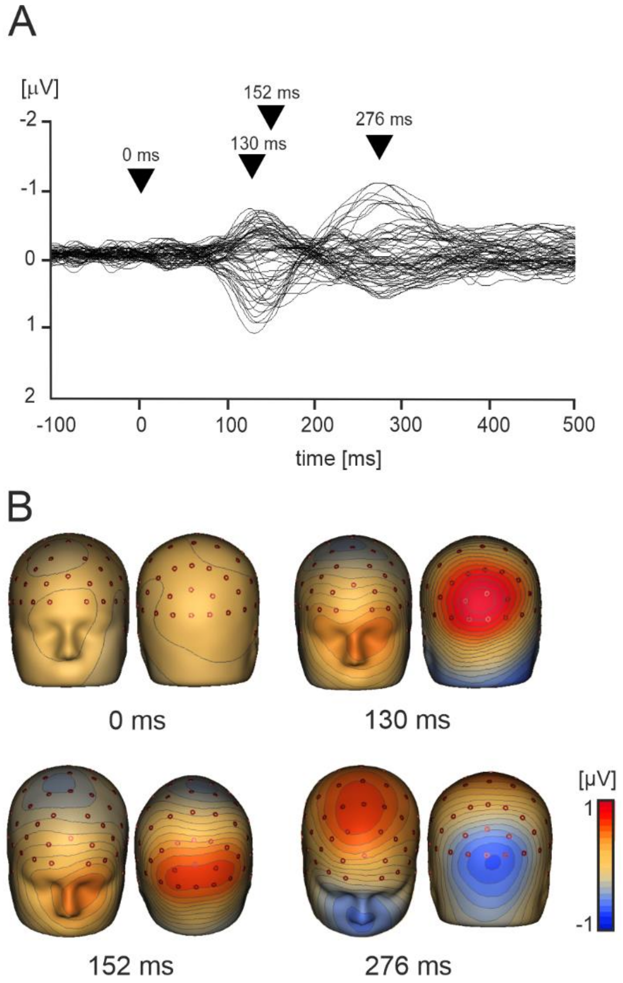

Figure 24. (A) Butterfly plot shows grand averaged EMRP waveforms across 27 participants and four value categories, with key time points of interest indicated with arrows. (B) 3-D whole head topographic maps at key latency points 0 ms, 130 ms, 152 ms and 276 ms.

6.4.4. EMRP independent component clusters

Of the 7 clusters produced in the k-means clustering solution, clusters 7, 8 and 9 were excluded (Figure 25A–C). Specifically, clusters 7 and 8 were excluded due to occurring in a low number of participants and containing a low number of ICs, demonstrating a lack of clear deviations from baseline and an atypical spreading of diverse sources across the scalp, suggesting that these clusters likely represented artefactual noise. Cluster 9 displayed a topography more typical of cortical activation, a distinctive peak around 200 ms and contained more ICs, however, it only occurred in 4 participants so was excluded from further analysis.

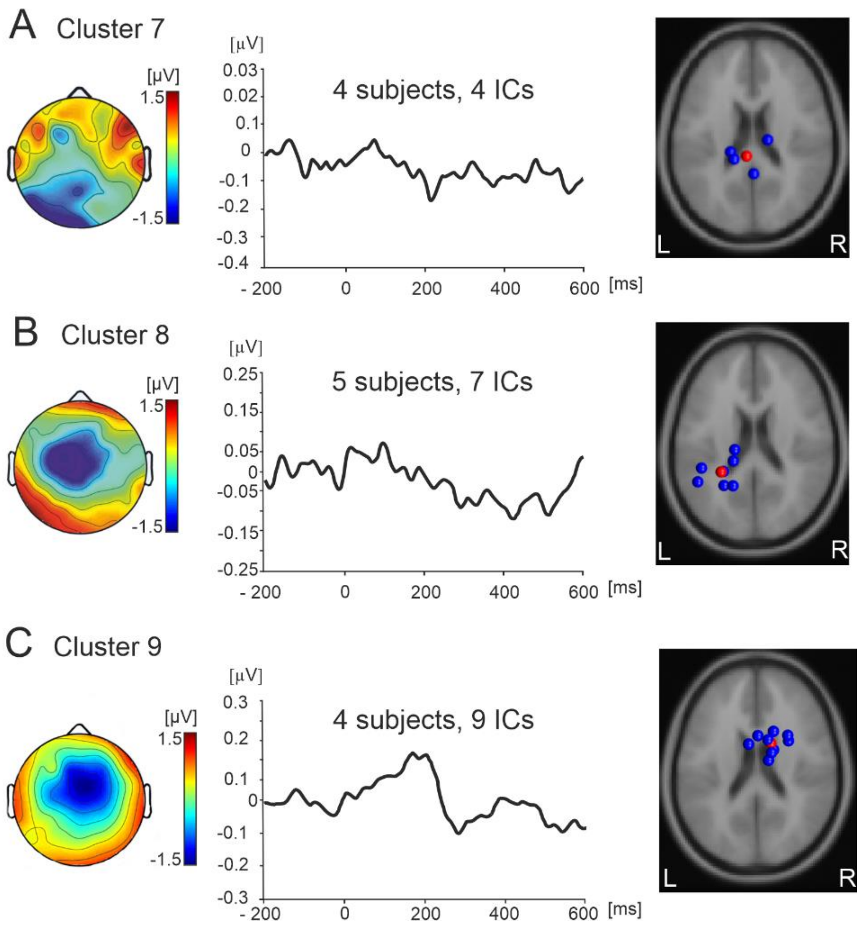

Figure 25. Topographic maps, grand averaged waveforms and source dipoles for artefactual clusters 7 (A), 8 (B) and cluster 9 (C) were excluded from further statistical analysis due a low number of ICs in a low number of participants < 5.

Four IC clusters containing >10 ICs occurring in a minimum of 8 participants (3, 4, 5, 6) showed significant modulation from baseline, with peaks between 143–331 ms. Figure 26A illustrates cluster 3 which showed a negative component peaking at 143 ms in central midline electrodes. The component originated in the posterior parietal cortex (PPC; Brodmann area 23, approximate Talairach coordinates $x = 0$, $y = -40$, $z = 23$) and explained 86.76% of variance. Figure 26B shows cluster 4 which presented a positive peak at 160 ms in right occipital electrodes, originating in the visual cortex (right BA 19; approximate Talairach coordinates x = 23 y = -82, z = 23) explaining 80.34 % variance. The component accounted for the lambda potential. Cluster 5 (Figure 26C) was featured by a positive peak at 152 ms originating in the left visual association area (Brodmann area 18, approximate Talairach coordinates; x = -28, y = -80, z = 3), explaining 79.2 % of variance. Cluster 6 (Figure 26D) peaked at 331 ms with activity originating from the midline and the left visual cortex (Brodmann area 19; approximate Talairach coordinates x = -7; y = -77; z = 31), and explained 77.7% variance.

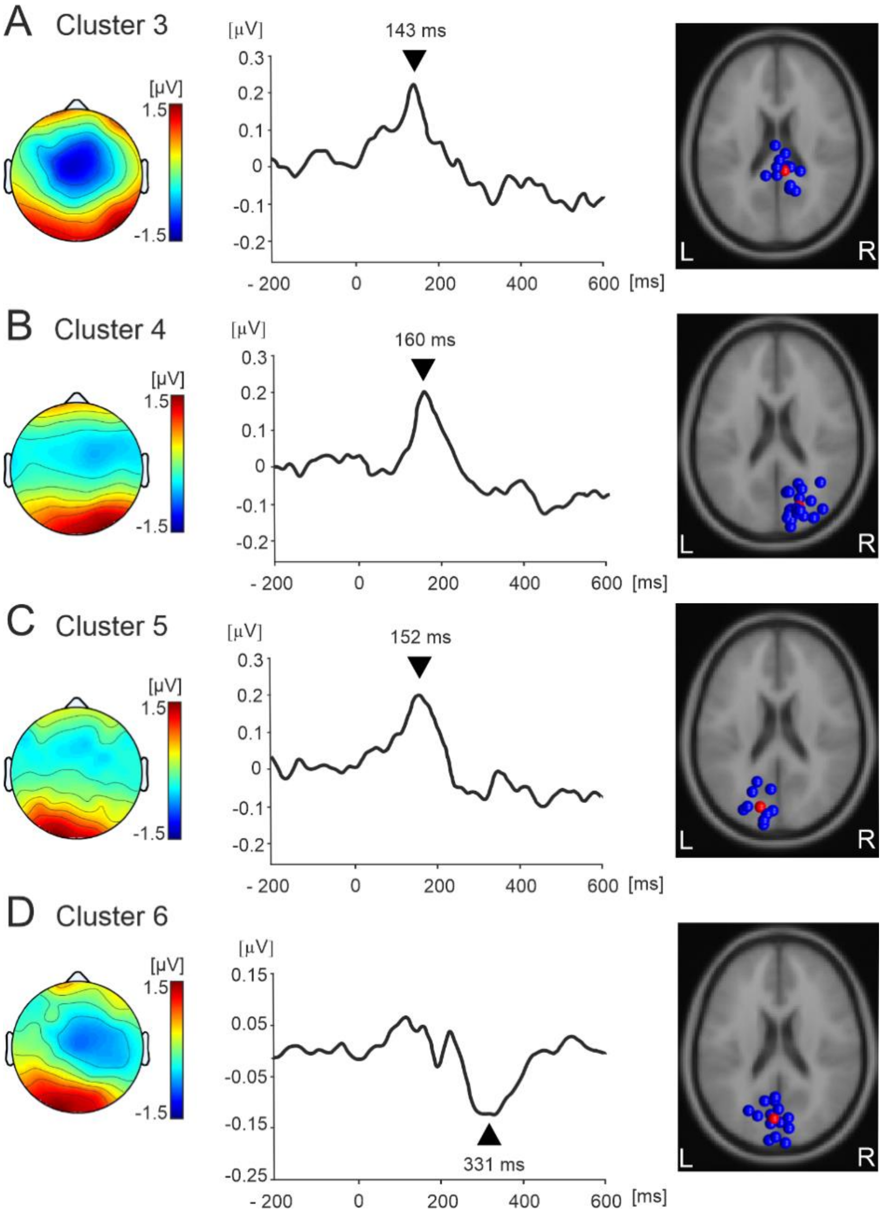

Figure 26. (A-D). Topographic maps, averaged IC (μV) waveforms collapsed across conditions and equivalent current dipoles for clusters 3-8 showing statistically significant deviations from baseline. The peak latencies are also indicated.

6.4.5. Effects of value categories on EMRP clusters

Cluster 3 showed significant modulation by the value category factor in two latency epochs (Figure 27A). In the first epoch 217–250 ms (*F*(3, 33) = 6.53, *p* = .001), cluster 3 amplitude was the smallest in high-medium category compared to low- (*p* = .033), low-medium (*p* = .005) or high-value products (*p* = .011). In the second epoch between 323–359 ms (*F*(3, 33) = 4.77, *p* = .006), low-value products showed significantly reduced amplitude compared to low-medium (*p* = .006), high-medium (*p* = .027) and high-value products (*p* = .008). In cluster 4 (Figure 27B), the statistically significant effects of value categories were present in epoch 129–139 ms (*F*(3, 45) = 3.128, *p* = .035). In this epoch, the amplitude of cluster 4 was stronger in low- and low-medium category compared to high-value products (*p* < .05). Cluster 5 was significantly modulated by value categories between 170 and 183 ms (*F*(3, 21) = 3.83, *p* = .01) (Figure 27C), with low-value products showing significantly reduced amplitude compared to low medium (*p* = .019), high-medium (*p* = .051) and high-value products (*p* = .053). Finally, a statistically significant effect of value category on cluster 6 amplitude occurred between 72–83 ms (*F*(3, 30) = 3.23, *p* = .026) (see Figure 27D), with low-value products showing significantly reduced amplitude compared to low-medium (*p* = .041) and high-value products (*p* = .017).

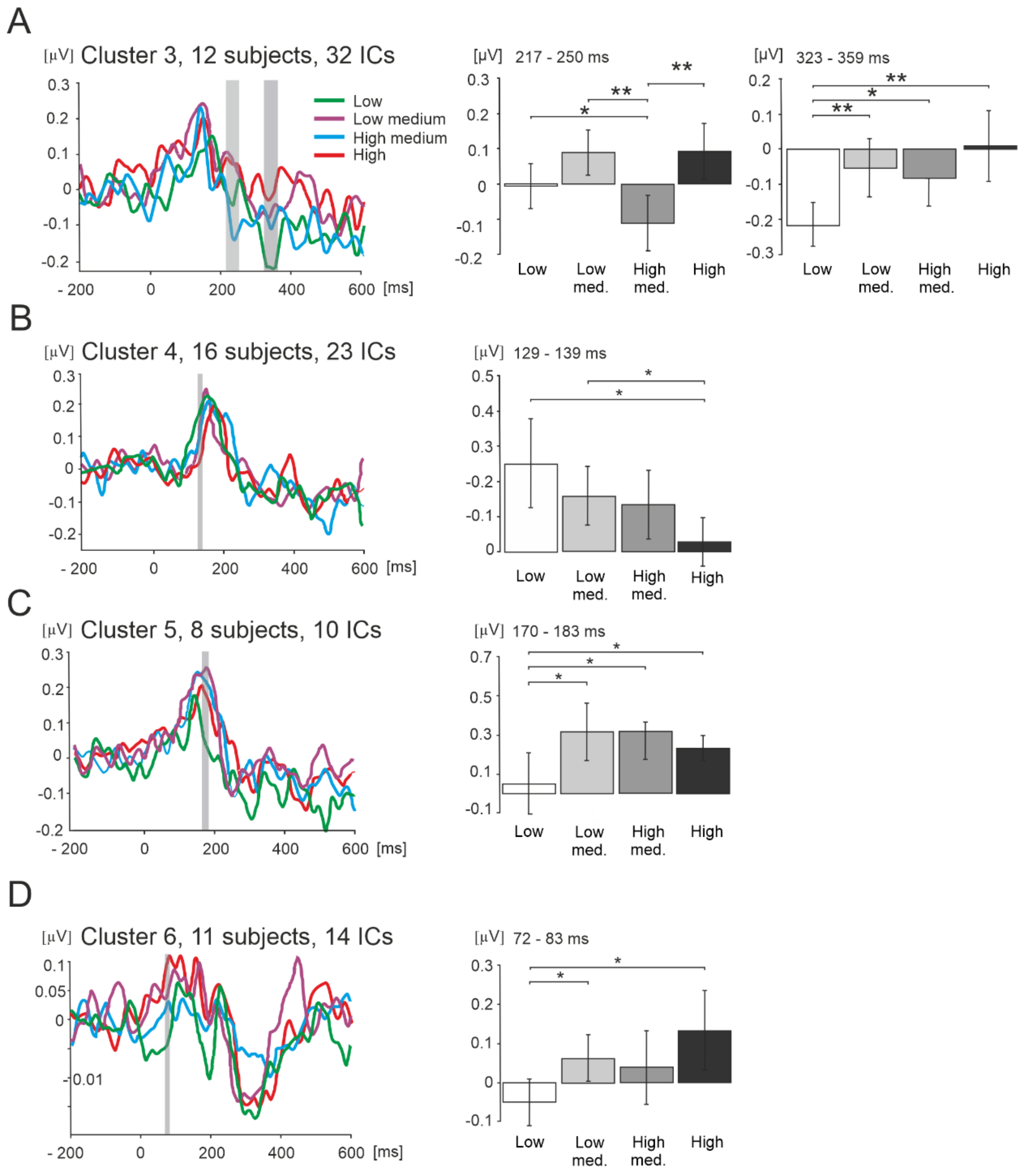

Figure 27. (A-D). IC waveforms showing effects of value categories on cluster activity in clusters 3–6. Bar graphs show significant modulation of value condition on cluster amplitude between 72–359 ms for clusters 3–6, respectively. * *p* > .05, ** *p* > .01.

6.4.6. Correlations between subjective value and IC amplitudes.

To examine whether individual WTP values in four value categories linearly influenced cluster amplitude, simple linear regressions were conducted for significant time intervals for each cluster with mean WTP in four value categories as the predictor and cluster amplitude as the observed variable. WTP significantly predicted cluster 3 amplitude between 323 – 359 ms, showing a comparatively weak but statistically significant positive relationship between amplitude and WTP across four value categories. The mean standardised β coefficient was 0.03 ± 0.05 and a one sample *t*-test showed that this was significantly different from zero ($t(11) = 2.89$, $p = .015$). A mean adjusted R^2 of 0.35 ± 0.28 was found across participants. WTP also significantly predicted cluster 4 amplitude between 129 – 139 ms. The association in cluster 4 was negative with a mean standardised β coefficient of 0.037 ± 0.043. The association was different from zero across the whole group of participant [$t(15) = 3.47$, $p = .003$], with a mean adjusted R^2 of 0.40 ± 0.34 across participants. No other clusters or time points showed any significant relationship with WTP (all $p > .05$).

6.5. Discussion

The current study examined wirelessly recorded EMRPs for real 3-D household and office products in a naturalistic mock shop environment. SVs of products were examined using a BDM auction. The experimental paradigm advanced previous research by producing environmental conditions that were more concordant with real-world economic decisions for products, examining early neural valuation responses to real 3-D products. In line with previous research (Roberts et al., 2018; Roberts et al., in preparation; Tyson-Carr et al., 2018; 2020), distinct cortical EMRP components were expected to uniquely and monotonically encode low-, high- and medium-value items, with neural prioritisation for low-value products reflected in reduced latency of the lambda and P200 EMRP components.

The present study revealed four distinct IC clusters of EMRPs that were significantly modulated by SV category, supporting previous findings observed when participants assigned SVs to 2-D product representations (Roberts et al., 2018; Roberts et al., in preparation; Tyson-Carr et al., 2018; Tyson-Carr et al., 2020), confirming that multiple cortical components of EMRPs represented different SVs of products at early latencies. Specifically, the data revealed that low-value products were binarily singled out against the highest-value category as early as 72 ms within the latency of the lambda component (Thickbroom et al., 1991; Yagi, 1979; Yagi, 1981a), replicating previous findings of early binary encoding of low-and higher-value (Roberts et al., 2018; Roberts et al., in preparation), and extending findings by observing enhanced activation exclusively for the highest value category. In line with previous studies, high- and low-medium value products were encoded slightly later in latencies exceeding 170 ms, and differentiated only after 217 ms. Importantly, unlike previous results (Roberts et al., 2018; Roberts et al., in preparation), the investigation of real 3-D products revealed significant linear modulation of SV within lambda component latency, and, for the first time, a P300-like component between 323 –359 ms, which also showed a positive linear association with SV.

At the earliest latency, enhanced amplitude was observed for high-value items compared to both low-value conditions in cluster 6 between 72–83 ms, followed by the opposite activation in cluster 4 between 129–139 ms, with both low-value conditions displaying enhanced amplitude compared to high-value items. The observed activation was consistent with the latency and topography of the lambda component which is reported to occur in visual cortex with a peak of 100 ms (Thickbroom et al., 1991; Yagi, 1979, 1981b). Importantly, cluster 4 amplitude displayed a positive linear relationship with SV, with the lowest SVs showing the lowest activation. A fast binary assignment of low- and high- SVs, reflected in early cortical responses within the latency of the lambda component, could reflect motivated automatic attention selection (Rellecke et al., 2011). The current findings partially replicate and extend previous results by observing enhanced amplitude for exclusively low- and exclusively high-value products, as opposed to low-value products versus higher-value products, demonstrated in previous research (Roberts et al., 2018; Roberts et al, in preparation).

A fast, binary separation of the lowest from the highest value suggests early detection and identification of goal relevant items, thereby preferentially avoiding costs associated with behaviours that are incongruent with current goals (e.g. approaching an unwanted item). Feedback between higher and lower visual areas has been reported to begin around 100 ms, supporting early conscious visual experience (Koivisto & Grassini, 2016). Enhanced lambda activation has been linked to selective attention during eye-movement (Yagi, 1981b). Likewise, the P100, the VEP equivalent of the lambda component, is modulated by attention and suppression of task irrelevant processing (Finnigan et al., 2011; Herrmann & Knight, 2001; Hillyard & Anllo-Vento, 1998), as demonstrated by enhanced processing of both positive and negative emotionally valenced stimuli (Burt et al., 2017; Rellecke et al., 2011; Ventura-Bort et al., 2016). Attention allocation precedes action selection (Armel et al., 2008; Krajbich et al., 2010) and an early binary neural system, revealed by enhanced lambda component activity in visual cortex for low- and high-value products (Clark & Hillyard, 1996; Hillyard & Anllo-Vento, 1998) could allow rapid and accurate categorisation of extreme values, planning and facilitation of approach and avoidance tendencies leading to goal accomplishment (Balconi et al., 2012; Helie et al., 2017; Simola et al., 2013), whilst navigating complex distraction-rich real-world environments (Barbot & Carrasco, 2018), promoting survival (Polanía et al., 2014).

The detection of cortical components responding exclusively to the highest value category, as well as the lowest value category, was not observed in previous studies involving 2-D product images (Roberts et al., 2018; Roberts et al., in preparation). The detection of the highest-value category could be due to the experimental paradigm used in the current study. Interaction with real 3-D products and their imminent availability could have selectively captured attention and triggered reward anticipation, specifically enhancing the relevance and salience of high-value products. Cues signalling imminent availability of products and related anticipatory processes can alter consumption behaviours due to reward signalling which enhances the motivation to consume the item and stimulates approach tendencies (Jędras et al., 2013). Thus, stimulating realistic approach-avoidance behaviours that could be seen in a real-world shopping environment during purchase decisions could potentially explain the additional effects for high-value products observed for real products compared to 2-D representations.

Cluster 5 showed significant modulation of SV in the occipital cortex between 170 –183 ms, displaying a positive linear relationship between SV and amplitude, with low-value products displaying the lowest amplitude compared to all other value conditions. The activation could reflect a slightly delayed visual lambda component (Van Humbeeck et al., 2018). The lambda component is sensitive to pre-saccadic activity such as saccade size and magnitude, which is modulated by the salience of stimuli during free-viewing (Ries et al., 2018b; Van Humbeeck et al., 2018) and linear encoding of SV within the lambda component could reflect an initial coarse estimation of intermediate value categories. A highly salient subsequent fixation location can reduce perisaccadic amplitude, whereas low salience can increase saccadic amplitude, suggesting that more attentional effort is required for less salient stimuli (Van

Humbeeck et al., 2018). The reduced saliency of intermediate value items could have delayed their initial categorisation, delaying the latency of the lambda component. A similar positive linear relationship with cluster 3 amplitude was also observed within the latency of the P300, which has been proposed to function as a mismatch detector for information encoded in earlier components (Polich, 2007). Therefore, initial rough categorisation of intermediate items within the lambda component could be later revised by P200 (Roberts et al., 2018; Roberts et al., in preparation) and then be moderated by top-down processing within the P300 component.

Following binary encoding of low- and high-value and initial rough linear encoding of intermediate SV in the lambda component, intermediate items were differentiated in latencies exceeding 217 ms in cluster 3, with reduced amplitude for high-medium items in the PPC.

Cluster 3 could reflect parietal P200 activity which further iteratively distinguished between medium-value products as the distinctions between intermediate-value categories is less extreme than the distinctions between low- and high-value categories. Therefore, more information could be required to precisely categorise intermediately-valued items in relation to each other. Enhanced processing for medium-value products reflected in the enhanced amplitude of cluster 3 for low-medium value items and the statistically significant lower amplitude of high-medium value items compared to all other value items could reflect a parietal P200 EMRP which underpins the more precise categorisation of more uncertain intermediately valued products. P200 EFRPs have been shown to distinguish between stimuli based on semantic or salient features (Baccino, 2012) and could index selective attention to stimuli during natural viewing (Fischer et al., 2013). It has been suggested that intermediately-valued items are associated with more uncertainty (Bobadilla-Suarez et al., 2020), and the P200 VEP, an analogue of the P200 EMRP, has been shown to be modulated by decision uncertainty and the predictability of decision outcomes (Polezzi et al., 2008; Beate Schuermann et al., 2012; Xu et al., 2011), as well as stimulus valence (Carretié et al., 2001a,b; Polezzi et al., 2008).

Cluster 3 amplitude showed a positive linear association with SV in the latency interval of 323 – 359 ms, with activation in central parietal electrodes which was generated by electrical source dipoles located in mid- and posterior parietal cortex, forming a distinct peak at 300 ms. The negative sign of the IC map corresponds to the positive potential at vertex seen in the grand average EMRP waveforms at 276 ms. Therefore, SV amplitude modulation in the 323 – 359 latency epoch could reflect an EMRP analogue of the P300 ERP component. It is possible that the initial rough categorisation of intermediate value items in Cluster 5, within the lambda component, is moderated within the P300 component and if the initial categorisation is congruent with the top-down interpretation, the ‘schema’ outlined by earlier components is maintained, otherwise, top-down attentional processes could update the mismatched representation within the P300 EMRP (Polich, 2007). Centroparietal P300 EMRP has been reliably detected during natural free-viewing for target objects (Devillez et al., 2015) and in naturalistic mobile EEG paradigms during locomotion (De Vos et al., 2014c; De Vos et al., 2014a), displaying similar topography and amplitudes to laboratory-recorded P300 VEP (De Vos et al., 2014b). The parietal P300 VEP component is thought to index goal-directed attention when salient stimuli activate the PPC (Bledowski et al., 2004; Corbetta & Shulman, 2002; Linden, 2005) and P300 could reflect a mismatch detector for information represented in earlier components such as the N100, P200 and N200 (Polich, 2007). Therefore, in the current study, the later activation of cluster 3 could be indicative of top-down attention to salient information during valuation, allowing for linear categorisation of intermediately valued products.

The detection of a clear component in the PPC within 300 ms, which likely reflects the P300 ERP component, was not observed in previous studies using 2-D product images (Roberts et al., 2018; Roberts et al., in preparation). The detection of a P300-like component in the current data, but not in previous data (Roberts et al., 2018; Roberts et al., in preparation), could be due to the use of 3-D products. The addition of depth afforded examination of the products from multiple viewpoints which could have different processing demands compared to 2-D items (Biederman & Gerhardstein, 1993; Murphy et al., 2013), producing later neural components. Observation of a previously unseen P300 component highlights the importance of considering potential processing differences when examining valuation responses to 2-D and 3-D products to ensure that the neural responses observed are reflective of those produced under naturalistic conditions. Moreover, the P300 has been related to enhanced attentional processing and attention allocation for motivationally salient products (Nijs et al., 2009) and other salient stimuli (Wu & Zhou, 2009; Yeung & Sanfey, 2004). In addition, the imminent availability of products could influence attentional bias (Jędras et al., 2019; Jones et al., 2012). In the current data, attentional bias for real products could manifest in facilitated avoidance responses for low-value products, as the P300 has been linked to behavioural inhibition or avoidance of dysfunctional behaviours (Balconi & Crivelli, 2010).

6.6. Conclusion

The current findings support previous research (Roberts et al., 2018; Roberts et al., in preparation; Tyson-Carr et al., 2018; Tyson-Carr et al., 2020), with SVs for 3-D products represented in multiple distinct components of EMRPs. Similarly, early binary encoding of low- and higher-value, and later representation of intermediate-value, was observed for 3-D products. Uniquely, 3-D products elicited encoding of high-value products and early linear encoding of SV in the occipital lambda component, potentially reflecting rough discrimination of SV. Furthermore, an analogue of the P300 ERP was observed, which demonstrated linear encoding, potentially reflecting further top-down categorisation of SV. The current findings support the interpretation of an automatic valuation system which serves to maximise economic resources by initially allocating enhanced visual attention to low- and high-value items, facilitating approach-avoidance to real products in a naturalistic shop environment.

7. GENERAL DISCUSSION AND CONCLUSIONS

The overarching aim of the current thesis was to utilise mobile EEG and eye-tracking methods to characterise the temporal dynamics underlying early subjective product valuation in increasingly realistic environments. A secondary aim was to improve the signal quality of EEG data collected in freely moving participants by identifying and removing artefactual components and enhancing synchronicity between EEG and eye-tracking data streams.

7.1. Summary of findings

- Different SVs of products were encoded in multiple distinct EMRP components documented in Studies 1–3.
- SV categories were modulated in the lambda component (Studies 2–3) and the P200 (Studies 1–3) EMRP latencies.
- In Studies 1–3, low-value products, compared to high-value products were always categorised early on in the EMRP suggesting early automatic processing.
- Higher-value products were also distinguished at early latencies (Studies 1–3), with exclusively high-value distinguished rapidly in Study 3, suggesting an early detection and binary separation of low- and high-value by the brain.
- Intermediate-value products were categorised following early binary discrimination of low- and high(er)-value items, potentially due to the increased processing demands required for intermediate-value products (Studies 1–3).
- Study 2 revealed a weak and limited linear encoding of SV in one component, however, Study 3 revealed linear encoding of SV in two component clusters of EMRPs.

- In Studies 2 and 3, guided saccade recordings and ASF allowed for effective removal of saccade-related artefacts demonstrating their suitability for research in natural settings.
- In Study 3, investigation of real 3-D products in a naturalistic shop produced an additional P300 EMRP component unseen during valuation of 2-D product images, which could reflect top-down valuation processes.

7.2. Overarching themes emerging from the data

7.2.1. Multiple distinct cortical components of EMRPs encode SV categories

Studies 1, 2 and 3 showed encoding of unique bands of SV in multiple distinct neural components. In Study 1, low-value products were encoded in a distinct neural component (IC7) from all other higher-value products (IC4) within the parietal P200 component latency; however, the spatio-temporal characteristics underpinning medium-value-products was not as clear. In Study 2, low-value products showed enhanced amplitude within the lambda component compared to higher-value products, beginning as early as 50 ms post stimulus, and low- and high-medium value products showed the strongest IC cluster activities in the latency epochs > 150 ms. In Study 3, low- and high-value products were binarily encoded in early components in the latency of the lambda component, whereas intermediate-value products were resolved in components exceeding 170 ms.

Few studies have examined the temporal dynamics of the BVS, and therefore, it is not well known how the brain encodes SVs. A fundamental question within the neuroeconomic literature is whether the brain automatically computes all SVs in a linear manner within the same value-related brain structures (Abitbol et al., 2015; Lebreton et al., 2009), or whether multiple distinct cortical clusters encode unique bands of SVs automatically within the BVS. The current findings provide support for the latter account (Studies 1-3), however, there is also evidence for linear encoding of SV within distinct cortical clusters, which was only observed for real products (Study 3).

In line with the account of unique cortical clusters encoding SV, previous research examining the temporal dynamics underpinning economic decisions for products have shown SV activation in unique cortical clusters. Tyson-Carr et al. (2020) reported non-linear encoding of SV for high-value items in the right parietal cortex, distinct encoding of intermediate SV in the frontal cortex, and separate encoding for low SV items in a different cluster of the frontal cortex. In line with the idea of distinct cortical encoding of SV, there is a plethora of research studies demonstrating distinct cortical activation patterns in voxels uniquely tuned to specific stimulus qualities (Bulthé et al., 2014; Diana et al., 2008; Haxby et al., 2001; Haxby et al., 2000; Howard et al., 2009; Kragel & LaBar, 2016). The results presented in the current thesis supports and extends previous findings by demonstrating, for the first time, unique encoding of SV in distinct cortical clusters in naturalistic environments, using mobile EEG. Specifically, in Studies 1, 2 and 3, components of EMRPs selectively encoded low-value compared to higher- or high-value products in early latencies, whereas intermediate-value products were resolved in later components of EMRPS.

A potential reason for multiple unique cortical clusters encoding SV is that simultaneous encoding of SV allows information in the environment to be rapidly encoded and acted upon for low- and high-value stimuli, facilitating avoidance and approach behaviours. In support of quick processing of multiple task-relevant objects, previous research has demonstrated that when two objects are presented nearly simultaneously, the second object can receive attentional focus within milliseconds of the first, whilst attention for the first object is maintained, suggesting rapid parallel attention for objects (Eimer & Grubert, 2014). The unique and fast encoding of SVs of products and preferential attention for low- and high-value products could function to facilitate motivated behaviours in natural environments.

In addition to unique cortical clusters encoding SV, Study 2 revealed a linear trend in some components, and Study 3 showed some linear encoding of SV within the lambda and P300 components. Previous research has attempted to ascertain whether neural coding of SV follows a linear or non-linear function (Abitbol et al., 2015; Bartra et al., 2013; Lebreton et al., 2009). However, the current findings suggest that SV is encoded in multiple distinct cortical components, some of which process SV linearly. In Study 3, the linearity of SV encoding can be interpreted as an initial coarse encoding of intermediate values within the lambda component, which could then be flagged for further top-down processing for more precise categorisation. In the P300, SV is more precisely encoded following a linear function, as top-down processes allow for categorisation of intermediate values. The current interpretation aligns with research which places the P300 as a mismatch detector for information encoded in earlier components (Polich, 2007) and accords with fMRI data which showed both linear and non-linear encoding of SV in distinct neural structures of the BVS (Bartra et al., 2013). Although research examining economic decisions suggests that SV follows either a linear function or non-linear function in distinct cortical clusters, the current data suggests that a combination of multiple unique cortical clusters, and linear processing within some of these clusters, are involved in processing SV.

7.2.2. *Facilitated neural processing for low-value products; a negativity bias in the brain*

Distinct and rapid neural encoding for low-value products was persistently observed throughout studies. In Study 1, unique clusters within the P200 EMRP showed enhanced amplitude for low-value products, compared to products of all other SVs in the parietal cortex. In Study 2, low-value stimuli elicited the strongest IC of EMRP activity within the latency of the lambda component, beginning as early as 50 ms post-stimulus onset. In Study 3, in a realistic shopping environment, low-value products were singled out against high-value products within two distinct ICs of the lambda component, beginning as early as 72 ms post stimulus. The consistent rapid encoding of low-value products implicates a negativity bias in the brain.

Facilitated neural encoding of products with low SV, reflected in early cortical responses, could facilitate goal-directed behaviour. From an evolutionary perspective, survival is afforded by prioritising avoidance of negative stimuli, such as poisonous food, before approaching positive stimuli (Polanía et al., 2014). The products used in the current research were not primarily aversive or directly threating stimuli as they were potentially rewarding, however, it has been shown that rewards can be considered aversive if they do not match expectations (Shenhav et al., 2018). Incongruencies between expectations and reality can generate avoidance responses and aversive motivational states, and the activation of valance and anxiety-related brain circuits (Blair et al., 2006; Shenhav et al., 2018). In the context of current experimental procedure and results, undesired low-value products could have violated expectations, thus triggering aversive responses, as reflected by the associated reduced latency of cortical components. Rapidly processing and avoiding low-value items could represent the negativity bias, affording avoidance of the risk of an unfavourable outcome such as selecting low-value products instead of preferred high-value products. The avoidance of risks associated with obtaining unfavourable outcomes by selecting low-value products could be considered as consistent with PT. PT stipulates that losses (such as the financial loss associated with purchasing unwanted low-value products) are weighted more heavily than gains, preserving financial resources and avoiding unwanted outcomes (Kahneman & Tversky, 1984).

In accordance with the current findings which indicate negativity bias for low-value products, numerous ERP studies have shown a negativity bias during value processing, reflected in reduced latency and enhanced amplitude of early neural components such as the P100 (Cacioppo & Berntson, 1994; Vaish et al., 2008; Williams et al., 2006; Yuan et al., 2015), the P200 (Carretié et al., 2001b; Correll et al., 2006; Gerdes et al., 2013; Huang & Luo, 2006; Rigoni et al., 2010; Schuermann et al., 2012; Wang & Han, 2014; Wang et al., 2012) and the N200 (Lithari et al., 2009; Tyson-Carr et al., 2018; 2020). Furthermore, enhanced motivational salience, arousal and facilitated neural activation have been observed for losses as opposed to gains of the same amount (Baumeister et al., 2001; Rozin & Royzman, 2001; Sokol-Hessner et al., 2009; Stancak et al., 2015).

Enhanced neural processing of low SV products is likely to coincide with System 1 outlined by Kahneman (2011). According to Kahneman, System 1 incorporates quick thinking that is usually in response to emotionally charged information and requires little to no conscious effort, operating continuously and automatically outside of conscious awareness. The early neural categorisation of low-value captured in the current studies was likely operating below conscious awareness as illustrated by the early latency of the components. In Study 1, low-value was categorised at ~ 200 ms, and in Studies 2 and 3, low-value was detected in the brain within the latency of the lambda component, as early as 50 ms post stimulus.

The negativity bias was characterised by neural components responding to the low-value categories as early as 50–63 ms, which is earlier than previously reported in laboratory-based EEG studies (Carretié et al., 2001b; Huang & Luo, 2006; Williams et al., 2006; Yuan et al., 2015). The reduced latency can be explained in terms of the free-viewing paradigm. As a result of parafoveal processing, inclusion of eye-movements can facilitate processing of unpleasant information with enhanced attentional capture during free-viewing. Covert attention can be allocated to a stimulus prior to the eyes reaching fixation during the saccade period (Simola et al., 2013). As a result, the naturalistic paradigms utilised in the current studies may have provided a more realistic insight into the way that low-value information is processed in real-world settings. By affording participants the ability to move and engage with the stimuli, the brain may need to process information more quickly to facilitate planning and to provide quick responses that will allow for the avoidance of negative goal incongruent stimuli (Helie et al., 2017; Simola et al., 2013).

7.2.3. Early binary SV resolution of low- and high-value within an automatic neural valuation system

Studies 1 and 2 showed rapid encoding of low- versus higher values in ICs of EMRPs in the latencies of the lambda component and P200 component. In Study 3, low-and high-value products were binarily discriminated. The observed early neural responses could reflect an adaptive dichotomous representation of low- and high- values within a domain-general BVS, facilitating both early avoidance and approach behaviours (Bartra et al., 2013; Westbrook et al., 2019). Binary isolation of low- and high- value item categories is a useful adaptation, prioritising the likelihood of one’s survival. Fast categorisation of items with the lowest and highest SVs stimulates quick avoidance responses for unwanted items and approach responses for wanted items, preserving resources and optimising time.

Motivationally salient cues can influence attention selection, action selection and response speed (Chelazzi et al., 2013; Eimer, 1996; Kiss et al., 2009; Mendelsohn et al., 2014). In addition to prompted avoidance responses triggered by negative cues, it has been shown that target detection is facilitated by reward-related cues (Kiss et al., 2009), and a history of positive reinforcement can facilitate attentional priority for those items (Anderson, 2013).

There is a large amount of research to suggest that there may be a common neural system facilitating avoidance and approach, with many studies reporting an overlap between neural circuits responsible for both processes (Delgado, 2007; Levy & Glimcher, 2012; Pessiglione & Delgado, Mauricio, 2015; Tyson-Carr et al., 2018). Supporting the overlap of salience processing in the BVS, early ERP components show reduced latency and enhanced amplitude for both negatively and positively valanced stimuli, including the P100 (Cacioppo & Berntson, 1994; Smith et al., 2003; Vaish et al., 2008; Williams et al., 2006; Yuan et al., 2015), P200 (Huang & Luo, 2006; Ma et al., 2018; Roberts et al., 2018; Schuermann et al., 2012) and N200 (Goto et al., 2017; Kiss et al., 2009; Lithari et al., 2010; Telpaz et al., 2015; Tyson-Carr et al., 2018, 2020).

Facilitated processing for low- and high- value stimuli could be related to decision confidence, as it has been suggested that SVs at the extreme end of the spectrum are more likely to be associated with a high level of decision confidence and consequent approach-avoidance behaviours (Bobadilla-Suarez et al., 2020). Alternatively, items of intermediate SV are considered to be associated with more uncertainty and lower decision confidence (Bobadilla-Suarez et al., 2020). The current interpretation links to the concepts of System 1 versus System 2 processing, as categorisation of low- and high- SV is likely to be carried out by System 1, which is thought to replicate reactions to similar events and rest more on emotional gut responses (Kahneman, 2011).

The detection of early components which exclusively responded to low- and high-value, compared to Studies 1 and 2 which showed components for low and higher-value categories, could be due to the experimental paradigm. The physical presence of products within a shopping environment in Study 3 might have stimulated real avoidance-approach behaviours which could be observed in a real-world shopping environment as the products were immediately in front of them in a simulated shop. As such, the environment may have created more of a sense of immediacy and urgency related to current goals of selecting a product to purchase, therefore, necessitating the fast detection of wanted and unwanted items to facilitate approach of the favoured item.

The above interpretation is supported by research demonstrating that imminent availability of products altered consumption behaviours (Jędras et al., 2013, 2019; Jones et al., 2012). The actual presence of products can act as conditioned stimuli signalling the imminent availability of the reward (Jędras et al., 2013), enhancing motivation and conditioned responses, such as approach tendencies, attentional processing and consumer behaviours. These effects are more pronounced when there are signals of availability that are consistent with the behavioural goals (Jędras et al., 2013), which, in Study 3, was ‘purchase at least one item’.

7.2.4. Later encoding of intermediate-value products within an early attention-based neural valuation system

The current findings indicate that a non-linear iterative process could occur whereby SV resolution becomes progressively refined over time to decipher the full range of SV categories. The data revealed that medium-value products were categorised following early binary discrimination of low- and high-value items, between 150 – 200 ms in Studies 1 and 2, and between 170 – 359 ms in Study 3, falling within the latencies of the P150, P200 and P300 EMRPs.

Delayed categorisation of medium-value products is likely due to the contrasts between intermediate values being less obvious than between more extreme low- and high-value items. Therefore, intermediate-value processing may represent a finer resolution of value. As a result, the neural system that affords rapid categorisation of low- and high-value may not allow comparable fast categorisation of medium-value items, suggesting that two systems may be involved in the processing of early SV, with intermediate values receiving further processing (Philiastides & Heekeren, 2009).

Whilst low- and high- value options are associated with high decision confidence, medium-value options are linked with lower decision confidence and more uncertainty (Bobadilla-Suarez et al., 2020). P200 can be modulated by outcome predictability and decision uncertainty (Polezzi et al., 2008; Schuermann et al., 2012; Xu et al., 2011). Consequently, categorisation of medium SV may require input from the ‘slow thinking’ System 2, which is deployed when further processing is required as the habitual, emotional responses of System 1 do not suffice (Kahneman, 2011). Supporting the current interpretation, resolution of medium SV corresponded with neural sources in areas of the cortex that are typically associated with the top-down attention function of System 2 (Kahneman, 2011), such as the dorsolateral PFC (Bartra et al., 2013; Hubert & Kenning, 2008; Mahesan et al., 2016; Morris et al., 2014; Plassman et al., 2007) (See Chapter 4), and the PPC (Shomstein, 2012; Small et al., 2005) (See Chapter 6).

7.2.5. Examining real 3-D products versus product images.

In Studies 1 and 2, images of products were displayed in a mock gallery, and neural activity corresponding with product valuation was recorded whilst participants freely roamed and evaluated products. In contrast, in Study 3, real 3-D products were displayed on shelves mimicking a realistic shopping environment, and neural activity corresponding with product valuation was recorded whilst participants freely roamed and evaluated products. Like Study 1 and 2, Study 3 results revealed multiple components of EMRPs encoding distinct SV, with early components encoding low- and high-value products, and intermediate products encoded by slightly later components in latencies exceeding 170 ms. Unlike Studies 1 and 2, Study 3 data revealed a later component within the latency of the P300, with a source in the PPC which showed an almost linear negative encoding of SV, with the lowest activation for low-value and the highest activation for high-value products.

Encoding of SV in the later P300 component could indicate a top-down verification of SV, whereby the initial rapid binary and intermediate-value products categorisations are checked. P300 has been shown to be associated with enhanced attentional processing of motivationally salient products (Cano et al., 2009; Conroy & Polich, 2007; Keil et al., 2002; Nijs et al., 2009; Onishi & Nakagawa, 2019; Yeung & Sanfey, 2004), and allocation of attention, when evaluating reward outcomes in terms of valence, magnitude and expectancy (Wu & Zhou, 2009; Yeung & Sanfey, 2004).

The P300 also promotes behavioural inhibition, allowing for avoidance of behaviours which could jeopardise goal achievement (Balconi & Crivelli, 2010). P300 can represent a later revision or mismatch-detection between incoming stimuli and the initial processing, which may have occurred in earlier components such as the N100, P200 and N200 (Polich, 2007). If the initial representation is congruent with the new updated representation, the ‘schema’ outlined by earlier components is maintained. However, if the stimulus is novel, higher-level processing involving working memory and attention-related processes update previous stimulus representations, and the mismatch could be indexed by P300 (Polich, 2007). Because the lowest-value products were categorised first, within the early binary system (in cluster 6 between 72-83 ms), it is possible that low-value items are used as a reference point against which all other items are checked in the P300, explaining why low-value products significantly differed from all other value conditions in the P300 component.

The later processing in the P300 could be associated more with the slow thinking System 2, outlined by Kahneman (2011), which is tasked with monitoring the progress of System 1 and exercising impulse control. System 2 is a more conscious and controlled neural system which requires attention and conscious effort, therefore, initial impressions developed by System 1 may be checked by System 2 within the P300.

The reason for the detection of a P300 in Study 3, but not in Studies 1 and 2, could be due to the additional depth dimension affording viewing from multiple perspectives, including atypical angles. Therefore, a moving subject might observe differences in product luminance, contrast, shape, size, and position over time (Murphy et al., 2013). It is possible that for 3-D products, compared to 2-D product images, the added complexity of spatial relations between these viewpoints need to be integrated over time to form a holistic visual representation (Meilinger et al., 2011). Additional visual information processing could be required for identification and valuation to occur (Biederman & Gerhardstein, 1993), necessitating the additional validation of the initial categorisation within the P300.

A further difference in the results of Study 3 compared to Studies 1 and 2 is the observation of a cluster encoding exclusively high-value items. The detection of neural components responding exclusively to high-value items could be a function of the shopping environment which, compared to the picture galleries used in Studies 1 and 2, signalled the imminent availability of products. Imminent availability of products can increase their motivational salience, enhancing attentional bias for product-related cues, (Jędras et al., 2013, 2019; Jones et al., 2012) and consumption behaviours (Maas et al., 2012; Painter et al., 2002). The imminent availability of products can increase their palatability, as less effort is needed to obtain them, and this is associated with activation of motivation-related reward circuits (Blechert et al., 2016). Therefore, although Study 2 increased the price range to allow for a finer resolution of SV in the brain, perhaps it is necessary to create environmental conditions which are congruent with consumption behaviours to observe realistic valuation responses and the full range of SV resolution in the brain. Conceptual and perceptual congruence between products and the environment can facilitate their positive evaluation and purchase selection by making them more accessible and easier to process (Berger & Fitzsimons, 2008; Fiore, 2008; Sherman et al., 1997), and equally, environmental irritants can negatively influence product evaluation (D’Astous, 2000). Characteristics of store environments can have a significant impact on emotions, affecting approach-avoidance behaviours reflected in the amount of money spent, number of products purchased and time spent shopping (Sherman et al., 1997).

7.2.6. Removing saccade-related artefacts in the wild

MoBI and eye-tracking methodologies can be combined to examine eye movements and neural dynamics during natural free-viewing, affording investigation of aspects of cognition which could not be observed under laboratory conditions (Dimigen, 2014; Fischer et al., 2013; Nikolaev et al., 2014, 2016). The present studies capitalised on recent methodological and technological progress in MoBI and eye-tracking research (Dimigen, 2014; Fischer et al., 2013; Gramann et al., 2010; Gramann et al., 2011; Gwin et al., 2010; Liao et al., 2012; Makeig et al., 2009; Nikolaev et al., 2014, 2016; Ojeda et al., 2014). to explore economic valuation of objects in freely behaving individuals. In the literature, co-registration of MoBI and eye-movement recordings for investigation of natural cognition has suffered from contamination of the neural signal by many saccade-related artefacts, which has severely hampered progress in the investigation of natural cognition. As such, to successfully examine the neural dynamics of value-based decisions in realistic environments, it was essential to develop a method for effectively removing saccade-related artefactual activity.

In Study 1, saccade-related artefacts were removed from the data using an ICA decomposition and back-projection technique (Debener et al., 2010). The grand averaged EMRP activity was decomposed into ICs and only individual ICs which were thought to reflect genuine cortical activity, based on their latency and topographies, were back-projected to the scalp. While the ICA back projection method was effective in removing saccade-related artefacts, some residual eye-movement artefacts remained in the data, preventing detection of later neural responses. Residual eye-movement contamination is evident in the increased artefactual noise >300 ms in Figure 10 (Chapter 4). As such, it was essential to mark out and remove saccades of each angle using advanced data cleaning methods. In Study 2, saccade-related artefacts were first detected using a short guided-saccade recording (Berg & Scherg, 1991) in which participants made saccades for 9 angles around a circle, beginning at a central fixation cross. The procedure allowed recording and quantification of a typical saccade topography for each angle of product viewing to be identified in the continuous EEG data for the valuation task. The saccades were subsequently removed using ASF in BESA (version 6.1) and the artefact topographies could then be imported and removed from the EEG recording obtained during the valuation task. The method of guided-saccade artefact removal showed a highly statistically significant decrease of residual activity in frontal electrodes compared to an eye-blink-corrected data and uncorrected data in Study 2 (Figure 16), demonstrating the effectiveness of the current method for saccade-related artefact correction. The guided saccade/ASF method was then further employed in Study 3 in the realistic mock shop experiment and effectively reduced artefactual noise in eye electrodes (Figure 23).

The utility of the current method for saccade-related artefact removal could have wide-reaching implications for MoBI research and studies employing co-registration of eye-tracking and EEG. Many methods have been developed to reduce the number of saccade-related artefacts contaminating MoBI recordings during free-viewing behaviour, including restriction of movement, regression (Jiang & Bian, 2019), PCA (Berg & Scherg, 1991), ICA (Bell & Sejnowski, 1995) and linear deconvolution methods (Ehinger et al., 2018). However, restriction of movement decreases the generalizability of findings to the real-world and restricts the investigation of certain behaviours such as those related to locomotion. Additionally, regressions are limited as they require one or more reference EOG and ECG channels (Jiang et al., 2019), and ICA and PCA methods cannot separate out similar artefacts unless they are marked out. Likewise, methods such as the Unfold Toolbox (Ehinger et al., 2018) require detailed information about saccade amplitude and angles to be utilised, which is not always possible to obtain in naturalistic settings. Alternatively, as shown in the current data, guided saccade recordings can be used to successfully detect saccades of every angle, which can then be removed using ASF, optimising decompositions using PCA and ICA techniques by marking out the data for removal. As the method can be utilised easily with any MoBI and eye-tracking system, it provides a necessary alternative to linear deconvolution methods as it does not require detailed information regarding saccades. When combined, guided saccade recordings and ASF are able to successfully remove a large portion of artefacts from the eye-orbits which would contaminate detection of neural signals in naturalistic settings during free-viewing. Many naturalistic paradigms can employ the method to successfully remove contamination during free-viewing recordings, opening up a range of new possibilities for investigation of brain dynamics underpinning natural viewing behaviours in real-world environments.

7.2.7. System 1 and System 2 (Kahneman, 2011) *and their relation to the lambda component, parietal P200 and centroparietal P300 of EMRPs*

In Studies 1, 2 and 3, low- and high-value products were categorised early on by the brain and there was a clear role of the parietal P200 in the processing of product SV in naturalistic settings. In Studies 2 and 3, the inclusion of a broader range of stimuli and removal of residual saccadic artefacts lead to the detection of earlier processing of low- and high-value products within the visual lambda component in the occipital cortex, in latencies beginning from 50 ms. In Study 3, examination of neural dynamics in a more naturalistic shop setting using real 3-D products, lead to the detection of a centroparietal P300 component which showed linear processing of SV. The current findings can be interpreted in the context of the System 1 and System 2 decision-making model, introduced by Kahneman (2011).

Due to the early latency modulation of SV within the lambda component, as early as 50 ms in Study 2 and 72 ms in Study 3, it is likely that SV was encoded automatically and without conscious awareness. Therefore, early encoding of salient low- versus high-value categories could form a part of System 1 (Kahneman, 2011). System 1 is an automatic and rapid neural system which categorises stimuli continually and with no expenditure of effort, relying on emotionally charged information as well as previous experience and heuristics. Supporting the current interpretation, the lambda component has been shown to index the afferent flow of information to the visual cortex and is modulated by bottom up low-level stimulus features such as luminance, contrast, size and spatial frequency (Kazai & Yagi, 2003; Ries et al., 2018a; Thickbroom et al., 1991; Yagi, 1979). As such, the lambda component likely operates within System 1, which automatically generates a limited set of basic assessments and impressions of stimuli, which are then later evaluated by System 2 (Kahneman, 2011). Furthermore, the lambda component is the EMRP equivalent of the VEP P100, which has been shown to be modulated by the value of a stimulus, reflecting bottom up rapid automatic valence detection and is considered to reflect System 1 processing (Marzi & Viggiano, 2007). The lambda component is also modulated by saccade size and magnitude, which are thought to be influenced by top-down attention (Ries et al., 2018a). This suggests that System 2 has top-down influence on the bottom-up processing of System 1 in order to plan and execute eye-movements in line with task demands. Kahneman (2011) supported the top-down influence of System 2 on System 1, suggesting that it is possible for System 2 to executively program the automatic System 1 functions of attention and memory.

Additionally, due to the early latency of components, the P200 has been linked to early value categorisation (Gui et al., 2016), in particular, directing visual attention to salient stimuli (Carretié et al., 2001a,b). Therefore, the P200 also likely forms a part of System 1 processing. However, intermediate value products were also processed slightly after low- and high-value items, within the latency of the P200. Therefore, it is possible that the P200 is able, to some extent, to recruit top-down processing for further fine-tuned categorisation of intermediate values within the early valuation system, or provide a rough estimate within System 1 which then flags intermediate items for further top-down processing by System 2. Supporting this interpretation, research has shown that both top-down and bottom-up processing occur when evaluating visual stimuli, with salient stimuli receiving bottom-up attention and task-relevant stimuli receiving volitional top-down attention (Ligeza et al., 2017). Furthermore, the P200 has been associated with functional reallocation of executive attentional resources (Lai et al., 2019).

In Study 3, a P300 was observed showing linear encoding of value, with low-value products showing significantly lower amplitude compared to all other value conditions, with a cortical source in the posterior parietal cortex. A small but statistically significant positive correlation was also observed for cluster 3 and WTP in the latency period of 323 – 359 ms, suggesting linear influence of value category on cluster 3 amplitude. The linear encoding of value in the P300 could reflect encoding of value in System 2 (Kahneman, 2011), which is responsible for top-down decision-making, deductive reasoning and conscious attention whenever System 1 is unable to adequately categorise a product. In the current data, it is possible that medium-value products were unable to be adequately categorised by System 1, which binarily encodes the more extreme low- and high-value products, therefore they are flagged by System 1, and System 2 is deployed to gather further evidence for categorization of more difficult intermediate-value items. The current interpretation is supported by research which suggests that P300 is a later revision or mismatch detection between incoming stimuli and initial processing conducted in components such as the P200. Therefore, if the stimulus is novel, additional attention is needed to update stimulus representations (Polich, 2007). Additionally, studies have linked the P300 to higher-level processing and attention-related processes (Polich, 2007; Shaw et al., 2018). P300 has also shown reduction in amplitude with increasing task demands during walking (Ladouce et al., 2019), suggesting that it is tapping into finite higher-level attentional resources, in line with System 2. Finally, the cortical source in the PPC supports the current interpretation that P300 relates to System 2, as the PPC is associated with attention, information processing and command related functions (Jagla et al., 2007; Kurtzberg & Vaughan, 1982).

The interpretation of the lambda, P200 and P300 components operating within Kahneman's System 1 and System 2 can be considered from the perspective of the cusp catastrophe model (CCM) (Thom, 1974). The CCM is a mathematical model which explains discontinuous and divergent phenomena (Zeeman, 1976). The CCM can be used to interpret the initial binary processing of low- and high-value within the lambda and P200 components within System 1, and the recruitment of System 2 to characterise more difficult intermediate stimuli, including the later top-down linear encoding of SV within the P300 (Figure 28).

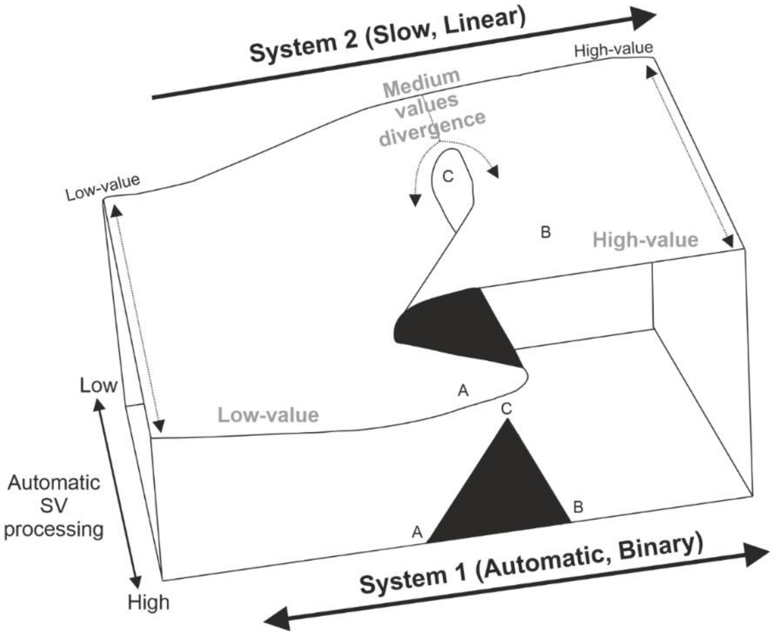

Figure 28. Schematic representation of the CCM, adapted from Zeeman (1976), integrating System 1 and System 2 to explain the rapid binary and slow linear encoding of product SV observed in the current data. The model shows automatic binary encoding of extreme low- and high-values within System 1. However, intermediate-value items are unavailable in relation to automatic bimodal categories of System 1 and must be categorised at the cusp point (C) by top-down, conscious and linear System 2. If the evidence gathered by System 2 makes the product less desirable, it will follow trajectory A (low-medium value), and if the evidence gathered by System 2 makes the product more desirable, it will follow trajectory B (high-medium value).12

In line with the CCM, the subjective valuation of products can be broken down into the initial bimodal categories of low-value (linked to avoidance behaviours) and high-value (linked to approach behaviours). These are both likely computed within the automatic and rapid System 1, which could correspond to the lambda and P200 components of EMRPs in the current data. SVs of all products must exist somewhere along the axis of values ranging from low- to high-value. According to the CCM, because of the splitting factor (i.e. categorisation automaticity), linear middle values are not accessible past the bifurcation point (C) (i.e. the border between linear and bimodal categorisation) as they do not fall into the bimodal set (A, B), causing the cusp catastrophe, to occur (Zeeman, 1976) (Figure 28). Further information is needed in order to categorise the intermediate items in relation to the bimodal categories, therefore, a trajectory must be chosen for intermediate items at point C (the cusp point). A graphical representation of this model can be seen in Figure 28. The further information required for categorisation of intermediate values at point C likely requires input from the top-down System 2, therefore intermediate-value items are initially categorized within the P200 and flagged for further top-down processing in the P300. If the evidence gathered makes the product less desirable, it will follow trajectory A and be categorized along the low-medium axis. If the information gathered makes the product more desirable, the intermediate-value item is categorized along trajectory B, and is categorized along the high-medium axis. In this way, small deviations in stimuli in intermediate categories in System 1 can produce relatively large changes in behaviour in System 2. Meanwhile, the relatively large qualitative difference between low- and high-value items in System 2 which are closely aligned to the bifurcation set can lead to small differences when evaluation is moved to System 1. However, the extreme low and high SVs remain constant across System 1 and 2, providing stable anchors for categorisation of intermediate SV. Further top-down categorisation of intermediate items could correspond to P300 processing in the current data. Hence, the model could provide a potential explanation why certain studies demonstrate linear categorisation whereas others represent binary categorisation, or both are demonstrated together (Bartra et al., 2013). The CCM topology provides a potential explanation for why the current data showed early binary encoding of SV in lambda and P200 components, and why later components such as the P300 followed a linear encoding of SV, as they include the ranked categorisation of intermediate values.

7.3. Limitations

Many factors can influence realistic purchasing behaviours in natural environments, and, although the data presented in the current thesis goes some way towards uncovering the neural dynamics underpinning real-world economic decisions for products, time limitations have meant that it was only possible to examine some of these factors. Research has shown that the shopping environment can influence purchase intentions and consumption behaviours by altering the consumers mood (Sherman et al., 1997). Mood was not explicitly measured in the current research, although we did measure more hedonic aspects of product valuation in terms of ‘pleasantness’ and ‘desirability’, which closely corresponded to SV in each Study.

Furthermore, to avoid explicitly questioning participants about their economic value ratings of products during the mobile EEG recording, participants later took part in an auction task in which they submitted their WTP value for each item, and these bid values retrospectively defined value conditions. It cannot be ruled out that participants did not consider other factors, such as visual appeal or current need, to form their economic value ratings for products in the product gallery and mock shop settings. These factors could theoretically influence attention or aversion of stimuli.

A further limitation of the current work is the inability to automatically detect stimulus onset in the real-world. Not only does manual tabulation introduce an element of subjectivity regarding what eye-tracking frame corresponds to stimulus onset, it also introduces time constraints associated with manual tabulation of many stimulus onsets over many experimental blocks and participants. However, due to the uncontrolled nature of naturalistic neuroimaging experiments, a degree of subjectivity is essential, as computers often cannot account for the variations caused by movement of the camera to reliably detect stimulus onset, and these factors must be considered to improve the quality of data in the future.

Although the method of synchronization in Study 3 both improved the synchronisation of the data streams and made it less intrusive than the method utilised in Studies 1 and 2, the synchronization between EEG and eye-tracking data stream can be further improved to reduce asynchrony. There are online synchronisation platforms available with greater synchronisation accuracy, such as the LSL (Kothe, 2014). However, they are more unreliable as the software is dependent on network signal making it susceptible to data loss if the participant falls out of range, and the LSL is only compatible with some hardware. Hardware synchronisation solutions are much more reliable and measures should be taken to improve their accuracy.

Contamination of eye-movements on brain potentials was addressed using ICA back projection in Study 1, and using guided saccade recordings and ASF in Studies 2 and 3, the latter of which was extremely effective in removing saccadic artefacts. Despite the reduction in amplitude around eye electrodes, some remnants of eye-movements may have remained in electrodes surrounding the eyes. In the current thesis, some effort was made to account for cortical potentials overlapping by not including stimulus onset triggers that were too close together. However, methods which extract the temporal overlap of neural events, such as Unfold Toolbox (Ehinger et al., 2018), could not be utilised in the current research as detailed information about gaze angle was not available. Additionally, Studies 1, 2 and 3 required fixation crosses to ensure that the gaze was aligned to confirm accurate stimulus onset, and a subtler method is required for a more naturalistic approach.

The effectiveness of the guided saccade and ASF method used in Studies 2 and 3 should be validated in future research in a range of increasingly realistic settings and, if found to be robust, should be incorporated as a standard practice in combined MoBI and eye-tracking research. Future research would benefit from identifying affordable and easily implementable solutions for marking out movement artefacts in a similar way that would allow them to be removed using ASF. This would afford investigation of later neural components associated with decision outcomes, and for more unconstrained paradigms to be successful in identifying neural components.

Another limitation of the current research is the spatial resolution of neural components. In Study 1, a source dipole analysis was conducted in BESA (version 6.1) using a sequential strategy, and in Studies 2 and 3, ECDs were fitted to mean cluster centroids in EEGLAB, producing a single dipole to explain the distribution of neural potentials. The sequential dipole fitting strategy, as used in Study 1, could more accurately represent the neural generators compared to the strategy used in Studies 2 and 3, as it does not produce a single mean cluster. Because the spatial resolution afforded by mobile EEG is limited, particularly due to movement due to locomotion, caution should be exercised when interpreting of cortical sources in Studies 1, 2 and 3.

Finally, in Studies 1, 2 and 3, participants were recruited primarily from the staff and student population at the University of Liverpool, which may not have produced a sample group that is representative of the entire population. Although it is possible that the sample used may have influenced economic decisions, socioeconomic background was checked in Study 3 and there was no statistically significant effects of socioeconomic status and value category on BDM auction bid. Moreover, there was quite a spread of socioeconomic status, with many participants in residing among the most deprived areas in England, and 8 participants in residing in the most privileged areas, suggesting that the sample was quite representative in terms of SES in England.

7.4. Directions for future research

The data presented in Studies 1, 2 and 3, for the first time, afforded investigation and characterisation of the spatiotemporal dynamics underpinning economic decisions for products in the real-world opening up new research avenues. There are many factors which could influence economic decisions in natural environments that, due to time constraints, were unable to be explored in the current thesis and should be examined in future research.

One avenue for exploration is the influence of product branding on SV processing in the brain. Research has shown that branding can have an important impact on consumer behaviour, explaining why companies carefully curate their brands so that visual features such as colour, shape, text and images are easily recognisable and capture early bottom up and top-down attention (Plassmann et al., 2012). Brand anticipation and associations could be important factors modulating SV of a product, highlighting the importance of memory-related processes in valuation (McClure et al., 2004). Furthermore, social factors, such as the presence of other shoppers, can modulate electrophysiological responses to brand type (Pozharliev et al., 2015). Therefore, future research should examine the influence of branding, learning processes and social context on early SV encoding of products using mobile EEG in naturalistic environments.

In a similar vein, familiarity and expertise with products and brands have been shown to influence economic decisions and should be considered as an avenue for further research (McClure et al., 2004; Morrin & Ratneshwar, 2000; Rossion et al., 2004; Schaefer et al., 2006). For instance, research has shown distinct cortical encoding for logos of culturally familiar brands (Schaefer et al., 2006) and ambient scents have been shown to increase recall for familiar brands but not for unfamiliar brands (Morrin & Ratneshwar, 2000). Brand familiarity might be particularly important with more expensive purchases (Schaefer et al., 2006), where knowledge could allow for avoiding financial risk, in line with PT, and thus, the impact of familiarity on SV could be of interest for future research. For instance, visual expertise with objects can also modulate early categorization processes (Rossion et al., 2004), and expert knowledge of products can alter consumer preferences regarding product attributes (Gustafson et al., 2016). Therefore, examination of the neural dynamics underlying product preferences for experts and non-experts could provide insight into the ways in which preferences are formed for different groups of consumers. The utilisation of MoBI in this area would allow for examination of expertise in the specific relevant context when the knowledge was originally encoded to investigate the impact of environmental congruence, expertise and SV (Park & Donaldson, 2019).

Other areas for future research include the role of packaging within the shopping environment to examine the early visual saliency effect (Milosavljevic et al., 2012). Packaging can have an important impact on consumer behaviour and SV (Milosavljevic et al., 2012) and is used as a marketing strategy to attract attention and to communicate key points about a products attributes. The perceived quality of a product is often determined by the quality of its packaging and its visual characteristics, and time constraints during purchasing can influence purchase behaviour through affecting bottom-up and top-down processing of products (Silayoi & Speece, 2004). Thus, future research could investigate to what extent product packaging affects encoding of SV and under what conditions. Such research could also have implications for public health and the investigation of the impact of health messages on products considered to be harmful.

Further factors which could influence EMRPs to products include the retail price of the product (Albari & Safitri, 2018), the motivation behind the purchase (Cui et al., 2021) and the emotional state of the consumer during the time of product evaluation. This can also be stimulated by the shopping context as companies often try to emotionally link products with particular experiences in a multisensory way to increase likelihood of purchase (Domenico, 2009; Helmefalk & Hultén, 2017). These factors could modulate SVs assigned to products in the real-world and merit investigation in future studies.

Future research could also benefit from examining the neural dynamics underpinning SVs for products using other MoBI neuroimaging modalities, such as mobile fNIRS, which has been applied in the field of marketing to examine the first choice brand effect (Krampe et al., 2018). Biological measurements of arousal such as heart rate (Klaassen et al., 2021), skin conductance (Klaassen et al., 2021), electromyography (Kozlik et al., 2015) and pupillometry (Mckinnon et al., 2020) could be used to examine autonomic arousal for salient stimuli and task related engagement during approach and avoidance of products in naturalistic environments.

The current work could also have clinical implications related to the measurement of approach and avoidance behaviours under naturalistic conditions where avoidance (e.g. anxiety, depression) and approach (e.g. substance use, gambling) tendencies, overvaluation of cues (Robinson & Berridge, 1993; Yiend, 2010) and value-based decision-making biases have a negative impact on mental and physical health (e.g. Boffo et al., 2018; Livermore et al., 2021; Martínez-Vispo et al., 2018). The utilisation of MoBI could allow for gaining better insight into valuation mechanisms associated with mental health problems in naturalistic settings, affording a better understanding of clinical populations and enabling more realistic, and hence more effective, validation of the efficacy of clinical or health interventions.

Finally, the current research would benefit from replications in other cultures. The current research was conducted in a Western society and therefore purchases can be influenced by culture specific phenomena and motivations. Therefore, replication in different cultures is essential to determine whether such neural dynamics underpinning economic decisions for products is culture specific or transcends cultural boundaries.

7.5. Concluding remarks

In contrast to traditional economic accounts, which posit that economic valuation is based on utilitarian functionality and the principle of utility maximisation, the current data suggest that early SV of products in realistic environments relies on low-level categorisation of SV, which is perhaps later validated by top-down processes. The data suggest that SV of products is encoded by multiple distinct neural clusters in naturalistic settings, and follows a non-linear function for low- and high-value items, which appear to be encoded binarily, rapidly and automatically, and could be encoded within Kahneman’s (2011) System 1. Conversely, medium-value products could follow a linear function in order to fine-tune the resolution of SV, with initial estimates within early EMRP components followed by top-down linear encoding of intermediate items within the P300, which could reflect Kahneman’s System 2. The rapid encoding of low-value items, as well as high-value items, could reflect facilitated processing by the brain to promote fast avoidance-approach behaviours. Low-value products received quick encoding compared to all other value conditions, reflected in the reduced latency and enhanced amplitude of many components throughout the Studies, and may have been used as an anchoring point of comparison for linear encoding in P300 in Study 3, supporting the negativity bias. Study 3 data suggest that 2-D images should not be assumed to produce identical responses to 3-D images, as 3-D products could require additional visual information processing and imminent availability could alter motivation, consumption behaviour and associated neural responses. Finally, the successful reduction of saccade-related artefactual activity using a combination of guided-saccade recordings and ASF could open up new possibilities for recording neural responses in naturalistic settings using combined eye-tracking and EEG. The current research enhances understanding of the spatiotemporal neural dynamics underpinning economic decisions for products in the real-world.

8. REFERENCES

Abitbol, R., Lebreton, M., Hollard, G., Richmond, B. J., Bouret, S., & Pessiglione, M. (2015). Neural mechanisms underlying contextual dependency of subjective values: converging evidence from monkeys and humans. *Journal of Neuroscience, 35*(5), 2308–2320. https://doi.org/10.1523/JNEUROSCI.1878-14.2015

Akar, E., Yüksel, H. F., & Bulut, Z. A. (2015). The Impact of Social Influence on the Decision-Making Process of Sports Consumers on Facebook. *Journal of Internet Applications and Management*, *6*(2), 5–27. https://doi.org/10.5505/iuyd.2015.40412

Albari, & Safitri, I. (2018). The influence of product price on consumers' purchasing decisions. *Review of Integrative Business and Economics Research*, *7*(2), 328–337.

Almeida, F. (2016). Society and brain: A complementary approach to Thorstein Veblen's conspicuous consumer based on Tibor Scitovsky's neuropsychology. *Nova Economia*, *26*(2), 347–367. https://doi.org/10.1590/0103-6351/2994

Alschuler, D., Tenke, C., Bruder, G. & Kayser, J. (2014). Identifying electrode bridging from electrical distance distribiutions: a survey of publicly-available EEG data using a new method. *Clinical Neurophysiology*, *125*(3), 484–490. https://doi.org/10.1016/j.clinph.2013.08.024.Identifying

Anderson, B. (2013). A value-driven mechanism of attentional selection. *Journal of Vision*, *13*(3), 1–16. https://doi.org/10.1167/13.3.7

Anderson, B., Laurent, P., & Yantis, S. (2011). Value-driven attentional capture. *Proceedings of the National Academy of Sciences*, *108*(25), 10367–10371. https://doi.org/10.1073/pnas.1104047108

Anderson, M., & College, M. (2016). The Brain Evolved to Guide Action. In *The Wiley Handbook of Evolutionary Neuroscience* (pp. 1–22). Germany: Wiley.

Anderson, S. J., & Jamniczky, H. A. Krigolson, O.E., Coderre, S.P. & Hecker, K.G. (2019). Quantifying two-dimensional and three-dimensional stereoscopic learning in anatomy using electroencephalography. *Npj Science of Learning*, *4*(10). https://doi.org/10.1038/s41539-019-0050-4

Andrade, C. (2018). Internal, external, and ecological validity in research design, conduct, and evaluation. In *Indian Journal of Psychological Medicine*, *40*(5), 498–499. https://doi.org/10.4103/IJPSYM.IJPSYM_334_18

Appelhans, B.M., Tangney, C.C., French, S.A., Crane, M.M., and Wang, Y. (2019). Delay discounting and household food purchasing decisions: the SHoPPER study. *Health Psychology*, *38*(4), 334–324. https://doi.org/10.1037/hea0000727.

Armel, K. C., Beaumel, A., & Rangel, A. (2008). Biasing simple choices by manipulating relative visual attention. *Judgment and Decision Making*, *3*(5), 396–403.

Artoni, F., Barsotti, A., Guanziroli, E., Micera, S., Landi, A., & Molteni, F. (2018). Effective synchronization of EEG and EMG for mobile brain/body imaging in clinical settings. *Frontiers in Human Neuroscience, 11*, 1–9. https://doi.org/10.3389/fnhum.2017.00652

Artoni, F., Fanciullacci, C., Bertolucci, F., Panarese, A., Makeig, S., Micera, S., & Chisari, C. (2017). Unidirectional brain to muscle connectivity reveals motor cortex control of leg muscles during stereotyped walking. *NeuroImage*, *159*, 403–416. https://doi.org/10.1016/j.neuroimage.2017.07.013

Ashby, F. G., Turner, B. O., & Horvitz, J. C. (2010). Cortical and basal ganglia contributions to habit learning and automaticity. *Trends in Cognitive Sciences, 14*(5), 208–215. https://doi.org/10.1016/j.tics.2010.02.001.Cortical

Ashley, V., Vuilleumier, C. A. P., & Swick, D. (2004). Time course and specificity of event-related potentials to emotional expressions. *NeuroReport, 15*(1), 211–216. https://doi.org/10.1097/01.wnr.0000091411.19795.f5

Ausubel, L. M., & Milgrom, P. (2013). The Lovely but Lonely Vickrey Auction. In *Combinatorial Auctions* (Issue January 2006). https://doi.org/10.7551/mitpress/9780262033428.003.0002

Baccino, T. (2012). Eye movements and concurrent event-related potentials: Eye fixation-related potential investigations in reading. *The Oxford Handbook of Eye Movements*, https://doi.org/10.1093/oxfordhb/9780199539789.013.0047

Bagozzi, R. P., Belanche, D., Casaló, L. V., & Flavian, C. (2016). The Role of Anticipated Emotions in Decision Making. *Paper Presented at a Conference on the Role of Anticipation and Regret in Decision Making, La Jolla, CA.* https://doi.org/10.1002/mar.20905.This

Balconi, M., & Crivelli, D. (2010). FRN and P300 ERP effect modulation in response to feedback sensitivity: The contribution of punishment-reward system (BIS/BAS) and Behaviour Identification of action. *Neuroscience Research*, *66*(2), 162–172. https://doi.org/10.1016/j.neures.2009.10.011

Balconi, M., Falbo, L., & Conte, V. A. (2012). BIS and BAS correlates with psychophysiological and cortical response systems during aversive and appetitive emotional stimuli processing. *Motivation and Emotion*, *36*(2), 218–231. https://doi.org/10.1007/s11031-011-9244-7

Banaei, M., Hatami, J., Yazdanfar, A., & Gramann, K. (2017). Walking through Architectural Spaces: The Impact of Interior Forms on Human Brain Dynamics. *Frontiers in Human Neuroscience*, *11*, 1–14. https://doi.org/10.3389/fnhum.2017.00477

Barbot, A., & Carrasco, M. (2018). Emotion and anxiety potentiate the way attention alters visual appearance. *Scientific Reports*, *8*(1), 1–10. https://doi.org/10.1038/s41598-018-23686-8

Barnett, M. W., & Larkman, P. M. (2007). The action potential. *Practical Neurology*, *7*(3), 192 – 197. http://pn.bmj.com/content/7/3/192.

Barnstaple, R., Protzak, J., DeSouza, J. F. X., & Gramann, K. (2020). Mobile brain/body Imaging in dance: A dynamic transdisciplinary field for applied research. *European Journal of Neuroscience*. https://doi.org/10.1111/ejn.14866

Barr, R. (2010). Transfer of learning between 2D and 3D sources during infancy: Informing theory and practice. *Developmental Review*, *30*(1), 128–154. https://doi.org/10.1016/j.dr.2010.03.001.Transfer

Bartra, O., McGuire, J. T., & Kable, J. W. (2013). The valuation system: A coordinate-based meta-analysis of BOLD fMRI experiments examining neural correlates of subjective value. *NeuroImage*, *76*, 412–427. https://doi.org/10.1016/j.neuroimage.2013.02.063

Basten, U., Biele, G., Heekeren, H. R., & Fiebach, C. J. (2010). How the brain integrates costs and benefits during decision making. *Proceedings of the National Academy of Sciences of the United States of America*, *107*(50), 21767–21772. https://doi.org/10.1073/pnas.0908104107

Baumeister, R. F., Bratslavsky, E., Finkenauer, C., & Vohs, K. D. (2001). Bad Is Stronger Than Good. *Review of General Psychology*, *5*(4), 323–370.

https://doi.org/10.1037/1089-2680.5.4.323

Bechara, A., & Damasio, A. R. (2005). The somatic marker hypothesis: A neural theory of economic decision. *Games and Economic Behavior*, *52*(2), 336–372. https://doi.org/10.1016/j.geb.2004.06.010

Becker, G. M., Degroot, M. H., & Marschak, J. (1964). Measuring utility by a single-response sequential method. *Behavioral Science*, *9*(3), 226–232. https://doi.org/10.1002/bs.3830090304

Bell, A.J., Sejnowski, T.J. (1995). An information-maximization approach to blind separation and blind deconvolution. *Neural Computation*, *7*(6), 1004–1034. https://doi.org/doi:10.1162/neco.1995.7.6.1129

Belouchrani, A., Abed-meraim, K., Cardoso, J-F. & Moulines, E. (1997). A Blind Source Separation Technique Using Second-Order Statistics. *IEEE TRANSACTIONS ON SIGNAL PROCESSING*, *45*(2), 434–444.

Beresford, B., & Sloper, P. (2008). *Understanding the dynamics of decision-making and choice: A scoping study of key psychological theories to inform the design and analysis of the panel study* (Issue January). http://www.york.ac.uk/inst/spru/pubs/pdf/decisionmaking.pdf

Berg, P., & Scherg, M. (1991). Dipole modelling of eye activity and its application to the removal of eye artefacts from the eeg and meg. *Clinical Physics and Physiological Measurement*, *12,* 49–54. https://doi.org/10.1088/0143-0815/12/A/010

Berg, P., & Scherg, M. (1994). A multiple source approach to the correction of eye artifacts. *Electroencephalography and Clinical Neurophysiology*, *90*(3), 229–241. https://doi.org/10.1016/0013-4694(94)90094-9

Berger, J., & Fitzsimons, G. (2008). Dogs on the street, pumas on your feet: How cues in the environment influence product evaluation and choice. *Journal of Marketing Research*, *45*(1), 1–14. https://doi.org/10.1509/jmkr.45.1.1

Bernays, E. L. (1928). *Propaganda*. Liveright: New York.

Berry, J., Fischer, G., & Guiteras, R. (2012). Eliciting and Utilizing Willingness to Pay: Evidence from Field Trials in Northern Ghana. *IGC Working Paper 12/0188, December*. http://personal.lse.ac.uk/fischerg/Assets/BFG-BDM-April-2012.pdf%5Cnhttp://www.economics.cornell.edu/jwb295/BFG-BDM-April-

2012.pdf

Biederman, I., & Gerhardstein, P. C. (1993). Recognizing Depth-Rotated Objects: Evidence and Conditions for Three-Dimensional Viewpoint Invariance. *Journal of Experimental Psychology: Human Perception and Performance*, *19*(6), 1162–1182. https://doi.org/10.1037/0096-1523.19.6.1162

Bishop, J. D. (1995). Adam Smiths Invisible Hand Argument. *Journal of Business Ethics*, *14*, 165–180.

Blair, K., Marsh, A. A., Morton, J., Vythilingam, M., Jones, M., Mondillo, K., Pine, D. C., Drevets, W. C., & Blair, J. R. (2006). Choosing the lesser of two evils, the better of two goods: Specifying the roles of ventromedial prefrontal cortex and dorsal anterior cingulate in object choice. *The Journal of Neuroscience*, *26*(44), 11379–11386. https://doi.org/10.1523/JNEUROSCI.1640-06.2006

Blechert, J., Klackl, J., Miedl, S. F., & Wilhelm, F. H. (2016). To eat or not to eat: Effects of food availability on reward system activity during food picture viewing. *Appetite*, *99*, 254–261. https://doi.org/10.1016/j.appet.2016.01.006

Bledowski, C., Prvulovic, D., Hoechstetter, K., Scherg, M., Wibral, M., Goebel, R., & Linden, D. E. J. (2004). Localizing P300 generators in visual target and distractor processing: A combined event-related potential and functional magnetic resonance imaging study. *Journal of Neuroscience*, *24*(42), 9353–9360. https://doi.org/10.1523/JNEUROSCI.1897-04.2004

Bobadilla-Suarez, S., Guest, O., & Love, B. C. (2020). Subjective value and decision entropy are jointly encoded by aligned gradients across the human brain. *Communications Biology*, *3*(1), 1–9. https://doi.org/10.1038/s42003-020-01315-3

Boffo, M., Smits, R., Salmon, J. P., Cowie, M. E., de Jong, D. T. H. A., Salemink, E., Collins, P., Stewart, S. H., & Wiers, R. W. (2018). Luck, come here! Automatic approach tendencies toward gambling cues in moderate- to high-risk gamblers. *Addiction*, *113*(2), 289–298. https://doi.org/10.1111/add.14071

Bondarenko, P. (2020). Microeconomics. In *Encyclopedia Britannica.*

Borck, C. (2018). *Brainwaves: A Cultural History of Electroencephalography*. Routledge.

Bossaerts, P., & Murawski, C. (2015). From behavioural economics to neuroeconomics to decision neuroscience: The ascent of biology in research on human decision making. *Current Opinion in Behavioral Sciences*, *5*, 37–42. https://doi.org/10.1016/j.cobeha.2015.07.001

Boto, E., Holmes, N., Leggett, J., Roberts, G., Shah, V., Meyer, S. S., Muñoz, L. D., Mullinger, K. J., Tierney, T. M., Bestmann, S., Barnes, G. R., Bowtell, R., & Brookes, M. J. (2018). Moving magnetoencephalography towards real-world applications with a wearable system. *Nature*, *555*(7698), 657–661. https://doi.org/10.1038/nature26147

Botvinick, M. M., Carter, C. S., Braver, T. S., Barch, D. M., & Cohen, J. D. (2001). Conflict monitoring and cognitive control. *Psychological Review*, *108*(3), 624–652. https://doi.org/10.1037/0033-295X.108.3.624

Bourisly, A. K., & Shuaib, A. (2018). Sex differences in electrophysiology: P200 event-related potential evidence. *Translational Neuroscience*, *9*(1), 72–77. https://doi.org/10.1515/tnsci-2018-0013

Bouzakraoui, M. S., Sadiq, A., & Enneya, N. (2017). Towards a framework for customer emotion detection. *Proceedings of IEEE/ACS International Conference on Computer Systems and Applications, AICCSA*. https://doi.org/10.1109/AICCSA.2016.7945830

Brainerd, C. J., & Reyna, V. F. (1990). Gist is the grist: Fuzzy trace theory and the new intuitionism. *Developmental Review*, *10*(1), 3–47. https://doi.org/10.1016/0273-2297(90)90003-M

Brofenbrenner, U. (1977). Toward an Experimental Ecology of Human Development. *American Psychologist*, *32*(7), 513–531. https://doi.org/10.1037/0003-066X.32.7.513

Brosch, T., & Sander, D. (2013). Neurocognitive mechanisms underlying value-based decision-making: from core values to economic value. *Frontiers in Human Neuroscience*, *7*, 398. https://doi.org/10.3389/fnhum.2013.00398

Bruner, G. C., & Pomazal, R. J. (1988). Problem recognition: The crucial first stage of the consumer decision process. *Journal of Services Marketing*, *2*(3), 43–53. https://doi.org/10.1108/eb024733

Bulthé, J., De Smedt, B., & Op de Beeck, H. P. (2014). Format-dependent representations of symbolic and non-symbolic numbers in the human cortex as revealed by multi-voxel pattern analyses. *NeuroImage, 87*, 311–322. https://doi.org/10.1016/j.neuroimage.2013.10.049

Bülthoff, H. H., Edelman, S. Y., & Tarr, M. J. (1995). How are three-dimensional objects represented in the brain? *Cerebral Cortex*, *5*(3), 247–260. https://doi.org/10.1093/cercor/5.3.247

Buonocore, A., Dimigen, O., & Melcher, D. (2020). Post-saccadic face processing is modulated by pre-saccadic preview: Evidence from fixation-related potentials. *Journal of Neuroscience*, *40*(11), 2305–2313. https://doi.org/10.1523/JNEUROSCI.0861-19.2020

Burt, A., Hugrass, L., Frith-Belvedere, T., & Crewther, D. (2017). Insensitivity to fearful emotion for early ERP components in high autistic tendency is associated with lower magnocellular efficiency. *Frontiers in Human Neuroscience, 11*, 1–12. https://doi.org/10.3389/fnhum.2017.00495

Cacioppo, J. T., & Berntson, G. G. (1994). Relationship between attitudes and evaluative space : A critical review , with emphasis on the separability of positive ... Relationship Between Attitudes and Evaluative Space : A Critical Review , With Emphasis on the Separability of Positive and Negative substrates. *Psychological Bulletin*, *115*(3), 401–423.

Callan, D. E., Durantin, G., & Terzibas, C. (2015). Classification of single-trial auditory events using dry-wireless EEG during real and motion simulated flight. *Frontiers in Systems Neuroscience*, *9*, 11. https://doi.org/10.3389/fnsys.2015.00011

Camerer, C. F., Loewenstein, G., & Prelec, D. (2004). Neuroeconomics: Why economics needs brains. *Scandinavian Journal of Economics*, *106*(3), 555–579. https://doi.org/10.1111/j.0347-0520.2004.00377

Cano, M. E., Class, Q. A., & Polich, J. (2009). Affective Valence, Stimulus Attributes, and P300: Color vs. Black/ White and Normal vs. Scrambled Images. *International Journal of Psychophysiology*, *71*(1), 17–24. https://doi.org/10.1016/j.ijpsycho.2008.07.016

Canosa, R. L. (2009). Real-world vision: Selective perception and task. *ACM Transactions on Applied Perception*, *6*(2). https://doi.org/10.1145/1498700.1498705

Cao, L., Chen, X., & Haendel, B. F. (2020). Overground Walking Decreases Alpha Activity and Entrains Eye Movements in Humans. *Frontiers in Human Neuroscience, 14*, 1–16. https://doi.org/10.3389/fnhum.2020.561755

Cao, X., Jiang, B., Gaspar, C., & Li, C. (2014). The overlap of neural selectivity between faces and words: Evidences from the N170 adaptation effect. *Experimental Brain Research*, *232*(9), 3015–3021. https://doi.org/10.1007/s00221-014-3986-x

Cappelletti, M., Lee, H. L., Freeman, E. D., & Price, C. J. (2010). The role of the right and left parietal lobes in the conceptual processing of numbers. *Journal of Cognitive Neuroscience*, *22*(2), 331–346. https://doi.org/10.1162/jocn.2009.21246.THE

Carare, O., & Rothkopf, M. (2005). Slow Dutch auctions. *Management Science, 51*(3), 365–373. https://doi.org/10.1287/mnsc.1040.0328

Cardinal, R. N., Parkinson, J. A., Hall, J., & Everitt, B. J. (2002). Emotion and motivation: The role of the amygdala, ventral striatum, and prefrontal cortex. *Neuroscience and Biobehavioral Reviews*, *26*(3), 321–352. https://doi.org/10.1016/S0149-7634(02)00007-6

Cardoso, J. F., & Souloumiac, A. (1993). Blind beamforming for non-Gaussian signals. *IEE Proceedings, Part F: Radar and Signal Processing, 140*(6), 362–370. https://doi.org/10.1049/ip-f-2.1993.0054

Carl, C., Açik, A., König, P., Engel, A. K., & Hipp, J. F. (2012). The saccadic spike artifact in MEG. *NeuroImage*, *59*(2), 1657–1667. https://doi.org/10.1016/j.neuroimage.2011.09.020

Carretié, L., Martin-Loeches, M., Hinojosa, J., & Mercado, F. (2001a). Emotion and Attenton Iteraction Studied through Event-Related Potentials. *Journal of Cognitive Neuroscience*, *13*(8), 1109–1128. https://doi.org/10.1016/S0167-8760(00)00195-1

Carretié, L., Mercado, F., Tapia, M., & Hinojosa, J. A. (2001b). Emotion, attention, and the “negativity bias”, studied through event-related potentials. *International Journal of Psychophysiology*, *41*(1), 75–85. https://doi.org/10.1016/S0167-8760(00)00195-1

Casarotto, S., Bianchi, A. M., Cerutti, S., & Chiarenza, G. A. (2004). Principal component analysis for reduction of ocular artefacts in event-related potentials of normal and dyslexic children. *Clinical Neurophysiology*, *115*, 609–619. https://doi.org/10.1016/j.clinph.2003.10.018

De cesarei, A., Peverato, I. A., Mastria, S. & Codispoti, M. (2015). Modulation of early ERPs by accurate categorization of objects in scenes. *Journal of Vision*, *15*(8), 1–14. https://doi.org/10.1167/15.8.14.doi

Chang, Y. K. (2016). Acute Exercise and Event-Related Potential: Current Status and Future Prospects. In *Exercise-Cognition Interaction: Neuroscience Perspectives*. Elsevier Inc. https://doi.org/10.1016/B978-0-12-800778-5.00005-0

Chawla, M., & Miyapuram, K. P. (2018). Context-Sensitive Computational Mechanisms of Decision Making. *Journal of Experimental Neuroscience*, *12*. https://doi.org/10.1177/1179069518809057

Chelazzi, L., Perlato, A., Santandrea, E., & Della Libera, C. (2013). Rewards teach visual selective attention. *Vision Research*, *85*, 58–72. https://doi.org/10.1016/j.visres.2012.12.005

Chib, V. S., Rangel, A., Shimojo, S., & O’Doherty, J. P. (2009). Evidence for a common representation of decision values for dissimilar goods in human ventromedial prefrontal cortex. *The Journal of Neuroscience*, *29*(39), 12315–12320. https://doi.org/10.1523/JNEUROSCI.2575-09.2009

Childs, M., & Jin, B. E. (2020). Retailer-brand collaborations: testing key strategies to increase consumers’ urgency to buy. *International Journal of Retail and Distribution Management*, *48*(4), 380–394. https://doi.org/10.1108/IJRDM-06-2019-0199

Chow, Y. L., & Ooi, J. T. L. (2014). First-price sealed-bid tender versus English open auction: Evidence from land auctions. *Real Estate Economics*, *42*(2), 253–278. https://doi.org/10.1111/1540-6229.12035

Cialdini, R. B. (2016). *Pre-Suasion*. Penguin Random House. https://books.google.co.uk/books?id=-GcNDQAAQBAJ

Clark, J., Hollona, N., & Phillips, P. (2012). Pavlovian valuation systems in learning and decision making. *Current Opinion in Neurobiology*, *22*(6), 1054–1061. https://doi.org/10.1016/j.conb.2012.06.004.Pavlovian

Clark, V. P., & Hillyard, S. A. (1996). Spatial Selective Attention Affects Early Extrastriate But Not Striate Components of the Visual Evoked Potential. *Journal of Cognitive Neuroscience*, *8*(5), 387–402. https://doi.org/10.1162/jocn.1996.8.5.387

Clithero, J.A., & Rangel, A. (2014). Informatic parcellation of the network involved in the computation of subjective value. *Social Cognitive and Affective Neuroscience*, *9*(9), 1289–1302. https://doi.org/10.1093/scan/nst106

Cluley, R. (2008). Psychoanalysis as marketing theory. *Marketing Theory Virtual Special Issue*, 5–26.

Cognolato, M., Atzori, M., & Müller, H. (2018). Head-mounted eye gaze tracking devices: An overview of modern devices and recent advances. *Journal of Rehabilitation and Assistive Technologies Engineering*, *5*, 205566831877399. https://doi.org/10.1177/2055668318773991

Conroy, M. A., & Polich, J. (2007). Affective valence and P300 when stimulus arousal level is controlled. *Cognition and Emotion*, *21*(4), 891–901. https://doi.org/10.1080/02699930600926752

Corbetta, M., & Shulman, G. L. (2002). Control of goal-directed and stimulus-driven attention in the brain. *Nature Reviews Neuroscience*, *3*(3), 201–215. https://doi.org/10.1038/nrn755

Corbin, J., Reyna, V., Weldon, R., & Brainerd, C. (2015). How reasoning, judgment, and decision making are colored by gist-based inutition: A fuzz-trace theory appraoch. *Journal of Applied Research in Memory and Cognition*, *4*(4), 344–355. https://doi.org/10.1146/annurev-immunol-032713-120240.Microglia

Cordell, V. (1997). Consumer Knowledge Measures as Predictors in Product Evaluation. *Psychology & Marketing*, *14*(3), 241–260.

Correll, J., Urland, G. R., & Ito, T. A. (2006). Event-related potentials and the decision to shoot: The role of threat perception and cognitive control. *Journal of Experimental Social Psychology*, *42*(1), 120–128. https://doi.org/10.1016/j.jesp.2005.02.006

Cortese, A., Yamamoto, A., Hashemzadeh, M., Sepulveda, P., Kawato, M., & de Martino, B. (2020). Value shapes abstraction during learning. *BioRxiv*, 1–36. https://doi.org/10.1101/2020.10.29.361469

Critchley, H. D., & Rolls, E. T. (1996). Hunger and satiety modify the responses of olfactory and visual neurons in the primate orbitofrontal cortex. *Journal of Neurophysiology*, *75*(4), 1673–1686. https://doi.org/Cited By (since 1996) 183\rExport Date 13 January 2012

Cruz-Garza. J., Chatufale, G., Robleto, D., Jose, L. &, & Vidal, C. (2020). Your Brain on Art: A New Paradigm to Study Artistic Creativity Based on the 'Exquisite Corpse' Using Mobile Brain-Body Imaging. In *"Brain art: Brain-computer interfaces for artistic expression"* (Vol. 7, Issues 1–2, pp. 36–37). https://doi.org/10.1080/2326263X.2020.1756573

Cui, L., Wang, Y., Chen, W., Wen, W., & Han, M. S. (2021). Predicting determinants of consumers' purchase motivation for electric vehicles: An application of Maslow's hierarchy of needs model. *Energy Policy*, *151*, 112167. https://doi.org/10.1016/j.enpol.2021.112167

D'Astous, A. (2000). Irritating aspects of the shopping environment. *Journal of Business Research*, *49*(2), 149–156. https://doi.org/10.1016/S0148-2963(99)00002-8

Daw, N. D., Niv, Y., & Dayan, P. (2005). Uncertainty-based competition between prefrontal and dorsolateral striatal systems for behavioral control. *Nature Neuroscience*, *8*(12), 1704–1711. https://doi.org/10.1038/nn1560

De Martino, B., Camerer, C. F., & Adolphs, R. (2010). Amygdala damage eliminates monetary loss aversion. *Proceedings of the National Academy of Sciences*, *107*(8), 3788–3792. https://doi.org/10.1073/pnas.0910230107

De Martino, B., Kumaran, D., Holt, B., & Dolan, R. J. (2009). The Neurobiology of Reference-Dependent Value Computation. *Journal of Neuroscience*, *29*(12), 3833–3842. https://doi.org/10.1523/JNEUROSCI.4832-08.2009

De Martino, Benedetto, Kumaran, D., Seymour, B., & Dolan, R. J. (2006). Frames, biases and rational decision-making in the human brain. *Science*, *313*(5787), 684–687. https://doi.org/10.1126/science.1128356

De Sanctis, P., Butler, J. S., Green, J. M., Snyder, A. C., & Foxe, J. J. (2012). Mobile brain/body imaging (MoBI): High-density electrical mapping of inhibitory processes during walking. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 1542–1545.

https://doi.org/10.1109/EMBC.2012.6346236

De Sanctis, P., Butler, J. S., Malcolm, B. R., & Foxe, J. J. (2014). Recalibration of inhibitory control systems during walking-related dual-task interference: A Mobile Brain-Body Imaging (MOBI) Study. *NeuroImage*, *94*, 55–64. https://doi.org/10.1016/j.neuroimage.2014.03.016

De Vos, M., Gandras, K., & Debener, S. (2014). Towards a truly mobile auditory brain-computer interface: Exploring the P300 to take away. *International Journal of Psychophysiology*, *91*(1), 46–53. https://doi.org/10.1016/j.ijpsycho.2013.08.010

De Vos, M., Kroesen, M., Emkes, R., & Debener, S. (2014a). P300 speller BCI with a mobile EEG system: comparison to a traditional amplifier. *Journal of Neural Engineering, 11*, 036008. https://doi.org/10.1088/1741-2560/11/3/036008

Debener, S., Minow, F., Emkes, R., Gandras, K., & de Vos, M. (2012). How about taking a low-cost, small, and wireless EEG for a walk? *Psychophysiology*, *49,* 1617–1621. https://doi.org/10.1111/j.1469-8986.2012.01471

Debener, S., Thorne, J., Schneider, T. R. & Campos Viola, F. (2010). Using ICA for the Analysis of Multi- Channel EEG Data. *Oxford Scholarship Online, 6*(38), 45–66. https://doi.org/DOI: 10.1093/acprof:oso/9780195372731.001.0001

Degno, F., & Liversedge, S. P. (2020). Eye movements and fixation-related potentials in reading: A review. *Vision*, *4*(1). https://doi.org/10.3390/vision4010011

Delgado, M. R., Nystrom, L. E., Fissell, C., Noll, D. C., & Fiez, J. A. (2000). Tracking the hemodynamic responses to reward and punishment in the striatum. *Journal of Neurophysiology, 84*(6), 3072–3077. https://doi.org/10.1152/jn.2000.84.6.3072

Delgado, M. R. (2007). Reward-related responses in the human striatum. *Annals of the New York Academy of Sciences, 1104*, 70–88. https://doi.org/10.1196/annals.1390.002

Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, *134*(1), 9–21. https://doi.org/10.1016/j.jneumeth.2003.10.009

Delorme, A., Mullen, T., Kothe, C., Akalin Acar, Z., Bigdely-Shamlo, N., Vankov, A., & Makeig, S. (2011). EEGLAB, SIFT, NFT, BCILAB, and ERICA: New tools for advanced EEG processing. *Computational Intelligence and Neuroscience, 2011*. https://doi.org/10.1155/2011/130714

Delorme, A., Sejnowski, T., & Makeig, S. (2007). Enhanced detection of artifacts in EEG data using higher-order statistics and independent component analysis. *NeuroImage*, *34*(4), 1443–1449. https://doi.org/10.1016/j.neuroimage.2006.11.004

Deneve, S. (2009). Bayesian decision making in two-alternative forced choices. In *Handbook of Reward and Decision Making*. Elsevier Inc. https://doi.org/10.1016/B978-0-12-374620-7.00021-2

Dennis, T. A., & Chen, C. C. (2007). Neurophysiological mechanisms in the emotional modulation of attention: The interplay between threat sensitivity and attentional control. *Biological Psychology*, *76*(1–2), 1–10. https://doi.org/10.1016/j.biopsycho.2007.05.001

Deppe, M., Schwindt, W., Kugel, H., Plassmann, H., & Kenning, P. (2005). Nonlinear responses within the medial prefrontal cortex reveal when specific implicit information influences economic decision making. *Journal of Neuroimaging*, *15*(2), 171–182. https://doi.org/10.1177/1051228405275074

Desrochers, J., & Outreville, J. F. (2013). Uncertainty, Ambiguity and Risk Taking: An Experimental Investigation of Consumer Behavior and Demand for Insurance. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2363870

Devillez, H., Guyader, N., & Guérin-Dugué, A. (2015). An eye fixation-related potentials analysis of the P300 potential for fixations onto a target object when exploring natural scenes. *Journal of Vision*, *15*(13), 1–31. https://doi.org/10.1167/15.13.20

Dewey, J. (1910). *How We Think*. D.C. Heath and Company.

Dhar, R., & Simonson, I. (2003). The Effect of Forced Choice on Choice. *Journal of Marketing Research*, *40*(2), 146–160. https://doi.org/10.3758/BF03209923

Diana, R. A., Yonelinas, A. P., & Ranganath, C. (2008). High-resolution multi-voxel pattern analysis of category selectivity in the medial temporal lobes. *Hippocampus*, *18*(6), 536–541. https://doi.org/10.1002/hipo.20433

Dias, J. C., Sajda, P., Dmochowski, J. P., & Parra, L. C. (2013). EEG precursors of detected and missed targets during freeviewing search. *Journal of Vision*, *13*(13), 1–19. https://doi.org/10.1167/13.13.13

Dickinson, A., & Balleine, B. (2002). The role of learning in the operation of motivational systems. In H. Pashler & R. Gallistel (Eds.), *Steven's Handbook of Experimental Psychology: Learning Motivation and Emotion* (Vol. 72, Issue 4, pp. 497–533). Hoboken, NJ: John Wiley & Sons Inc. https://doi.org/10.7326/0003-4819-72-4-616_7

Dien, J., Frishkoff, G. (2005). Principal components analysis of event-related potential datasets. In *Event-related potentials: A methods handbook* (pp. 189–208).

Dien, J. (1998). Addressing misallocation of variance in principal components analysis of event-related potentials. *Brain Topography*, *11*(1), 43–55. https://doi.org/10.1023/A:1022218503558

Dien, J. (2012). Applying principal components analysis to event-related potentials: A tutorial. *Developmental Neuropsychology*, *37*(6), 497–517. https://doi.org/10.1080/87565641.2012.697503

Dimigen, O. (2014). Co-registration of eye movements and EEG during active vision. *Thesis Dissertation*.

Dimigen, O. (2020). Optimizing the ICA-based removal of ocular EEG artifacts from free viewing experiments. *NeuroImage*, *207*, 116117. https://doi.org/10.1016/j.neuroimage.2019.116117

Dimigen, O., & Ehinger, B. V. (2019). Analyzing combined eye-tracking/EEG experiments with (non)linear deconvolution models. *BioRxiv*, 0–49. https://doi.org/10.1101/735530

Dimigen, O., Sommer, W., Hohlfeld, A., Jacobs, A. M., & Kliegl, R. (2011). Coregistration of eye movements and EEG in natural reading: Analyses and review. *Journal of Experimental Psychology: General*, *140*(4), 552–572. https://doi.org/10.1037/a0023885

Ding, C., & He, X. (2004). K-means clustering via principal component analysis. *Proceedings, Twenty-First International Conference on Machine Learning, ICML 2004*, 225–232.

Dollard, J., & Miller, N. E. (1950). *Personality and Psychotherapy; an Analsyis in Terms of Learning, Thinking, and Culture, by John Dollard and Neal E. Miller*. McGraw-Hill. https://books.google.co.uk/books?id=-jZtcgAACAAJ

Domenico, C. (2009). "Emotions That Influence Purchase Decisions And Their Electronic Processing ". *Annales Universitatis Apulensis Series Oeconomica*, *2*(11), 996–1008. https://doi.org/10.29302/oeconomica.2009.11.2.45

Duchowski, A. T. (2017). Eye tracking methodology: Theory and practice: Third edition. In *Eye Tracking Methodology: Theory and Practice: Third Edition*. https://doi.org/10.1007/978-3-319-57883-5

Durka, P. J., Matysiak, A., Montes, E. M., Sosa, P. V., & Blinowska, K. J. (2005). Multichannel matching pursuit and EEG inverse solutions. *Journal of Neuroscience Methods*, *148*(1), 49–59. https://doi.org/10.1016/j.jneumeth.2005.04.001

Ehinger, B. V. & Dimigen, O. (2018). Unfold: An integrated toolbox for overlap correction, non-linear modeling, and regression-based EEG analysis. *BioRxiv*, *2018*, 360156. https://doi.org/10.1101/360156

Ehrlinger, J., Readinger, W. O., & Kim, B. (2016). Decision-Making and Cognitive Biases. *Encyclopedia of Mental Health: Second Edition*, *October*, 5–12. https://doi.org/10.1016/B978-0-12-397045-9.00206-8

Eimer, M. (1996). The N2pc component as an indicator of attentional selectivity. *Electroencephalography and Clinical Neurophysiology*, *99*(3), 225–234. https://doi.org/10.1016/s0921-884x(96)95711-2

Eimer, Martin, & Grubert, A. (2014). Spatial attention can be allocated rapidly and in parallel to new visual objects. *Current Biology*, *24*(2), 193–198. https://doi.org/10.1016/j.cub.2013.12.001

Elliott, R., Friston, K. J., & Dolan, R. J. (2000). Dissociable neural responses in human reward systems. *Journal of Neuroscience*, *20*(16), 6159–6165. https://doi.org/10.1523/jneurosci.20-16-06159.2000

Elster, J. (2001). Rational Choice Theory: Cultural Concerns. In *International Encyclopedia of the Social & Behavioral Sciences* (pp. 12763–12768).

Essig, K., Pomplun, M., & Ritter, H. (2006). A neural network for 3D gaze recording with binocular eye trackers. *International Journal of Parallel, Emergent and*

Distributed Systems, *21*(2), 79–95. https://doi.org/10.1080/17445760500354440

Fehr, E., & Rangel, A. (2011). Neuroeconomic foundations of economic choice-recent advances. *Journal of Economic Perspectives*, *25*(4), 3–30. https://doi.org/10.1257/jep.25.4.3

Calhoun, V. D., Liu, J., & Adali, T. (2009). A review of group ICA for fMRI data and ICA for joint inference of imaging, genetic, and ERP data. *Neuroimage, 45*(1), 1–21. https://doi.org/10.1016/j.neuroimage.2008.10.057.A

Fine, B. (2008). *Consumers and Demand*. SOAS University of London. https://eprints.soas.ac.uk/6072/5/diegocons.pdf

Finnigan, S., O'Connell, R. G., Cummins, T. D. R., Broughton, M., & Robertson, I. H. (2011). ERP measures indicate both attention and working memory encoding decrements in aging. *Psychophysiology*, *48*(5), 601–611. https://doi.org/10.1111/j.1469-8986.2010.01128.x

Fiore, A. M. (2008). The shopping experience. In *Product Experience*. Elsevier Ltd. https://doi.org/10.1016/B978-008045089-6.50030-7

Fischer, T., Graupnera, S., Velichkovsky, B., & Pannasch, S. (2013). Attentional dynamics during free picture viewing: evidence from oculomotor behaviour and electrocortical activity. *Frontiers in Systems Neuroscience*, *7*(17), 1–9. https://doi.org/10.3389/fnsys.2013.00017

Fjaellingsdal, T. G., Schwenke, D., Ruigendijk, E., Scherbaum, S., & Bleichner, M. G. (2020). Studying brain activity during word-by-word interactions using wireless EEG. *PLoS ONE*, *15*(3), 1–21. https://doi.org/10.1371/journal.pone.0230280

Flynn, N., Kah, C., & Kerschbamer, R. (2016). Vickrey auction vs BDM: difference in bidding behaviour and the impact of other-regarding motives. *Journal of the Economic Science Association*, *2*(2), 101–108. https://doi.org/10.1007/s40881-016-0027-5

Forbes, C. E., & Leitner, J. B. (2014). Stereotype threat engenders neural attentional bias toward negative feedback to undermine performance. *Biological Psychology*, *102*(1), 98–107. https://doi.org/10.1016/j.biopsycho.2014.07.007

Forgacs, P. B., Von Gizycki, H., Selesnick, I., Syed, N. A., Ebrahim, K., Avitable, M., Amassian, V., Lytton, W., & Bodis-Wollner, I. (2008). Perisaccadic parietal and occipital gamma power in light and in complete darkness. *Perception*, *37*(3), 419–432. https://doi.org/10.1068/p5875

Freberg, L. (2015). *Discovering Behavioral Neuroscience: An Introduction to Biological Psychology*. Cengage Learning. https://books.google.co.uk/books?id=duouBgAAQBAJ

Furl, N., & Averbeck, B. B. (2011). Parietal Cortex and Insula Relate to Evidence Seeking Relevant to Reward-Related Decisions. *Journal of Neuroscience*, *31*(48), 17572–17582. https://doi.org/10.1523/JNEUROSCI.4236-11.2011

Gaarder, K., Krauskopf, J., Graf, V., Kropfl, W., & Armington, J. C. (1964). Averaged Brain Activity Following Saccadic Eye Movement. *Science*, *146*(3650), 1481–1483.

Gajewski, P. D., Drizinsky, J., Zülch, J., & Falkenstein, M. (2016). ERP correlates of simulated purchase decisions. *Frontiers in Neuroscience*, *10*(AUG), 1–13. https://doi.org/10.3389/fnins.2016.00360

Galandra, C., Basso, G., Cappa, S., & Canessa, N. (2018). The alcoholic brain: neural bases of impaired reward-based decision-making in alcohol use disorders. *Neurological Sciences*, *39*(3), 423–435. https://doi.org/10.1007/s10072-017-3205-1

Gallagher, S. (2018). Decentering the brain: Embodied cognition and the critique of neurocentrism and narrow-minded philosophy of mind. *Constructivist Foundations*, *14*(1), 8–21.

Gazzaniga, M. S., Ivry, R. B., & Mangun, G. R. (2002). *Cognitive neuroscience: The biology of the mind*. Norton: New York.

Gerdes, A. B. M., Wieser, M. J., Bublatzky, F., Kusay, A., Plichta, M. M., & Alpers, G. W. (2013). Emotional sounds modulate early neural processing of emotional pictures. *Frontiers in Psychology*, *4*, 1–12. https://doi.org/10.3389/fpsyg.2013.00741

Gidlöf, K., Anikin, A., Lingonblad, M., & Wallin, A. (2017). Looking is buying. How visual attention and choice are affected by consumer preferences and properties of the supermarket shelf. *Appetite*, *116*, 29–38. https://doi.org/10.1016/j.appet.2017.04.020

Gidlöf, K., Wallin, A., Dewhurst, R., & Holmqvist, K. (2013). Using eye tracking to trace a cognitive process: Gaze behaviour during decision making in a natural environment. *Journal of Eye Movement Research*, *6*(1). https://doi.org/10.16910/jemr.6.1.3

Gligorijevic, D., Zhou, T., Shetty, B., Kitts, B., Pan, S., Pan, J., & Flores, A. (2020). Bid Shading in the Brave New World of First-Price Auctions. *ArXiv*, 2453–2460.

Glimcher, P. W., & Fehr, E. (2013). Neuroeconomics: Decision Making and the Brain: Second Edition. In *Neuroeconomics: Decision Making and the Brain: Second Edition*. https://doi.org/10.1016/C2011-0-05512-6

Glimcher, P. W., & Fehr, E. (2014). Introduction: A Brief History of Neuroeconomics. In *Neuroeconomics*. Elsevier Inc. https://doi.org/10.1016/B978-0-12-416008-8.00035-8

Gluth, S., Rieskamp, J., & Buchel, C. (2012). Deciding When to Decide: Time-Variant Sequential Sampling Models Explain the Emergence of Value-Based Decisions in the Human Brain. *Journal of Neuroscience*, *32*(31), 10686–10698. https://doi.org/10.1523/JNEUROSCI.0727-12.2012

Gold, J. I., & Shadlen, M. N. (2007). The neural basis of decision making. *Annual Reviews Neuroscience*, *30*, 535–574. https://doi.org/10.1146/annurev.neuro.29.051605.113038

Goto, N., Mushtaq, F., Shee, D., Lim, X. L., Mortazavi, M., Watabe, M., & Schaefer, A. (2017). Neural signals of selective attention are modulated by subjective preferences and buying decisions in a virtual shopping task. *Biological Psychology*, *128*, 11–20. https://doi.org/10.1016/j.biopsycho.2017.06.004

Gottlieb, J. (2007). Review From Thought to Action : The Parietal Cortex as a bridge between perception action and cognition. *Neuron*, *53*, 9–16. https://doi.org/10.1016/j.neuron.2006.12.009

Grabenhorst, F., & Rolls, E. T. (2009). Different representations of relative and absolute subjective value in the human brain. *NeuroImage*, *48*(1), 258–268. https://doi.org/10.1016/j.neuroimage.2009.06.045

Grabenhorst, F., & Rolls, E. T. (2011). Value, pleasure and choice in the ventral prefrontal cortex. *Trends in Cognitive Sciences*, *15*(2), 56–67.

https://doi.org/10.1016/j.tics.2010.12.004

Gramann, K. (2014). An introduction to mobile brain / body imaging (MoBI). *Brain Products Press Release*, 1–4.

Gramann, K., Gwin, J., Bigdely-Shamlo, N., Ferris, D., & Makeig, S. (2010). Visual evoked responses during standing and walking. *Frontiers in Human Neuroscience*, *4*, 202. https://doi.org/10.3389/fnhum.2010.00202

Gramann, K., Jung, T.-P., Ferris, D., Lin, C.-T., & Makeig, S. (2014). Toward a new cognitive neuroscience: modeling natural brain dynamics. *Frontiers in Human Neuroscience, 8*(444), 1–3. https://doi.org/10.3389/fnhum.2014.00444

Gramann, K, Gwin, J. T., Bigdely-Shamlo, N., Ferris, D. P., & Makeig, S. (2010). Visual evoked responses during standing and walking. *Frontiers in Human Neuroscience*, *4*(202), 1–12. https://doi.org/10.3389/fnhum.2010.00202

Gramann, K., Gwin, J. T., Ferris, D. P., Oie, K., Jung, T. P., Lin, C. T., Liao, L. De, & Makeig, S. (2011). Cognition in action: Imaging brain/body dynamics in mobile humans. *Reviews in the Neurosciences*, *22*(6), 593–608. https://doi.org/10.1515/RNS.2011.047

Grech, R., Cassar, T., Muscat, J., Camilleri, K. P., Fabri, S. G., Zervakis, M., Xanthopoulos, P., Sakkalis, V., & Vanrumste, B. (2008). *Review on solving the inverse problem in EEG source analysis*. *33*, 1–33. https://doi.org/10.1186/1743-0003-5-25

Green., J. (1957). Some observations on lambda waves and peripheral stimulation. *Electroencephalography and Clinical Neurophysiology*, *9*(4), 691–704. https://doi.org/10.1016/0013-4694(57)90089-5

Griskevicius, V., Goldstein, N. J., Mortensen, C. R., Sundie, J. M., Cialdini, R. B., & Kenrick, D. T. (2009). Fear and loving in las vegas: Evolution, emotion, and persuasion. *Journal of Marketing Research*, *46*(3), 384–395. https://doi.org/10.1509/jmkr.46.3.384

Grueschow, M., Polania, R., Hare, T. A., & Ruff, C. C. (2015). Automatic versus Choice-Dependent Value Representations in the Human Brain. *Neuron*, *85*(4), 874–885. https://doi.org/10.1016/j.neuron.2014.12.054

Grzesiuk, A., & Cypryjański, J. (2017). Reflections on Research Process: Online Experiments on Allegro Platform. In N. Kesra & M. Łatuszyńska (Eds.), *Neuroeconomic and Behavioral Aspects of Decision Making* (pp. 397–408). Springer International Publishing. https://doi.org/10.1007/978-3-319-62938-4_18

Gui, D. Y., Li, J. Z., Li, X., & Luo, Y. J. (2016). Temporal dynamics of the interaction between reward and time delay during intertemporal choice. *Frontiers in Psychology*, *7*, 1–9. https://doi.org/10.3389/fpsyg.2016.01526

Gustafson, C. R., Lybbert, T. J., & Sumner, D. A. (2016). Consumer knowledge affects valuation of product attributes: Experimental results for wine. *Journal of Behavioral and Experimental Economics*, *65*, 85–94. https://doi.org/10.1016/j.socec.2016.08.004

Gwin, J., Gramann, K., Makeig, S., & Ferris, D. (2011). Electrocortical activity is coupled to gait cycle phase during treadmill walking. *NeuroImage*, *54,* 1289–1296. https://doi.org/10.1016/j.neuroimage.2010.08.066

Gwin, J., Gramann, K., Makeig, S., & Ferris, D. P. (2010). Removal of Movement Artifact From High-Density EEG Recorded During Walking and Running. *Journal of Neurophysiology*, *103*(6), 3526–3534. https://doi.org/10.1152/jn.00105.2010

Gwon, S. Y., Cho, C. W., Lee, H. C., Lee, W. O., & Park, K. R. (2014). Gaze tracking system for user wearing glasses. *Sensors*, *14*(2), 2110–2134. https://doi.org/10.3390/s140202110

Hajcak, G., & Olvet, D. M. (2008). The Persistence of Attention to Emotion: Brain Potentials During and After Picture Presentation. *Emotion*, *8*(2), 250–255. https://doi.org/10.1037/1528-3542.8.2.250

Hajihosseini, A., & Holroyd, C. B. (2013). Frontal midline theta and N200 amplitude reflect complementary information about expectancy and outcome evaluation. *Psychophysiology*, *50*(6), 550–562. https://doi.org/10.1111/psyp.12040

Hakim, A., & Levy, D. J. (2019). A gateway to consumers’ minds: Achievements, caveats, and prospects of electroencephalography-based prediction in neuromarketing. *Wiley Interdisciplinary Reviews: Cognitive Science*, *10*(2), 1–21. https://doi.org/10.1002/wcs.1485

Hanatani, T., Sumi, N., Taguchi, S., Fugimoto, O., Nan-no, H., & Takeda, M. (2005). Event-related potentials in panic disorder and generalized anxiety disorder. *Psychiatry and Clinical Neurosciences*, *59*, 83–88.

Handy, T., Smilek, D., Geiger, L., Liu, C., & Schooler, J. (2010). ERP evidence for rapid hedonic evaluation of logos. *Journal of Cognitive Neuroscience*, *22*(1), 124–138. https://doi.org/10.1162/jocn.2008.21180

Hare, T. A., Camerer, C. F., Knoepfle, D. T., O'Doherty, J. P., & Rangel, A. (2010). Value Computations in Ventral Medial Prefrontal Cortex during Charitable Decision Making Incorporate Input from Regions Involved in Social Cognition. *Journal of Neuroscience*, *30*(2), 583–590. https://doi.org/10.1523/JNEUROSCI.4089-09.2010

Hare, T. A, O'Doherty, J.P., Camerer, C. F., Schultz, W., & Rangel, A. (2008). Dissociating the role of the orbitofrontal cortex and the striatum in the computation of goal values and prediction errors. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience*, *28*(22), 5623–5630. https://doi.org/10.1523/JNEUROSCI.1309-08.2008

Haridasan, A. C., & Fernando, A. G. (2018). Online or in-store: unravelling consumer's channel choice motives. *Journal of Research in Interactive Marketing*, *12*(2), 215–230. https://doi.org/10.1108/JRIM-07-2017-0060

Harris, T.A., Adolphs, R., Camerer, C.F., & Rangel, A. (2011). Dynamic construction of stimulus values in the ventromedial prefrontal cortex. *PLoS ONE*, *6*(6). https://doi.org/10.1371/journal.pone.0021074

Hassoumi, A., Peysakhovich, V., & Hurter, C. (2019). Improving eye-tracking calibration accuracy using symbolic regression. *PLoS ONE*, *14*(3), 1–22. https://doi.org/10.1371/journal.pone.0213675

Hawkins, D. I., & Mothersbaugh, D. L. (2010). *Consumer Behaviour:Building Marketing Strategies*. www.mhhe.com

Haxby, J. V., Gobbini, M. I., Furey, M. L., Ishai, A., Schouten, J. L., & Pietrini, P. (2001). Distributed and overlapping representations of faces and objects in ventral temporal cortex. *Science*, *293*, 2425–2430.

Haxby, J. V, Hoffman, E. A., & Gobbini, M. I. (2000). The distributed human neural system for face perception. *Trends in Cognitive Sciences*, *4*(6), 223–233.

Heilbronner, S. R., Hayden, B. Y., & Platt, M. L. (2011). Decision salience signals in posterior cingulate cortex. *Frontiers in Neuroscience*, *5*, 1–9.

https://doi.org/10.3389/fnins.2011.00055

Helie, Sebastien., Shamloo, Farzon., Novak, Keisha., Foti, D. (2017). The roles of valuation and reward processing in cognitive function and psychiatric disorders. *Annals of the New York Academy of Sciences*, *1395*(1), 33–48. https://doi.org/10.1117/12.2549369.Hyperspectral

Helmefalk, M., & Hultén, B. (2017). Multi-sensory congruent cues in designing retail store atmosphere: Effects on shoppers' emotions and purchase behavior. *Journal of Retailing and Consumer Services*, *38*, 1–11. https://doi.org/10.1016/j.jretconser.2017.04.007

Herculano-Houzel, S. (2009). The human brain in numbers: A linearly scaled-up primate brain. *Frontiers in Human Neuroscience, 3*(31), 1–11. https://doi.org/10.3389/neuro.09.031.2009

Herrmann, C. S., & Knight, R. T. (2001). Mechanisms of human attention: Event-related potentials and oscillations. *Neuroscience and Biobehavioral Reviews*, *25*(6), 465–476. https://doi.org/10.1016/S0149-7634(01)00027-6

Hess, S., Daly, A., & Batley, R. (2018). Revisiting consistency with random utility maximisation: theory and implications for practical work. *Theory and Decision*, *84*(2), 181–204. https://doi.org/10.1007/s11238-017-9651-7

Hillyard, S. A., & Anllo-Vento, L. (1998). Event-related brain potentials in the study of visual selective attention. *Proceedings of the National Academy of Sciences of the United States of America*, *95*(3), 781–787. https://doi.org/10.1073/pnas.95.3.781

Hodgson, G. M. (2004). Veblen and Darwinism. *International Review of Sociology*, *14*(3), 343–361. https://doi.org/10.1080/0390670042000318241

Hoechstetter, K., Berg, P., & Scherg, M. (2010). *BESA Research Tutorial 4 : Distributed Source Imaging BESA Research Tutorial 4 :* 1–29.

Hofmann, M. J., Kuchinke, L., Tamm, S., Võ, M. L. H., & Jacobs, A. M. (2009). Affective processing within 1/10th of a second: High arousal is necessary for early facilitative processing of negative but not positive words. *Cognitive, Affective and Behavioral Neuroscience*, *9*(4), 389–397. https://doi.org/10.3758/9.4.389

Holland, P. C., & Gallagher, M. (2004). Amygdala-frontal interactions and reward expectancy. *Current Opinion in Neurobiology*, *14*(2), 148–155. https://doi.org/10.1016/j.conb.2004.03.007

Hollingworth, A., Richard, A., & Luck, S. (2008). Understanding the Function of Visual Short-Term Memory: Transsaccadic Memory, Object Correspondence, and Gaze Correction. *Journal of Experimental Psychological Gen*, *137*(1), 163–181. https://doi.org/10.1037/0096-3445.137.1.163.Understanding

Holmqvist, K., Nystrom, M., Andersson, R., Dewhurt, R., Jarodzka, H., & Van De Weijer, J. (2011). Eye tracking: A comprehensive guide to methods and measures. In *Journal of Materials Processing Technology* (Vol. 1, Issue 1). Oxford University Press. http://dx.doi.org/10.1016/j.cirp.2016.06.001%0Ahttp://dx.doi.org/10.1016/j.powtec.2016.12.055%0Ahttps://doi.org/10.1016/j.ijfatigue.2019.02.006%0Ahttps://doi.org/10.1016/j.matlet.2019.04.024%0Ahttps://doi.org/10.1016/j.matlet.2019.127252%0Ahttp://dx.doi.o

Holroyd, C. B., & Coles, M. G. H. (2002). The neural basis of human error processing: Reinforcement learning, dopamine, and the error-related negativity. *Psychological Review*, *109*(4), 679–709. https://doi.org/10.1037/0033-295X.109.4.679

Hornik, J., & Zakay, D. (1996). Psychological Time: The Case of Time and Consumer Behaviour. *Time & Society*, *5*(3), 385–397. https://doi.org/10.1177/0961463X96005003007

Howard, J. D., Plailly, J., Grueschow, M., Haynes, J. D., & Gottfried, J. A. (2009). Odor quality coding and categorization in human posterior piriform cortex. *Nature Neuroscience*, *12*(7), 932–938. https://doi.org/10.1038/nn.2324

Hsu, C.-W., & Goh, J. O. S. (2016). Distinct and Overlapping Brain Areas Engaged during Value-Based, Mathematical, and Emotional Decision Processing. *Frontiers in Human Neuroscience*, *10*, 1–20. https://doi.org/10.3389/fnhum.2016.00275

Hu, B., Rao, J., Li, X., Cao, T., Li, J., Majoe, D., & Gutknecht, J. (2017). Emotion Regulating Attentional Control Abnormalities In Major Depressive Disorder: An Event-Related Potential Study. *Scientific Reports*, *7*(1), 1–21. https://doi.org/10.1038/s41598-017-13626-3

Huang, M., Aine, C. J., Supek, S., Best, E., Ranken, D., & Flynn, E. R. (1998). Multi-start downhill simplex method for spatio-temporal source localization in magnetoencephalography. *Electroencephalography and clinical Neurophysiology*, *108,* 32–44.

Huang, Y-x., & Luo, Y. (2006). Temporal course of emotional negativity bias : An ERP study. *Neuroscience Letters*, *398*, 91–96. https://doi.org/10.1016/j.neulet.2005.12.074

Huang, Yi, & Yu, R. (2014). The feedback-related negativity reflects “more or less” prediction error in appetitive and aversive conditions. *Frontiers in Neuroscience, 8*, 1–6. https://doi.org/10.3389/fnins.2014.00108

Hubert, M. & Kenning, P. (2008). A current overview of consumer neuroscience. *Journal of Consumer Behaviour*, *7*, 272–292. https://doi.org/10.1002/cb

Hyvärinen, A. (1999). Fast and robust fixed-point algorithms for independent component analysis. *IEEE Transactions on Neural Networks*, *10*(3), 626–634. https://doi.org/10.1109/72.761722

Ille, N., Berg, P., & Scherg, M. (2002). Artifact correction of the ongoing EEG using spatial filters based on artifact and brain signal topographies. *Journal of Clinical Neurophysiology*, *19*(2), 113–124. https://doi.org/10.1097/00004691-200203000-00002

Iriarte, J., Urrestarazu, E., Valencia, M., Alegre, M., Malanda, A., Viteri, C., & Artieda, J. (2003). Independent component analysis as a tool to eliminate artifacts in EEG: a quantitative study. *Journal of Clinical Neurophysiology : Official Publication of the American Electroencephalographic Society*, *20*(4), 249–257. https://doi.org/10.1097/00004691-200307000-00004

Itthipuripat, S., Cha, K., Rangsipat, N., & Serences, J. T. (2015). Value-based attentional capture influences context-dependent decision-making. *Journal of Neurophysiology*, *114*(1), 560–569. https://doi.org/10.1152/jn.00343.2015

Iyer, A., Lindner, A., Kagan, I., & Andersen, R. A. (2010). Motor preparatory activity in posterior parietal cortex is modulated by subjective absolute value. *PLoS Biology*, *8*(8), 23–24. https://doi.org/10.1371/journal.pbio.1000444

Jaadi, Z. (2019). *A Step-by-Step Explanation of Principal Component Analysis*. Built in expert contributor network.

Jagla, F., Jergelová, M., & Riecanský, I. (2007). Saccadic eye movement related potentials. *Physiological Research / Academia Scientiarum Bohemoslovaca*, *56*(6), 707–713.

Jędras, P., Jones, A., & Field, M. (2013). The role of anticipation in drug addiction and reward. *Neuroscience and Neuroeconomics*, 1. https://doi.org/10.2147/nan.s35917

Jędras, P., Jones, A., Stancak, A., & Field, M. (2019). The effects of reward and loss anticipation on attentional bias for reward-related stimuli. *Appetite*, *133*, 93–100. https://doi.org/10.1016/j.appet.2018.10.007

Jensen, J., McIntosh, A. R., Crawley, A. P., Mikulis, D. J., Remington, G., & Kapur, S. (2003). Direct activation of the ventral striatum in anticipation of aversive stimuli. *Neuron*, *40*(6), 1251–1257. https://doi.org/10.1016/S0896-6273(03)00724-4

Jia, Y., & Tyler, C. W. (2019). Measurement of saccadic eye movements by electrooculography for simultaneous EEG recording. *Behavior Research Methods*, *51*(5), 2139–2151. https://doi.org/10.3758/s13428-019-01280-8

Jiang, C., Buchanan, T. W., Yao, Z., Zhang, K., Wu, J., & Zhang, L. (2017). Acute Psychological Stress Disrupts Attentional Bias to Threat-Related Stimuli. *Scientific Reports*, *7*(1), 1–12. https://doi.org/10.1038/s41598-017-14138-w

Jiang, X., Bian, G., & Tian, Z. (2019). Removal of Artifacts from EEG Signals : A Review. *Sensors*, *19*(987), 1–18. https://doi.org/10.3390/s19050987

Jin, J., Zhang, W., & Chen, M. (2017). How consumers are affected by product descriptions in online shopping: Event-related potentials evidence of the attribute framing effect. *Neuroscience Research*, *125*, 21–28. https://doi.org/10.1016/j.neures.2017.07.006

Jones, A., Hogarth, L., Christiansen, P., Rose, A. K., Martinovic, J., & Field, M. (2012). Reward expectancy promotes generalized increases in attentional bias for rewarding stimuli. *Quarterly Journal of Experimental Psychology*, *65*(12), 2333–2342. https://doi.org/10.1080/17470218.2012.686513

Jones, W., Childers, T., & Jiang, Y. (2012). The shopping brain: Math anxiety modulates brain responses to buying decisions. *Biological Psychology*, *89*(1), 201–213. https://doi.org/10.1016/j.biopsycho.2011.10.011

Jung, T., Makeig, S., Humphries, C., Lee, T., McKeown, M. J., Iragui, I., & Sejnowski, T. J. (2000). Removing Electroencephalographic aretfacts by blind source seperation. *Psychophysiology*, *37*(02), 163–178. https://doi.org/10.1111/1469-8986.3720163

Jungnickel, E., & Gramann, K. (2016). Mobile Brain/Body Imaging (MoBI) of Physical Interaction with Dynamically Moving Objects. *Frontiers in Human Neuroscience*, *10*, 306. https://doi.org/10.3389/fnhum.2016.00306

Kable, J. W., & Glimcher, P. W. (2009). The Neurobiology of Decision: Consensus and Controversy. *Neuron*, *63*(6), 733–745. https://doi.org/10.1016/j.neuron.2009.09.003

Kagel, J., Levin, D., Battalio, R., & Meyer, D. (1989). First-Price Common Value Auctions: Bidder Behavior and the “Winner’S Curse.” *Economic Inquiry*, *27*(2), 241–258. https://doi.org/10.1111/j.1465-7295.1989.tb00780.x

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1990). Experimental Tests of the Endowment Effect and the Coase Theorem. *Journal of Political Economy*, *98*(6), 1325–1348.

Kahneman, D., Knetsch, J., & Thaler, R. (1991). Anomalies: The endowment effect, loss aversion, and status quo bias. *Journal of Economic Perspectives*, *5*(1), 159–170. https://doi.org/10.1017/CBO9780511803475.009

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, *47*(2), 263–291. https://doi.org/10.1111/j.1536-7150.2011.00774.x

Kahneman, D., & Tversky, A. (1984). Choices , Values , and Frames. *American Psycologist*, *39*(4), 341–350. https://doi.org/10.1037/0003-066X.39.4.341

Kahneman, D. (2011). *Thinking, Fast and Slow*. Straus and Giroux: New York.

Kahneman, D. & Tversky, A. (1979). Prospect Theory : An Analysis of Decision under Risk, *Econometrica, 47*(2), 263–292.

Kamakura, W. A., & Mazzon, J. A. (2013). Socioeconomic status and consumption in an emerging economy. *International Journal of Research in Marketing*, *30*(1), 4–18. https://doi.org/10.1016/j.ijresmar.2011.12.001

Kanske, P., & Kotz, S. A. (2010). Modulation of early conflict processing: N200 responses to emotional words in a flanker task. *Neuropsychologia*, *48*(12), 3661–3664. https://doi.org/10.1016/j.neuropsychologia.2010.07.021

Kassner, M., Patera, W., & Bulling, A. (2014). Pupil: An Open Source Platform for Pervasive Eye Tracking and Mobile Gaze-based Interaction. *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication*, 1151–1160. https://doi.org/10.1145/2638728.2641695

Kaur, H., & Singh, C. D. (2019). Family and Consumer Behaviour. *International Journal of Management and Social Sciences Research*, *2*(7), 2319–4421. https://doi.org/10.4324/9780367810276

Kazai, K., & Yagi, A. (2003). Comparison between the lambda response of eye-fixation-related potentials and the P100 component of pattern-reversal visual evoked potentials. *Cognitive, Affective and Behavioral Neuroscience*, *3*(1), 46–56. https://doi.org/10.3758/CABN.3.1.46

Keil, A., Bradley, M. M., Hauk, O., Rockstroh, B., Elbert, T., & Lang, P. J. (2002). Large-scale neural correlates of affective picture processing. *Psychophysiology*, *39*(5), 641–649. https://doi.org/10.1111/1469-8986.3950641

Keller, L., Segal, U., & Wang, T. (1993). the Becker-DeGroot-Marschak mechanism and generalized utility theories: Theoretical predictions and empirical observations. *Theory and Decision*, *34*(2), 83–97.

Kemp, E., Bui, M., & Chapa, S. (2012). The role of advertising in consumer emotion management. *International Journal of Advertising*, *31*(3). https://doi.org/10.2501/IJA-31-2-339-353

Keren, A. S., Yuval-Greenberg, S., & Deouell, L. Y. (2010). Saccadic spike potentials in gamma-band EEG: Characterization, detection and suppression. *NeuroImage*, *49*(3), 2248–2263. https://doi.org/10.1016/j.neuroimage.2009.10.057

Khan, N., Rahmani, S. H. R., Hoe, H. Y., & Chen, T. B. (2014). Causal Relationships among Dimensions of Consumer-Based Brand Equity and Purchase Intention: Fashion Industry. *International Journal of Business and Management*, *10*(1), 1833–8119. https://doi.org/10.5539/ijbm.v10n1p172

Khushaba, R. N., Wise, C., Kodagoda, S., Louviere, J., Kahn, B. E., & Townsend, C. (2013). Consumer neuroscience: Assessing the brain response to marketing stimuli using electroencephalogram (EEG) and eye tracking. *Expert Systems with Applications*, *40*(9), 3803–3812. https://doi.org/10.1016/j.eswa.2012.12.095

Kilner, J. M., & Lemon, R. N. (2013). What we know currently about mirror neurons. *Current Biology*, *23*(23), R1057–R1062. https://doi.org/10.1016/j.cub.2013.10.051

Kirchner, H., & Thorpe, S. J. (2006). Ultra-rapid object detection with saccadic eye movements : Visual processing speed revisited. *Vision Research*, *46*(11), 1762–1776. https://doi.org/10.1016/j.visres.2005.10.002

Kirkpatrick, S. (1984). Optimization by simulated annealing: quantitative studies. *Journal of Statistical Physics*, *34*, 975–986.

Kiss, M., Driver, J., & Eimer, M. (2009). Reward priority of visual target singletons modulates ERP signatures of attentional selection. *Psychological Science*, *20*(2), 245–251. https://doi.org/10.1111/j.1467-9280.2009.02281.x.Reward

Klaassen, F. H., Held, L., Figner, B., O’Reilly, J. X., Klumpers, F., de Voogd, L. D., & Roelofs, K. (2021). Defensive freezing and its relation to approach-avoidance decision-making under threat. *BioRxiv*, 2021.01.29.428809. http://biorxiv.org/content/early/2021/02/01/2021.01.29.428809.abstract

Klem, G. H., Luders, H. O., Jasper, H. H., & Elger, C. (1999). The ten–twenty electrode system of the International Federation. In *Recommendations for the Practice of Clinical Neurophysiology: Guidelines of the International Federation of Clinical Physiology EEG* (Vol. 52, pp. 1–4).

Klucharev, V., Smidts, A., & Fernández, G. (2008). Brain mechanisms of persuasion: How “expert power” modulates memory and attitudes. *Social Cognitive and Affective Neuroscience*, *3*(4), 353–366. https://doi.org/10.1093/scan/nsn022

Klug, M., & Gramann, K. (2020). Identifying key factors for improving ICA-based decomposition of EEG data in mobile and stationary experiments. *European Journal of Neuroscience*, 1–15. https://doi.org/10.1111/ejn.14992

Knutson, B., Adams, C. M., Fong, G. W., & Hommer, D. (2001). Anticipation of increasing monetary reward selectively recruits nucleus accumbens. *The Journal of Neuroscience*, *21*(16), 1–5. https://doi.org/10.1523/jneurosci.21-16-

j0002.2001

Ko, L. W., Lai, P. W., Yang, B. J., & Lin, C. T. (2015). Mobile EEG & ECG integration system for monitoring physiological states in peforming simulated war game training. *2015 IEEE Conference on Computational Intelligence and Games, CIG 2015 - Proceedings*, 542–543. https://doi.org/10.1109/CIG.2015.7317900

Koivisto, M., & Grassini, S. (2016). Neural processing around 200 ms after stimulus-onset correlates with subjective visual awareness. *Neuropsychologia*, *84*, 235–243. https://doi.org/10.1016/j.neuropsychologia.2016.02.024

Kokmotou, K., Cook, S., Xie, Y., Wright, H., Soto, V., Fallon, N., Giesbrecht, T., Pantelous, A., & Stancak, A. (2017). Effects of loss aversion on neural responses to loss outcomes: An event-related potential study. *Biological Psychology*, *126*(April), 30–40. https://doi.org/10.1016/j.biopsycho.2017.04.005

Kolakowski, S. M., & Pelz, J. B. (2005). Compensating for eye tracker camera movement. *Eye Tracking Research and Applications Symposium (ETRA)*, 79–85. https://doi.org/10.1145/1117309.1117348

Konig, S., & Buffalo, E. A. (2014). A Nonparametric Method for Detecting Fixations and Saccades Using Cluster Analysis: Removing the Need for Arbitrary Thresholds. *Journal of Neuroscientific Methods*, *227*, 121–131. https://doi.org/10.1016/j.jneumeth.2014.01.032.A

Konovalov, A., & Krajbich, I. (2019). Over a Decade of Neuroeconomics: What Have We Learned? *Organizational Research Methods*, *22*(1), 148–173. https://doi.org/10.1177/1094428116644502

Kothe, C. A. (2014). Demo 1 : The Lab Streaming Layer. *Https://Github. Com/Sccn/Labstreaminglayer. Accessed in May*.

Kotler, P. (1965). Behavioral Models for Analyzing Buyers. *Journal of Marketing*, *29*(4), 37–45. https://doi.org/10.2307/1249700

Kozlik, J., Neumann, R., & Lozo, L. (2015). Contrasting motivational orientation and evaluative coding accounts: On the need to differentiate the effectors of approach/avoidance responses. *Frontiers in Psychology*, *6*, 1–10. https://doi.org/10.3389/fpsyg.2015.00563

Kragel, P. A., & LaBar, K. S. (2016). Decoding the Nature of Emotion in the Brain. *Trends in Cognitive Sciences*, *20*(6), 444–455. https://doi.org/10.1016/j.tics.2016.03.011

Krajbich, I., Armel, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, *13*(10), 1292–1298. https://doi.org/10.1038/nn.2635

Krampe, C., Gier, N. R., & Kenning, P. (2018). The application of mobile fNIRS in marketing research—detecting the "first-choice-brand" effect. *Frontiers in Human Neuroscience*, *12*, 1–11. https://doi.org/10.3389/fnhum.2018.00433

Kräplin, A., Dshemuchadse, M., Behrendt, S., Scherbaum, S., Goschke, T., & Bühringer, G. (2014). Dysfunctional decision-making in pathological gambling: Pattern specificity and the role of impulsivity. *Psychiatry Research*, *215*(3), 675–682. https://doi.org/10.1016/j.psychres.2013.12.041

Krawczyk, D. C., Gazzaley, A., & D'Esposito, M. (2007). Reward modulation of prefrontal and visual association cortex during an incentive working memory task. *Brain Research*, *1141*(1), 168–177. https://doi.org/10.1016/j.brainres.2007.01.052

Kretch, K. S., & Adolph, K. E. (2015). Active vision in passive locomotion: Real-world free viewing in infants and adults. *Developmental Science*, *18*(5), 736–750. https://doi.org/10.1111/desc.12251

Krieglmeyer, R., De Houwer, J., & Deutsch, R. (2013). On the nature of automatically triggered approach-avoidance behavior. *Emotion Review*, *5*(3), 280–284. https://doi.org/10.1177/1754073913477501

Krieglmeyer, R., Deutsch, R., de Houwer, J., & de Raedt, R. (2010). Being moved: Valence activates approach-avoidance behavior independently of evaluation and approach-avoidance intentions. *Psychological Science*, *21*(4), 607–613. https://doi.org/10.1177/0956797610365131

Krishna, A. (2012). An integrative review of sensory marketing: Engaging the senses to affect perception, judgment and behavior. *Journal of Consumer Psychology*, *22*(3), 332–351. https://doi.org/10.1016/j.jcps.2011.08.003

Kurniawan, I. T., Guitart-Masip, M., Dayan, P., & Dolan, R. J. (2013). Effort and valuation in the brain: The effects of anticipation and execution. *Journal of*

Neuroscience, *33*(14), 6160–6169. https://doi.org/10.1523/JNEUROSCI.4777-12.2013

Kurtzberg, D., & Vaughan, H. G. (1982). Topographic analysis of human cortical potentials preceding self-initiated and visually triggered saccades. *Brain Research*, *243*(1), 1–9. https://doi.org/10.1016/0006-8993(82)91115-5

Laarne, P. H., Tenhunen-Eskelinen, M. L., Hyttinen, J. K., & Eskola, H. J. (2000). Effect of EEG electrode density on dipole localization accuracy using two realistically shaped skull resistivity models. *Brain Topography*, *12*(4), 249–254. https://doi.org/10.1023/A:1023422504025

Ladouce, S., Donaldson, D. I., Dudchenko, P. A., & Ietswaart, M. (2017). Understanding Minds in Real-World Environments: Toward a Mobile Cognition Approach. *Frontiers in Human Neuroscience*, *10*, 1–14. https://doi.org/10.3389/fnhum.2016.00694

Ladouce, S., Donaldson, D. I., Dudchenko, P. A., & Ietswaart, M. (2019). Mobile EEG identifies the re-allocation of attention during real-world activity. *Scientific Reports*, *9*(1), 1–10. https://doi.org/10.1038/s41598-019-51996-y

Lai, L. Y., Frömer, R., Festa, E. K., & Heindel, W. C. (2019). Age-Related Changes in the Neural Dynamics of Bottom-Up and Top-Down Processing During Visual Object Recognition: An Electrophysiological Investigation. *BioRxiv*, *401*. https://doi.org/10.1101/608240

Lang, P. J., & Bradley, M. M. (2010). Emotion and the motivational brain. *Biological Psychology*, *84*(3), 437–450. https://doi.org/10.1016/j.biopsycho.2009.10.007

Lange, L., & Osinsky, R. (2020). Aiming at ecological validity—Midfrontal theta oscillations in a toy gun shooting task. *European Journal of Neuroscience*, *August*, 1–11. https://doi.org/10.1111/ejn.14977

Langlois, D., Chartier, S., & Gosselin, D. (2010). An Introduction to Independent Component Analysis: InfoMax and FastICA algorithms. *Tutorials in Quantitative Methods for Psychology*, *6*(1), 31–38. https://doi.org/10.1002/1099-128X(200005/06)14:3<123::AID-CEM589>3.0.CO;2-1

Larsen, T., & O'Doherty, J. P. (2014). Uncovering the spatio-temporal dynamics of value-based decision-making in the human brain: a combined fMRI-EEG study. *Philosophical Transactions of the Royal Society B: Biological Sciences, 369*(1655), 20130473–20130473. https://doi.org/10.1098/rstb.2013.0473

Lau-Zhu, A., Lau, M. P. H., & McLoughlin, G. (2019). Mobile EEG in research on neurodevelopmental disorders: Opportunities and challenges. *Developmental Cognitive Neuroscience, 36*, 100635. https://doi.org/10.1016/j.dcn.2019.100635

Lau, T. M., Gwin, J. T., & Ferris, D. P. (2012). How Many Electrodes Are Really Needed for EEG-Based Mobile Brain Imaging? *Journal of Behavioral and Brain Science*, *2*(3), 387–393. https://doi.org/10.4236/jbbs.2012.23044

Lebreton, M., Jorge, S., Michel, V., Thirion, B., & Pessiglione, M. (2009). An Automatic Valuation System in the Human Brain: Evidence from Functional Neuroimaging. *Neuron, 64*(3), 431–439. https://doi.org/10.1016/j.neuron.2009.09.040

Lee, D., & Seo, H. (2007). Mechanisms of reinforcement learning and decision making in the primate dorsolateral prefrontal cortex. *Annals of the New York Academy of Sciences, 1104*, 108–122. https://doi.org/10.1196/annals.1390.007

Leleu, A., Godard, O., Dollion, N., Durand, K., & Schaal, B. (2015). Neuropsychologia Contextual odors modulate the visual processing of emotional facial expressions : An ERP study. *Neuropsychologia*, *77*, 366–379. https://doi.org/10.1016/j.neuropsychologia.2015.09.014

Lepora, N. F., & Pezzulo, G. (2015). Embodied Choice: How Action Influences Perceptual Decision Making. *PLoS Computational Biology*, *11*(4), 1–22. https://doi.org/10.1371/journal.pcbi.1004110

Leske, S., & Dalal, S. S. (2019). Reducing power line noise in EEG and MEG data via spectrum interpolation. *NeuroImage*, *189*, 763–776. https://doi.org/10.1016/j.neuroimage.2019.01.026

Levy, D. J., & Glimcher, P. W. (2012). The root of all value: A neural common currency for choice. *Current Opinion in Neurobiology*, *22*(6), 1027–1038. https://doi.org/10.1016/j.conb.2012.06.001

Levy, I., Lazzaro, S. C., Rutledge, R. B., & Glimcher, P. W. (2011). Choice from Non-Choice: Predicting Consumer Preferences from Blood Oxygenation Level-Dependent Signals Obtained during Passive Viewing. *Journal of Neuroscience,* *31*(1), 118–125. https://doi.org/10.1523/JNEUROSCI.3214-10.2011

Liao, L. De, Chen, C. Y., Wang, I. J., Chen, S. F., Li, S. Y., Chen, B. W., Chang, J. Y., & Lin, C. T. (2012). Gaming control using a wearable and wireless EEG-based brain-computer interface device with novel dry foam-based sensors. *Journal of NeuroEngineering and Rehabilitation*, *9*(1). https://doi.org/10.1186/1743-0003-9-5

Libera, C. Della, & Chelazzi, L. (2009). Learning to Attend and to Ignore Is a Matter of Gains and Losses. *Psychological Science*, *20*(6), 778–784.

Ligeza, T. S., Tymorek, A. D., & Wyczesany, M. (2017). Top-down and bottom-up competition in visual stimuli processing. *Acta Neurobiologiae Experimentalis*, *77*(4), 305–316. https://doi.org/10.21307/ane-2017-063

Lim, S. L., O’Doherty, J. P., & Rangel, A. (2011). The decision value computations in the vmPFC and striatum use a relative value code that is guided by visual attention. *Journal of Neuroscience*, *31*(37), 13214–13223. https://doi.org/10.1523/JNEUROSCI.1246-11.2011

Lin, A., Adolphs, R., & Rangel, A. (2012). Social and monetary reward learning engage overlapping neural substrates. *Social Cognitive and Affective Neuroscience*, *7*(3), 274–281. https://doi.org/10.1093/scan/nsr006

Lin, H., & Vartanian, O. (2017). A Neuroeconomic Framework for Creative Cognition. *BioRxiv*, *53*(9), 1–43.

Linden, D. E. J. (2005). The P300: Where in the brain is it produced and what does it tell us? *Neuroscientist*, *11*(6), 563–576. https://doi.org/10.1177/1073858405280524

Lithari, C., Pappas, C., Bamidis, P. D., Ioannides, A. A., Kourtidou-Papadeli, C., Frantzidis, C. A., Vivas, A. B., Klados, M. A., & Papadelis, C. (2010). Are Females More Responsive to Emotional Stimuli? A Neurophysiological Study Across Arousal and Valence Dimensions. *Brain Topography*, *23*(1), 27–40. https://doi.org/10.1007/s10548-009-0130-5

Liu, X., Hairston, J., Schrier, M., & Fan, J. (2011). Common and distinct networks underlying reward valence and processing stages: A meta-analysis of functional neuroimaging studies. *Neuroscience and Biobehavioral Reviews*, *35*(5), 1219–1236. https://doi.org/10.1016/j.neubiorev.2010.12.012

Livermore, J. J. A., Klaassen, F. H., Bramson, B., Hulsman, A. M., Meijer, S. W., Held, L., Klumpers, F., de Voogd, L. D., & Roelofs, K. (2021). Approach-Avoidance Decisions Under Threat: The Role of Autonomic Psychophysiological States. *Frontiers in Neuroscience*, *15,* 1–12. https://doi.org/10.3389/fnins.2021.621517

Liversedge, S. P., & Findlay, J. M. (2000). Saccadic eye movements and cognition. *Trends in Cognitive Sciences*, *4*(1), 6–14. https://doi.org/10.1016/S1364-6613(99)01418-7

Lobaugh, N. J., West, R., & McIntosh, A. R. (2001). Spatiotemporal analysis of experimental differences in event-related potential data with partial least squares. *Psychophysiology*, *38*(3), 517–530. https://doi.org/10.1017/S0048577201991681

Lodish, H., Berk, A., Zipursky, S. L., Matsudaira, P., Baltimore, D., & Darnell, J. (2000). Molecular Cell Biology. In *W. H. Freeman* (4th edition). W. H. Freeman.

Logothetis, N. K., Pauls, J., Augath, M., Trinath, T., & Oeltermann, A. (2001). Neurophysiological investigation of the basis of the fMRI signal. *Nature*, *412*(6843), 150–157. https://doi.org/10.1038/35084005

Lopez Rincon, A., & Shimoda, S. (2016). The inverse problem in electroencephalography using the bidomain model of electrical activity. *Journal of Neuroscience Methods*, *274*, 94–105. https://doi.org/10.1016/j.jneumeth.2016.09.011

Luck, S. J. (2005). *An Introduction to the Event-related Potential Technique*. MIT Press: Cambridge. https://books.google.co.uk/books?id=r-BqAAAAMAAJ

Lusk, J. L., Feldkamp, T., & Schroeder, T. C. (2004). Experimental auction procedure: Impact on valuation of quality differentiated goods. *American Journal of Agricultural Economics*, *86*(2), 389–405. https://doi.org/10.1111/j.0092-5853.2004.00586.x

Lystad, R. P., & Pollard, H. (2009). Functional neuroimaging: a brief overview and feasibility for use in chiropractic research. *The Journal of the Canadian Chiropractic Association*, *53*(1), 59–72. http://www.ncbi.nlm.nih.gov/pubmed/19421353%0Ahttp://www.pubmedcentra l.nih.gov/articlerender.fcgi?artid=PMC2652631

Ma, Y., Jin, J., Yu, W., Zhang, W., Xu, Z., & Ma, Q. (2018). How Is the Neural Response to the Design of Experience Goods Related to Personalized Preference? An Implicit View. *Frontiers in Neuroscience*, *12*, 1–8. https://doi.org/10.3389/fnins.2018.00760

Maas, J., de Ridder, D. T. D., de Vet, E., & de Wit, J. B. F. (2012). Do distant foods decrease intake? The effect of food accessibility on consumption. *Psychology and Health*, *27*(SUPPL. 2), 59–73. https://doi.org/10.1080/08870446.2011.565341

Mahesan, D., Chawla, M., & Miyapuram, K. P. (2016). The effect of reward information on perceptual decision-making. In A. Hirose, S. Ozawa, K. Doya, K. Ikeda, M. Lee, & D. Liu (Eds.), *Neural Information Processing ICONIP 2016, Part IV* (pp. 156–163). Springer International Publishing.

Makeig, S., Bell, A., Jung, T.-P. & Sejnowski, T. (1996). Independent Component Analysis of Electroencephalographic Data. *Advances in Neural Information Processing Systems, 2*(3), 1548–1551. https://doi.org/10.1109/ICOSP.2002.1180091

Makeig, S., Debener, S., Onton, J., & Delorme, A. (2004). Mining event-related brain dynamics. *Trends in Cognitive Sciences*, *8*(5), 204–210. https://doi.org/10.1016/j.tics.2004.03.008

Makeig, S., Gramann, K., Jung, T-P., Sejnowski, T. & Poizner, H. (2009). Linking brain, mind and behavior. *International Journal of Psychophysiology*, *73*(2), 95–100. https://doi.org/10.1016/j.ijpsycho.2008.11.008.Linking

Makeig, S. & Jung, T.-P. (1996). Tonic, phasic and transient EEG correlates of auditory awareness in drowsiness. *Cognitive Brain Research*, *4*, 15–25.

Makeig, S., & Onton, J. (2011). ERP Features and EEG Dynamics. *The Oxford Handbook of Event-Related Potential Components*, *July*, 1–37. http://oxfordhandbooks.com/view/10.1093/oxfordhb/9780195374148.001.0001/oxfordhb-9780195374148-e-003

Makeig, S., Westerfield, M., Townsend, J., Jung, T. P., Courchesne, E., & Sejnowski, T. J. (1999). Functionally independent components of early event-related potentials in a visual spatial attention task. *Philosophical Transactions* *of the Royal Society B: Biological Sciences*, *354*(1387), 1135–1144. https://doi.org/10.1098/rstb.1999.0469

Makeig, S., Westerfield, M., Jung, T. P., Enghoff, S., Townsend, J., Courchesne, E., & Sejnowski, T. J. (2002). Dynamic brain sources of visual evoked responses. *Science*, *295*(5555), 690–694. https://doi.org/10.1126/science.1066168

Marini, F., Lee, C., Wagner, J., Makeig, S., & Gola, M. (2019). A comparative evaluation of signal quality between a research-grade and a wireless dry-electrode mobile EEG system. *Journal of Neural Engineering*, *16*(5). https://doi.org/10.1088/1741-2552/ab21f2

Maris, E., & Oostenveld, R. (2007). Nonparametric statistical testing of EEG- and MEG-data. *Journal of Neuroscience Methods*, *164*(1), 177–190. https://doi.org/10.1016/j.jneumeth.2007.03.024

Marquardt, D. (1963). An Algorithm for Least-Squares Estimation of Nonlinear Parameters. *Journal of the Society for Industrial and Applied Mathematics*, *11*(2), 431–441.

Marshall, A. (1890). *Principles of Economics* (Issue v. 1). Macmillan and Company. https://books.google.co.uk/books?id=bykoAAAAYAAJ

Martínez-Vispo, C., Martínez, Ú., López-Durán, A., Fernández del Río, E., & Becoña, E. (2018). Effects of behavioural activation on substance use and depression: A systematic review. *Substance Abuse: Treatment, Prevention, and Policy*, *13*(1), 1–13. https://doi.org/10.1186/s13011-018-0173-2

Martins, J. M., Yusuf, F., & Swanson, D. A. (2011). *Consumer Demographics and Behaviour: Markets are People*. Springer: Netherlands. https://books.google.co.uk/books?id=80FtZVMIDZgC

Marzi, T., & Viggiano, M. P. (2007). Interplay between familiarity and orientation in face processing: An ERP study. *International Journal of Psychophysiology*, *65*(3), 182–192. https://doi.org/10.1016/j.ijpsycho.2007.04.003

Maslow, A. H., Frager, R., Holtzman, W. G., & Murphy, G. (1970). *Motivation and Personality*. Harper & Row. https://books.google.co.uk/books?id=0V5qAAAAMAAJ

McClure, S. M., Li, J., Tomlin, D., Cypert, K. S., Montague, L. M., & Montague, P. R. (2004). Neural correlates of behavioral preference for culturally familiar drinks. *Neuron*, *44*(2), 379–387. https://doi.org/10.1016/j.neuron.2004.09.019

McGinty, V. B., Rangel, A., & Newsome, W. T. (2016). Orbitofrontal Cortex Value Signals Depend on Fixation Location during Free Viewing. *Neuron*, *90*(6), 1299–1311. https://doi.org/10.1016/j.neuron.2016.04.045

Mckinnon, A. I., Gray, N. S., & Snowden, R. J. (2020). Enhanced emotional response to both negative and positive images in post-traumatic stress disorder: Evidence from pupillometry. *Biological Psychology*, *154*, 107922. https://doi.org/10.1016/j.biopsycho.2020.107922

McNay, D., Michielssen, E., Rogers, R. L., Taylor, S. A., Akhtari, M., & Sutherling, W. W. (1996). Multiple source localization using genetic algorithms. *Journal of Neuroscience Methods*, *64*(2), 163–172. https://doi.org/10.1016/0165-0270(95)00122-0

Meilinger, T., Berthoz, A., & Wiener, J. M. (2011). The integration of spatial information across different viewpoints. *Memory and Cognition*, *39*(6), 1042–1054. https://doi.org/10.3758/s13421-011-0088-x

Melcher, D. (2007). Predictive remapping of visual features precedes saccadic eye movements. *Nature Neuroscience*, *10*(7), 903–907. https://doi.org/10.1038/nn1917

Melcher, D., & Colby, C. L. (2008). Trans-saccadic perception. *Trends in Cognitive Sciences*, *12*(12), 466–473. https://doi.org/10.1016/j.tics.2008.09.003

Mendelsohn, A., Pine, A., & Schiller, D. (2014). Between Thoughts and Actions: Motivationally Salient Cues Invigorate Mental Action in the Human Brain. *Neuron*, *81*(1), 207–217. https://doi.org/10.1016/j.neuron.2013.10.019

Menon, V., Rivera, S. M., White, C. D., Glover, G. H., & Reiss, A. L. (2000). Dissociating prefrontal and parietal cortex activation during arithmetic processing. *NeuroImage*, *12*(4), 357–365. https://doi.org/10.1006/nimg.2000.0613

Michon, R., Chebat, J. C., & Turley, L. W. (2005). Mall atmospherics: The interaction effects of the mall environment on shopping behavior. *Journal of Business Research*, *58*(5), 576–583. https://doi.org/10.1016/j.jbusres.2003.07.004

Milosavljevic, M., Koch, C., & Rangel, A. (2011). Consumers can make decisions in as little as a third of a second. *Judgement and Decision Making*, *6*(6), 520–530.

Milosavljevic, M., Malmaud, J., Huth, A., Koch, C., & Rangel, A. (2010). The drift diffusion model can account for value-based choice response times under high and low time pressure. *Judgement & Decision Making*, *5*(6), 437–449. https://www.researchgate.net/profile/Alexander_Huth/publication/47630977_The_Drift_Diffusion_Model_Can_Account_for_the_Accuracy_and_Reaction_Time_of_Value-Based_Choices_Under_High_and_Low_Time_Pressure/links/0046352f10dfd424ce000000.pdf

Milosavljevic, M., Navalpakkam, V., Koch, C., & Rangel, A. (2012). Relative visual saliency differences induce sizable bias in consumer choice. *Journal of Consumer Psychology*, *22*(1), 67–74. https://doi.org/10.1016/j.jcps.2011.10.002

Minati, L., Grisoli, M., Franceschetti, S., Epifani, F., Granvillano, A., Medford, N., Harrison, N. A., Piacentini, S., & Critchley, H. D. (2012). Neural signatures of economic parameters during decision-Making: A functional MRI (fMRI), electroencephalography (EEG) and autonomic monitoring study. *Brain Topography*, *25*(1), 73–96. https://doi.org/10.1007/s10548-011-0210-1

Minguillon, J., Lopez-Gordo, M. A., & Pelayo, F. (2017). Trends in EEG-BCI for daily-life: Requirements for artifact removal. *Biomedical Signal Processing and Control*, *31*(January), 407–418. https://doi.org/10.1016/j.bspc.2016.09.005

Mlot, E. G., Bahmani, H., Wahl, S., & Kasneci, E. (2016). 3D gaze estimation using eye vergence. *HEALTHINF 2016 - 9th International Conference on Health Informatics, Proceedings; Part of 9th International Joint Conference on Biomedical Engineering Systems and Technologies, BIOSTEC 2016*, *January*, 125–131. https://doi.org/10.5220/0005821201250131

Mohamed, A., Da Silva, M., & Courboulay, V. (2007). *A history of eye gaze tracking Abdallahi Ould Mohamed*. *May*, 1–19. http://hal.archives-ouvertes.fr/docs/00/21/59/67/PDF/Rapport_interne_1.pdf

Mongin, P. (1998). Expected Utility Theory. *Handbook of Economic Methodology*, 342–350. https://doi.org/10.2139/ssrn.1033982

Montague, P. R., & Berns, G. S. (2002). Neural economics and the biological substrates of valuation. *Neuron*, *36*(2), 265–284. https://doi.org/10.1016/S0896-

6273(02)00974-1

Morrin, M., & Ratneshwar, S. (2000). The Impact of Ambient Scent on Evaluation, Attention, and Memory for Familiar and Unfamiliar Brands. *Journal of Business Research*, *49*, 157–165.

Morris, R. W., Dezfouli, A., Griffiths, K. R., & Balleine, B. W. (2014). Action-value comparisons in the dorsolateral prefrontal cortex control choice between goal-directed actions. *Nature Communications*, *5*. https://doi.org/10.1038/ncomms5390

Moscati, I. (2016). Retrospectives: How economists came to accept expected utility theory: The case of samuelson and savage. *Journal of Economic Perspectives*, *30*(2), 219–236. https://doi.org/10.1257/jep.30.2.219

Mosher, J. C., Leahy, R. M., & Lewis, P. S. (1999). EEG and MEG: Forward solutions for inverse methods. *IEEE Transactions on Biomedical Engineering*, *46*(3), 245–259. https://doi.org/10.1109/10.748978

Murphy, A. P., Ban, H., & Welchman, A. E. (2013). Integration of texture and disparity cues to surface slant in dorsal visual cortex. *Journal of Neurophysiology*, *110*(1), 190–203. https://doi.org/10.1152/jn.01055.2012

Mussweiler, T., & Strack, F. (2000). Numeric Judgments under Uncertainty: The Role of Knowledge in Anchoring. *Journal of Experimental Social Psychology*, *36*(5), 495–518. https://doi.org/10.1006/jesp.1999.1414

Natraj, N., Alterman, B., Basunia, S., & Wheaton, L. A. (2018). The Role of Attention and Saccades on Parietofrontal Encoding of Contextual and Grasp-specific Affordances of Tools: An ERP Study. *Neuroscience*, *394*, 243–266. https://doi.org/10.1016/j.neuroscience.2018.10.019

Nayeem, T. (2012). Cultural Influences on Consumer Behaviour. *International Journal of Business and Management*, *7*(21), 78–91. https://doi.org/10.5539/ijbm.v7n21p78

Nee, D. E., Wager, T. D., & Jonides, J. (2007). Interference resolution : Insights from a meta-analysis of neuroimaging tasks. *Cognitive, Affective, & Behavioral Neuroscience 2007*, *7*(1), 1–17.

Neisser, U. (1976). Cognition and reality: Principles and implications of cognitive psychology. In *Cognition and reality: Principles and implications of cognitive* *psychology*. W H Freeman/Times Books/ Henry Holt & Co.

Nelder, J. A., & Mead, R. (1965). A Simplex Method for Function Minimization. *The Computer Journal*, *7*(4), 308–313. https://doi.org/10.1093/comjnl/7.4.308

Niehorster, D. C., Santini, T., Hessels, R. S., Hooge, I. T. C., Kasneci, E., & Nyström, M. (2020). The impact of slippage on the data quality of head-worn eye trackers. *Behavior Research Methods*, *52*(3), 1140–1160. https://doi.org/10.3758/s13428-019-01307-0

Nijs, I. M. T., Franken, I. H. A., & Muris, P. (2009). Enhanced processing of food-related pictures in female external eaters. *Appetite*, *53*(3), 376–383. https://doi.org/10.1016/j.appet.2009.07.022

Nikolaev, A. R., Jurica, P., Nakatani, C., Plomp, G., & Van Leeuwen, C. (2013). Visual encoding and fixation target selection in free viewing: Presaccadic brain potentials. *Frontiers in Systems Neuroscience*, *7*, 1–12. https://doi.org/10.3389/fnsys.2013.00026

Nikolaev, A. R., Meghanathan, R. N., & van Leeuwen, C. (2016). Combining EEG and eye movement recording in free viewing: Pitfalls and possibilities. *Brain and Cognition*, *107*, 55–83. https://doi.org/10.1016/j.bandc.2016.06.004

Nikolaev, A. R., Meghanathan, R. N., & van Leeuwen, C. (2018). Refixation control in free viewing: A specialized mechanism divulged by eye-movement-related brain activity. *Journal of Neurophysiology*, *120*(5), 2311–2324. https://doi.org/10.1152/jn.00121.2018

Nikolaev, A. R., Nakatani, C., Plomp, G., Jurica, P., & van Leeuwen, C. (2011). Eye fixation-related potentials in free viewing identify encoding failures in change detection. *NeuroImage*, *56*(3), 1598–1607. https://doi.org/10.1016/j.neuroimage.2011.03.021

Nikolaev, A. R., Pannasch, S., Ito, J., & Belopolsky, A. V. (2014). Eye movement-related brain activity during perceptual and cognitive processing. *Frontiers in Systems Neuroscience*, *8*(1 APR), 2013–2014. https://doi.org/10.3389/fnsys.2014.00062

Noble, S. M., Griffith, D. A., & Weinberger, M. G. (2005). Consumer derived utilitarian value and channel utilization in a multi-channel retail context. *Journal of Business Research*, *58*(12), 1643–1651.

https://doi.org/10.1016/j.jbusres.2004.10.005

Noseworthy, T. J., Muro, F. Di, & Murray, K. B. (2014). The role of arousal in congruity-based product evaluation. *Journal of Consumer Research, 41*(4), 1108–1126. https://doi.org/10.1086/678301

Nunez, P. L., Nunez, M. D., & Srinivasan, R. (2019). Multi-Scale Neural Sources of EEG: Genuine, Equivalent, and Representative. A Tutorial Review. *Brain Topography*, *32*(2), 193–214. https://doi.org/10.1007/s10548-019-00701-3

Nunez, P., & Srinivasan, R. (2006). Electric Fields of the Brain: The neurophysics of EEG. In *Electric Fields of the Brain: The neurophysics of EEG*. https://doi.org/10.1093/acprof:oso/9780195050387.001.0001

Nwankwo, S., Hamelin, N., & Khaled, M. (2014). Consumer values, motivation and purchase intention for luxury goods. *Journal of Retailing and Consumer Services, 21*(5), 735–744. https://doi.org/10.1016/j.jretconser.2014.05.003

Oberauer, K. (2019). Working Memory and Attention – A Conceptual Analysis and Review. *Journal of Cognition*, *2*(1), 1–23. https://doi.org/10.5334/joc.58

Ojeda, A., Bigdely-Shamlo, N., & Makeig, S. (2014). MoBILAB: an open source toolbox for analysis and visualization of mobile brain/body imaging data. *Frontiers in Human Neuroscience*, *8*, 121. https://doi.org/10.3389/fnhum.2014.00121

Olejniczak, P. (2006). Neurophysiologic basis of EEG. *Journal of Clinical Neurophysiology*, *23*(3), 186–189. https://doi.org/10.1097/01.wnp.0000220079.61973.6c

Oliveira, A. S., Schlink, B. R., Hairston, W. D., König, P., & Ferris, D. P. (2016). Proposing metrics for benchmarking novel EEG technologies towards real-world measurements. *Frontiers in Human Neuroscience*, *10*, 1–15. https://doi.org/10.3389/fnhum.2016.00188

Onishi, A., & Nakagawa, S. (2019). How does the degree of valence influence affective auditory P300-based BCIs? *Frontiers in Neuroscience, 13*, 1–8. https://doi.org/10.3389/fnins.2019.00045

Orlov, T., & Zohary, E. (2018). Object representations in human visual cortex formed through temporal integration of dynamic partial shape views. *Journal of Neuroscience*, *38*(3), 659–678. https://doi.org/10.1523/JNEUROSCI.1318-

17.2017

Padoa-Schioppa, C. (2011). Neurobiology of economic choice: a good-based model. *Annual Review of Neuroscience*, *34*, 333–359. https://doi.org/10.1146/annurev-neuro-061010-113648

Padoa-Schioppa, C. (2013). Neuronal origins of choice variability in economic decisions. *Neuron*, *80*(5), 1322–1336. https://doi.org/10.1016/j.neuron.2013.09.013

Padoa-Schioppa, C., & Assad, J. A. (2006). Neurons in the orbitofrontal cortex encode economic value. *Nature*, *441*(7090), 223–226. https://doi.org/10.1038/nature04676

Padoa-Schioppa, C., & Cai, X. (2011). The orbitofrontal cortex and the computation of subjective value: Consolidated concepts and new perspectives. *Annals of the New York Academy of Sciences*, *1239*(1), 130–137. https://doi.org/10.1111/j.1749-6632.2011.06262.x

Padoa-Schioppa, C., & Conen, K. E. (2017). Orbitofrontal Cortex: A Neural Circuit for Economic Decisions. *Neuron*, *96*(4), 736–754. https://doi.org/10.1016/j.neuron.2017.09.031

Painter, J. E., Wansink, B., & Hieggelke, J. B. (2002). How visibility and convenience influence candy consumption. *Appetite*, *38*(3), 237–238. https://doi.org/10.1006/appe.2002.0485

Palmer, J. A., Makeig, S., Kreutz-Delgado, K., & Rao, B. D. (2008). Newton method for the ica mixture model. *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, 1805–1808. https://doi.org/10.1109/ICASSP.2008.4517982

Palmer, J., Kreutz-Delgado, K., & Makeig, S. (2011). AMICA: An Adaptive Mixture of Independent Component Analyzers with Shared Components. *San Diego, CA: Technical Report, Swartz Center for Computational Neuroscience, January*, 1–15. http://sccn.ucsd.edu/~jason/amica_a.pdf%5Cnpapers2://publication/uuid/E6296FC1-7F6B-400C-85D0-3A292A27F710

Parada, F.J., Grasso-Cladera, A., Rossi, A., Costa-Cordella, S., & Fuchs, N. F. (2020). Mobile Brain/Body Imaging (MoBI): Epistemological and 2 methodological challenges and opportunities for the implementation 3 of research programs based on the 4E approach to cognition. *PsyArXiv Preprints*, *4*(434), 1–2.

Parada, F. J. (2018). Understanding Natural Cognition in Everyday Settings: 3 Pressing Challenges. *Frontiers in Human Neuroscience*, *12*, 1–5. https://doi.org/10.3389/fnhum.2018.00386

Park, J. L., & Donaldson, D. I. (2019). Detecting the neural correlates of episodic memory with mobile EEG: Recollecting objects in the real world. *NeuroImage*, *193*, 1–9. https://doi.org/10.1016/j.neuroimage.2019.03.013

Park, J. L., Dudchenko, P. A., & Donaldson, D. I. (2018). Navigation in real-world environments: New opportunities afforded by advances in mobile brain imaging. *Frontiers in Human Neuroscience*, *12*, 1–12. https://doi.org/10.3389/fnhum.2018.00361

Patel, S. H., & Azzam, P. N. (2005). Characterization of N200 and P300: Selected studies of the Event-Related Potential. *International Journal of Medical Sciences*, *2*(4), 147–154. https://doi.org/10.7150/ijms.2.147

Pauwels, K., & Neslin, S. A. (2015). Building With Bricks and Mortar: The Revenue Impact of Opening Physical Stores in a Multichannel Environment. *Journal of Retailing*, *91*(2), 182–197. https://doi.org/10.1016/j.jretai.2015.02.001

Peck, J., & Wiggins, J. (2006). It just feels good: Customers' affective response to touch and its influence on persuasion. *Journal of Marketing*, *70*(4), 56–69. https://doi.org/10.1509/jmkg.70.4.56

Pessiglione, M., & Delgado, Mauricio. (2015). The good, the bad and the brain: Neural correlates of appetitive and aversive values underlying decision making. *Current Opinion in Behavioural Sciences*, *5*, 78–84. https://doi.org/10.1016/j.cobeha.2015.08.006.The

Pessoa, L., & Engelmann, J. B. (2010). Embedding reward signals into perception and cognition. *Frontiers in Neuroscience*, *4*, 1–17. https://doi.org/10.3389/fnins.2010.00017

Peters, J., & Büchel, C. (2010). Neural representations of subjective reward value. *Behavioural Brain Research*, *213*(2), 135–141. https://doi.org/10.1016/j.bbr.2010.04.031

Peters, Jan, & Büchel, C. (2009). Overlapping and distinct neural systems code for subjective value during intertemporal and risky decision making. *Journal of Neuroscience, 29*(50), 15727–15734. https://doi.org/10.1523/JNEUROSCI.3489-09.2009

Petit, O., Basso, F., Merunka, D., Spence, C., Cheok, A., & & Oullier, O. (2016). Understanding the Acceptance of Mobile SMS Advertising among Young Chinese Consumers. *Psychology & Marketing, 33*(8), 608–619. https://doi.org/10.1002/mar

Pexman, P. M., Hargreaves, I. S., Edwards, J. D., Henry, L. C., & Goodyear, B. G. (2007). The Neural Consequences of Semantic Richness When More Comes to Mind , Less Activation Is Observed. *Psychological science,18*(5), 401–407.

Philiastides, M. G., & Heekeren, H. R. (2009). Spatiotemporal characteristics of perceptual decision making in the human brain. In *Handbook of Reward and Decision Making*. Elsevier Inc. https://doi.org/10.1016/B978-0-12-374620-7.00008-X

Philiastides, M. G., & Ratcliff, R. (2013). Influence of Branding on Preference-Based Decision Making. *Psychological Science, 24*(7), 1208–1215. https://doi.org/10.1177/0956797612470701

Picton, T., Bentin, S., & Berg, P. (2000). Guidelines for using human event-related potentials to study cognition: Recording standards and publication criteria. *Psychophysiology, 37*, 127–152. https://doi.org/doi/10.1111/1469-8986.3720127

Plassman, H., Kenning, P., & Ahlert, D. (2007). Why companies should make their customers happy: The neural correlates of customer loyalty. *Advances in Consumer Research, 34*, 735–739.

Plassmann, H., O'Doherty, J., & Rangel, A. (2007). Orbitofrontal Cortex Encodes Willingness to Pay in Everyday Economic Transactions. *Journal of Neuroscience, 27*(37), 9984–9988. https://doi.org/10.1523/JNEUROSCI.2131-07.2007

Plassmann, H., O'Doherty, J., & Rangel, A. (2010). Appetitive and aversive goal values are encoded in the medial orbitofrontal cortex at the time of decision making. *The Journal of Neuroscience, 30*(32), 10799–10808.

https://doi.org/10.1523/JNEUROSCI.0788-10.2010

Plassmann, H., Ramsøy, T. &, & Milosavljevic, M. (2012). Branding the brain: A critical review and outlook. *Journal of Consumer Psychology*, *22*(1), 18–36. https://doi.org/10.1016/j.jcps.2011.11.010

Plassmann, H., O'Doherty, J., Shiv, B., & Rangel, A. (2008). Marketing actions can modulate neural representations of experienced pleasantness. *Proceedings of the National Academy of Sciences of the United States of America*, *105*(3), 1050–1054. https://doi.org/10.1073/pnas.0706929105

Plöchl, M., Ossandón, J. P., & König, P. (2012). Combining EEG and eye tracking: Identification, characterization, and correction of eye movement artifacts in electroencephalographic data. *Frontiers in Human Neuroscience, 6*, 1–23. https://doi.org/10.3389/fnhum.2012.00278

Polanía, R., Krajbich, I., Grueschow, M., & Ruff, C. C. (2014). Neural Oscillations and Synchronization Differentially Support Evidence Accumulation in Perceptual and Value-Based Decision Making. *Neuron, 82*(3), 709–720. https://doi.org/10.1016/j.neuron.2014.03.014

Polezzi, D., Lotto, L., Daum, I., Sartori, G., & Rumiati, R. (2008). Predicting outcomes of decisions in the brain. *Behavioural Brain Research*, *187*(1), 116–122. https://doi.org/10.1016/j.bbr.2007.09.001

Polich, J. (2007). Updating P300: An Integrative Theory of P3a and P3b. *Clinical Neurophysiology*, *118*(10), 2128–2148. https://doi.org/10.1016/j.clinph.2007.04.019.Updating

Polich, J., Alexander, J. E., Bauer, L. O., Kuperman, S., Morzorati, S., O'Connor, S. J., Porjesz, B., Rohrbaugh, J., & Begleiter, H. (1997). P300 topography of Amplitude/Latency correlations. *Brain Topography, 9*(4), 275–282. https://doi.org/10.1007/BF01464482

Pozharliev, R., Verbeke, W. J. M. I., Strien, J. W. Van, & Bagozzi, R. P. (2015). Merely Being with You Increases My Attention to Luxury Products: Using EEG to Understand Consumers' Emotional Experience with Luxury Branded Products. *Journal of Marketing Research*, *52*(4), 546–558. https://doi.org/10.1509/JMR.13.0560

Pradeep, A. K. (2010). *The Buying Brain: Secrets for Selling to the Subconscious*

Mind. Wiley. https://books.google.co.uk/books?id=-1juDwAAQBAJ

Prime, S. L., Vesia, M., & Crawford, J. D. (2011). Cortical mechanisms for trans-saccadic memory and integration of multiple object features. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *366*(1564), 540–553. https://doi.org/10.1098/rstb.2010.0184

Protzak, J., & Gramann, K. (2018). Investigating established EEG parameter during real-world driving. *Frontiers in Psychology, 9*, 1–11. https://doi.org/10.3389/fpsyg.2018.02289

Pushkarskaya, H., Tolin, D., Ruderman, L., Henick, D., Kelly, J. M., Pittenger, C., Levy, I., Haven, N., Haven, N., Haven, N., Hospital, H., Haven, N., & Haven, N. (2017). Value-based decision making under uncertainty in hoarding and obsessive-compulsive disorders. *Psychiatry Research*, *258,* 305–315. https://doi.org/10.1016/j.psychres.2017.08.058.Value-based

Puto, C. P. (1987). The Framing of Buying Decisions. *Journal of Consumer Research, 14*(3), 301–315.

Raney, G. E., Campbell, S. J., & Bovee, J. C. (2014). Using eye movements to evaluate the cognitive processes involved in text comprehension. *Journal of Visualized Experiments*, *83*, 1–7. https://doi.org/10.3791/50780

Rangel, A., Camerer, C., & Montague, P. R. (2008). A framework for studying the neurobiology of value-based decision making. *Nature Reviews Neuroscience*, *9*(7), 545–556. https://doi.org/10.1038/nrn2357

Rangel, A., & Hare, T. (2010). Neural computations associated with goal-directed choice. *Current Opinion in Neurobiology*, *20*(2), 262–270. https://doi.org/10.1016/j.conb.2010.03.001

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*(2), 59–108.

Ray, S., Bhutani, N., Kapoor, V., & Murthy, A. (2011). Trans-saccadic processing of visual and motor planning during sequential eye movements. *Experimental Brain Research*, *215*(1), 13–25. https://doi.org/10.1007/s00221-011-2866-x

Reis, P. M. R., Hebenstreit, F., Gabsteiger, F., Von Tscharner, V., Lochmann, M., König, P., & Busan, P. (2014). Methodological aspects of EEG and body dynamics measurements during motion. *Frontiers in human neuroscience, 8,* 1-

156. https://doi.org/10.3389/fnhum.2014.00156

Reiser, J. E., Wascher, E., & Arnau, S. (2019). Recording mobile EEG in an outdoor environment reveals cognitive-motor interference dependent on movement complexity. *Scientific Reports*, *9*(1), 1–14. https://doi.org/10.1038/s41598-019-49503-4

Rellecke, J., Palazova, M., Sommer, W., & Schacht, A. (2011). On the automaticity of emotion processing in words and faces: Event-related brain potentials evidence from a superficial task. *Brain and Cognition*, *77*(1), 23–32. https://doi.org/10.1016/j.bandc.2011.07.001

Ries, A. J., Slayback, D., & Touryan, J. (2018a). The Effect of Visual Task Difficulty on the Fixation-Related Lambda Response. *2016 49th Hawaii International Conference on System Sciences (HICSS), ARL-TR-829*, 1226–1235. https://apps.dtic.mil/sti/citations/AD1048416

Ries, A. J., Slayback, D., & Touryan, J. (2018b). The fixation-related lambda response: Effects of saccade magnitude, spatial frequency, and ocular artifact removal. *International Journal of Psychophysiology*, *134*, 1–8. https://doi.org/10.1016/j.ijpsycho.2018.09.004

Rigoni, D., Polezzi, D., Rumiati, R., Guarino, R., & Sartori, G. (2010). When people matter more than money: An ERPs study. *Brain Research Bulletin*, *81*(4–5), 445–452. https://doi.org/10.1016/j.brainresbull.2009.12.003

Roberts, H., Soto, V., Tyson-Carr, J., Kokmotou, K., Cook, S., Fallon, N., Giesbrecht, T., & Stancak, A. (2018). Tracking Economic Value of Products in Natural Settings: A Wireless EEG Study. *Frontiers in Neuroscience, 12*, 1–16. https://doi.org/10.3389/fnins.2018.00910

Robinson, T. E., & Berridge, K. C. (1993). The neural basis of drug craving: An incentive-sensitization theory of addiction. *Brain Research Reviews, 18*(3) 247–291. https://doi.org/10.1016/0165-0173(93)90013-P

Robles, D., Kuziek, J., Wlasitz, N., Bartlett, N., Hurd, P., & Mathewson, K. (2020). *EEG in Motion: Using an Oddball Task to Explore Motor Interference in Active Skateboarding*. https://doi.org/10.1101/2020.06.08.136960

Rossion, B., Kung, C. C., & Tarr, M. J. (2004). Visual expertise with nonface objects leads to competition with the early perceptual processing of faces in the human occipitotemporal cortex. *Proceedings of the National Academy of Sciences of the United States of America*, *101*(40), 14521–14526. https://doi.org/10.1073/pnas.0405613101

Rozan, A., Stenger, A., & Willinger, M. (2004). Willingness-to-pay for food safety: An experimental investigation of quality certification on bidding behaviour. *European Review of Agricultural Economics*, *31*(4), 409–425. https://doi.org/10.1093/erae/31.4.409

Rozin, P., & Royzman, E. B. (2001). Negativity bias, negativity dominance, and contagion. *Personality and Social Psychology Review*, *5*(4), 296–320. https://doi.org/10.1207/S15327957PSPR0504_2

Ruff, C., & Fehr, E. (2014). The neurobiology of rewards and values in social decision making. *Nature Reviews Neuroscience*, *15*(8), 549–562. https://doi.org/10.1038/nrn3776

Rutherford, M. (2011). *The Institutionalist Movement in American Economics, 1918–1947: Science and Social Control*. Cambridge University Press. https://books.google.co.uk/books?id=XfX72hARkpsC

Salvucci, D. D., & Goldberg, J. H. (2000). Identifying fixations and saccades in eye-tracking protocols. *Proceedings of the Symposium on Eye Tracking Research & Applications - ETRA '00*, 71–78. https://doi.org/10.1145/355017.355028

Samuelson, P. (1937). Note on Measurement of Utility. *The Review of Economic Studies*, *4*(2), 155–161. https://doi.org/10.1016/0001-6918(58)90027-1

San Martín, R. (2012). Event-related potential studies of outcome processing and feedback-guided learning. *Frontiers in Human Neuroscience*, *6*, 1–40. https://doi.org/10.3389/fnhum.2012.00304

Sanfey, A. G., Loewenstein, G., McClure, S. M., & Cohen, J. D. (2006). Neuroeconomics: Cross-currents in research on decision-making. *Trends in Cognitive Sciences*, *10*(3), 108–116. https://doi.org/10.1016/j.tics.2006.01.009

Saraiva, A. C., & Marshall, L. (2015). Dorsolateral–ventromedial prefrontal cortex interactions during value-guided choice: A function of context or difficulty? *Journal of Neuroscience*, *35*(13), 5087–5088. https://doi.org/10.1523/JNEUROSCI.0271-15.2015

Savage, L. J. (1954). *The Foundations of Statistics*. Wiley.

Scalf, P. E., Torralbo, A., Tapia, E., & Beck, D. M. (2013). Competition explains limited attention and perceptual resources: Implications for perceptual load and dilution theories. *Frontiers in Psychology*, *4*, 1–9. https://doi.org/10.3389/fpsyg.2013.00243

Schaefer, A., Buratto, L. G., Goto, N., & Brotherhood, E. V. (2016). The feedback-related negativity and the P300 brain potential are sensitive to price expectation violations in a virtual shopping task. *PLoS ONE*, *11*(9), 1–21. https://doi.org/10.1371/journal.pone.0163150

Schaefer, M., Berens, H., Heinze, H. J., & Rotte, M. (2006). Neural correlates of culturally familiar brands of car manufacturers. *NeuroImage*, *31*(2), 861–865. https://doi.org/10.1016/j.neuroimage.2005.12.047

Schaefer, M., & Rotte, M. (2007). Thinking on luxury or pragmatic brand products: Brain responses to different categories of culturally based brands. *Brain Research*, *1165*(1), 98–104. https://doi.org/10.1016/j.brainres.2007.06.038

Schall, J. D. (2013). Production, Control, and Visual Guidance of Saccadic Eye Movements. *ISRN Neurology*, *2013*, 1–17. https://doi.org/10.1155/2013/752384

Scherg, M. (1990). Fundamentals of Dipole Source Potential analysis. In *Auditory evoked magnetic fields and electric potentials* (6th ed., pp. 40–69).

Scherg, M., & Von Cramon, D. (1986). Evoked dipole source potentials of the human auditory cortex. *Electroencephalography and Clinical Neurophysiology*, *65*(5), 344–360. https://doi.org/10.1016/0168-5597(86)90014-6

Scherg, M., Ille, N., Bornfleth, H., & Berg, P. (2002). Advanced Tools for Digital EEG Review: *Journal of Clinical Neurophysiology*, *19*(2), 91–112. https://doi.org/10.1097/00004691-200203000-00001

Schienele, A., Scharmuller, W., & Schwab, D. (2017). Clinical Neurophysiology Processing of visual food cues during bitter taste perception in female patients with binge-eating symptoms : A cross-modal ERP study. *Clinical Neurophysiology*, *128*(11), 2184–2190. https://doi.org/10.1016/j.clinph.2017.08.017

Schirmer, A., Teh, K. S., Wang, S., Vijayakumar, R., Ching, A., Nithianantham, D., Escoffier, N., & Cheok, A. D. (2011). Squeeze me, but don’t tease me: Human and mechanical touch enhance visual attention and emotion discrimination.

Social Neuroscience, *6*(3), 219–230. https://doi.org/10.1080/17470919.2010.507958

Schuermann, B, Endrass, T., & Kathmann, N. (2012). Neural correlates of feedback processing in decision-making under risk. *Front Hum Neurosci*, *6*, 204. https://doi.org/10.3389/fnhum.2012.00204

Schultz, W., Apicella, P., & Ljungberg, T. (1993). Responses of monkey dopamine neurons to reward and conditioned stimuli during successive steps of learning a delayed response task. *The Journal of Neuroscience*, *13*(3), 900–913. https://doi.org/8441015

Schupp, H. T., Cuthbert, B. N., Bradley, M. M., Cacioppo, J. T., Ito, T., & Lang, P. J. (2000). Affective picture processing: The late positive potential is modulated by motivacional relevance. *Psychophysiology, 37*, 257–261.

Seghier, M. L. (2013). *The Angular Gyrus : Multiple Functions and Multiple Subdivisions*. https://doi.org/10.1177/1073858412440596

Severens, M., Nienhuis, B., Desain, P., & Duysens, J. (2012). Feasibility of measuring event Related Desynchronization with electroencephalography during walking. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, *May*, 2764–2767. https://doi.org/10.1109/EMBC.2012.6346537

Shaw, E. P., Rietschel, J. C., Hendershot, B. D., Pruziner, A. L., Miller, M. W., Hatfield, B. D., & Gentili, R. J. (2018). Measurement of attentional reserve and mental effort for cognitive workload assessment under various task demands during dual-task walking. *Biological Psychology*, *134*, 39–51. https://doi.org/10.1016/j.biopsycho.2018.01.009

Shenhav, A., Cohen, J. D., & Botvinick, M. M. (2016). Dorsal anterior cingulate cortex and the value of control. *Nature Neuroscience*, *19*(10), 1286–1291. https://doi.org/10.1038/nn.4382

Shenhav, Amitai, Dean Wolf, C. K., & Karmarkar, U. R. (2018). The evil of banality: When choosing between the mundane feels like choosing between the worst. *Journal of Experimental Psychology: General*, *147*(12), 1892–1904. https://doi.org/10.1037/xge0000433

Sherman, E., Mathur, A., & Smith, R. B. (1997). Store Environment and Consumer

Purchase Behavior: Mediating Role of Consumer Emotions. *Psychology & Marketing*, *14*(4), 361–379.

Shomstein, S. (2012). Cognitive functions of the posterior parietal cortex: Top-down and bottom-up attentional control. *Frontiers in Integrative Neuroscience*, *6*, 1–7. https://doi.org/10.3389/fnint.2012.00038

Silayoi, P., & Speece, M. (2004). Packaging and purchase decisions An exploratory study on the impact of involvement level and time pressure. *British Food Journal*, *106*(8), 607–628.

Simola, J., Le Fevre, K., Torniainen, J., & Baccino, T. (2015). Affective processing in natural scene viewing: Valence and arousal interactions in eye-fixation-related potentials. *NeuroImage*, *106*, 21–33. https://doi.org/10.1016/j.neuroimage.2014.11.030

Simola, J., Torniainen, J., Moisala, M., Kivikangas, M., & Krause, C. M. (2013). Eye movement related brain responses to emotional scenes during free viewing. *Frontiers in Systems Neuroscience*, *7*(JUL), 1–16. https://doi.org/10.3389/fnsys.2013.00041

Singh, H., & Singh, J. (2012). Human Eye Tracking and Related Issues: A Review. *International Journal of Scientific and Research Publications*, *2*(1), 2250–3153. www.ijsrp.org

Slama, M. E., & Tashchian, A. (1985). Selected Socioeconomic and Demographic Characteristics Associated with Purchasing Involvement. *Journal of Marketing*, *49*(1), 72. https://doi.org/10.2307/1251177

Slotnick, S. D. (2005). Source localization of ERP generators. In T. C. Handy (Ed.), *Event- Related Potentials: A Methods Handbook* (pp. 149–166). The MIT Press.

Small, D. M., Gitelman, D., Simmons, K., Bloise, S. M., Parrish, T., & Mesulam, M. M. (2005). Monetary incentives enhance processing in brain regions mediating top-down control of attention. *Cerebral Cortex*, *15*(12), 1855–1865. https://doi.org/10.1093/cercor/bhi063

Smith, A. (1759). *The Theory of Moral Sentiments* (D. Raphael & A. Macfie (eds.)). Liberty Press.

Smith, N., Cacioppo, J., Larsen, J., & Chartrand, T. (2003). May I have your attention, please: Electrocortical responses to positive and negative stimuli. *Neuropsychologia*, *41*(2), 171–183. https://doi.org/10.1016/S0028-3932(02)00147-1

Smith, D. V., Hayden, B. Y., Truong, T. K., Song, A. W., Platt, M. L., & Huettel, S. A. (2010). Distinct value signals in anterior and posterior ventromedial prefrontal cortex. *Journal of Neuroscience*, *30*(7), 2490–2495. https://doi.org/10.1523/JNEUROSCI.3319-09.2010

Sokol-Hessner, P., Hsu, M., Curley, N. G., Delgado, M. R., Camerer, C. F., & Phelps, E. a. (2009). Thinking like a trader selectively reduces individuals' loss aversion. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(13), 5035–5040. https://doi.org/10.1073/pnas.0806761106

Soon, C. S., Brass, M., Heinze, H. J., & Haynes, J. D. (2008). Unconscious determinants of free decisions in the human brain. *Nature Neuroscience*, *11*(5), 543–545. https://doi.org/10.1038/nn.2112

Soto, V., Tyson-Carr, J., Kokmotou, K., Roberts, H., Cook, S., Fallon, N., Giesbrecht, T., & Stancak, A. (2018). Brain responses to emotional faces in natural settings: A wireless mobile EEG recording study. *Frontiers in Psychology*, *9*. https://doi.org/10.3389/fpsyg.2018.02003

Speckman, E.-J., Elger, C., & Gorgi, A. (2011). Neurophysiologic Basis of EEG and DC Potentials. In D. Schomer & F. Lopes da Silva (Eds.), *Niedermeyer's Electroencephalography: Basic Principles, Clinical Applications, and Related Fields: Sixth Edition* (pp. 17–32). Wolters Kluwer LIPPINCOTT WILLIAMS & WILKINS,.

Spencer, K. M., Dien, J., & Donchin, E. (2001). Spatiotemporal analysis of the late ERP responses to deviant stimuli. *Psychophysiology*, *38*(2), 343–358. https://doi.org/10.1017/S0048577201000324

Stancak, A., Hoechstetter, K., Tintera, J., Vrana, J., Rachmanova, R., Kralik, J., & Scherg, M. (2002). Source activity in the human secondary somatosensory cortex depends on the size of corpus callosum. *Brain Research*, *936*(1–2), 47–57. https://doi.org/10.1016/S0006-8993(02)02502-7

Stancak, A., Xie, Y., Fallon, N., Bulsing, P., Giesbrecht, T., Thomas, A., & Pantelous, A. A. (2015). Unpleasant odors increase aversion to monetary losses.

Biological Psychology, *107*, 1–9. https://doi.org/10.1016/j.biopsycho.2015.02.006

Stephani, T., Kirk Driller, K., Dimigen, O., & Sommer, W. (2019). Eye contact in active and passive viewing: Event-related brain potential evidence from a combined eye tracking and EEG study. *BioRxiv*, 0–36. https://doi.org/10.1101/669341

Stolz, C., Endres, D., & Mueller, E. M. (2019). Threat-conditioned contexts modulate the late positive potential to faces—A mobile EEG/virtual reality study. *Psychophysiology*, *56*(4), 1–15. https://doi.org/10.1111/psyp.13308

Stott, J., & Redish, D. (2015). Representations of value in the brain: An embarrassment of riches? *PLoS Biology*, *13*(6), 1–7. https://doi.org/10.1371/journal.pbio.1002174

Strüber, D., & Polich, J. (2002). P300 and slow wave from oddball and single-stimulus visual tasks: Inter-stimulus interval effects. *International Journal of Psychophysiology*, *45*(3), 187–196. https://doi.org/10.1016/S0167-8760(02)00071-5

Suwazono, S., MacHado, L., & Knight, R. T. (2000). Predictive value of novel stimuli modifies visual event-related potentials and behavior. *Clinical Neurophysiology*, *111*(1), 29–39. https://doi.org/10.1016/S1388-2457(99)00186-8

Swirski, L., Bulling, A., & Dodgson, N. (2012). Robust real-time pupil tracking in highly off-axis images. *Etra*, 1–4. https://doi.org/10.1145/2168556.2168585

Świrski, L., Bulling, A., & Dodgson, N. (2012). Robust real-time pupil tracking in highly off-axis images. *Eye Tracking Research and Applications Symposium (ETRA)*, 173–176. https://doi.org/10.1145/2168556.2168585

Tanaka, C. S., Doya, K., Okada, G., Ueda, K., Okamoto, Y., & Yamawaki, S. (2004). Prediction of immediate and future rewards differentially recruits cortico-basal ganglia loops. *Nature Neuroscience*, *7*(8), 887–893. https://doi.org/10.1038/nn1279

Telpaz, A., Webb, R., & Levy, D. J. (2015). Using EEG to Predict Consumers' Future Choices. *Journal of Marketing Research*, *52*(4), 511–529. https://doi.org/10.1509/jmr.13.0564

Thibault, R. T., Lifshitz, M., Jones, J. M., & Raz, A. (2014). Posture alters human resting-state. *Cortex*, *58*, 199–205. https://doi.org/10.1016/j.cortex.2014.06.014

Thibault, R. T., Lifshitz, M., & Raz, A. (2015). Body position alters human resting-state: Insights from multi-postural magnetoencephalography. *Brain Imaging and Behavior*. https://doi.org/10.1007/s11682-015-9447-8

Thickbroom, G. W., Knezevič, W., Carroll, W. M., & Mastaglia, F. L. (1991). Saccade onset and offset lambda waves: relation to pattern movement visually evoked potentials. *Brain Research*, *551*(1–2), 150–156. https://doi.org/10.1016/0006-8993(91)90927-N

Thickbroom, G. W., & Mastaglia, F. L. (1986). Presaccadic spike potential. Relation to eye movement direction. *Electroencephalography and Clinical Neurophysiology*, *64*(3), 211–214. https://doi.org/10.1016/0013-4694(86)90167-7

Thom, R. (1974). Stabilité structurelle et morphogenèse. *Poetics*, *3*(2), 7–19. https://doi.org/https://doi.org/10.1016/0304-422X(74)90010-2

Tjan, B. S., & Legge, G. E. (1998). The viewpoint complexity of an object-recognition task. *Vision Research*, *38*(15–16), 2335–2350. https://doi.org/10.1016/S0042-6989(97)00255-1

Toelch, U., Bach, D. R., & Dolan, R. J. (2014). The neural underpinnings of an optimal exploitation of social information under uncertainty. *Social Cognitive and Affective Neuroscience*, *9*(11), 1746–1753. https://doi.org/10.1093/scan/nst173

Tovar, D. A., Murray, M. M., & Wallace, M. T. (2019). Selective enhancement of object representations through multisensory integration. *BioRxiv*. https://doi.org/10.1101/740555

Tremblay, C. H. (2018). Neuroeconomic studies in industrial organization: Brand, advertising and price effects on consumer valuation and choice. *Handbook of Behavioral Industrial Organization*, 343–367. https://doi.org/10.4337/9781784718985.00020

Tusche, A., Bode, S., & Haynes, J.-D. (2010). Neural Responses to Unattended Products Predict Later Consumer Choices. *Journal of Neuroscience*, *30*(23), 8024–8031. https://doi.org/10.1523/JNEUROSCI.0064-10.2010

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4157), 1124–1131. https://doi.org/10.4324/9781912282562

Tversky, A. (1975). A critique of expected utility theory: Descriptive and normative considerations. *Erkenntnis*, *9*(2), 163–173. https://doi.org/10.1007/BF00226380

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Experiments in Environmental Economics*, *211*, 173–178. https://doi.org/10.1007/978-1-4613-2391-4_2

Tweed, D., & Vilis, T. (1990). *Geometric Relations of Eye Position and*. *30*(1), 111–127.

Tymula, A., & Plassmann, H. (2016). Context-dependency in valuation. *Current Opinion in Neurobiology*, *40*, 59–65. https://doi.org/10.1016/j.conb.2016.06.015

Tyson-Carr, J., Kokmotou, K., Soto, V., Cook, S., Fallon, N., Giesbrecht, T., & Stancak, A. (2018). The neural correlates of economic value and valuation context: An event-related potentials study. *Journal of Neurophysiology*, *119*, 1924–1933. https://doi.org/10.1152/jn.00524.2017

Tyson-Carr, J., Soto, V., Kokmotou, K., Roberts, H., Fallon, N., Byrne, A., Giesbrecht, T., & Stancak, A. (2020). Neural underpinnings of value-guided choice during auction tasks: An eye-fixation related potentials study. *NeuroImage*, *204*, 116–213. https://doi.org/10.1016/j.neuroimage.2019.116213

Tzovara, A., Chavarriaga, R., & De Lucia, M. (2015). Quantifying the time for accurate EEG decoding of single value-based decisions. *Journal of Neuroscience Methods*, *250*, 114–125. https://doi.org/10.1016/j.jneumeth.2014.09.029

Unger, A., Papastamatelou, J., Okan, E. Y., & Aytas, S. (2014). How the economic situation moderates the influence of available money on compulsive buying of students - A comparative study between Turkey and Greece. *Journal of Behavioral Addictions*, *3*(3), 173–181. https://doi.org/10.1556/JBA.3.2014.018

Vainikka, B. (2015). *Psychological factors influencing consumer behaviour* (pp. 1–46). Centria University of Applied Sciences. https://doi.org/10.1109/ispsd.2003.1225237

Vaish, A., Grossmann, T., & Woodward, A. (2008). Not All Emotions Are Created

Equal: The Negativity Bias in Social-Emotional Development. *Psychological Bulletin*, *134*(3), 383–403. https://doi.org/10.1037/0033-2909.134.3.383

Van den Bos, W., Li, J., Lau, T., Maskin, E., Cohen1, J., Montague, R., & McClure, S. (2008). The value of victory: social origins of the winner’s curse incommon value auctions. *Judgement & Decision Making*, *3*(7), 483–492.

Van Humbeeck, N., Meghanathan, R. N., Wagemans, J., van Leeuwen, C., & Nikolaev, A. R. (2018). Presaccadic EEG activity predicts visual saliency in free-viewing contour integration. *Psychophysiology*, *55*(12), 1–22. https://doi.org/10.1111/psyp.13267

Vassena, E., Deraeve, J., & Alexander, W. H. (2020). Surprise, value and control in anterior cingulate cortex during speeded decision-making. *Nature Human Behaviour*, *4*(4), 412–422. https://doi.org/10.1038/s41562-019-0801-5

Veblen, T. (1899). *The Theory of the Leisure Class*. Macmillan. https://books.google.co.uk/books?id=WqVq6SDhtjQC

Ventura-Bort, C., Löw, A., Wendt, J., Dolcos, F., Hamm, A. O., & Weymar, M. (2016). When neutral turns significant: brain dynamics of rapidly formed associations between neutral stimuli and emotional contexts. *European Journal of Neuroscience*, *44*(5), 2176–2183. https://doi.org/10.1111/ejn.13319

Vickrey, W. (1961). American Finance Association Counterspeculation , Auctions , and Competitive Sealed Tenders Author (s): William Vickrey Source : The Journal of Finance , Vol . 16 , No . 1 (Mar ., 1961), pp . 8-37 Published by : Wiley for the American Finance Associat. *The Journal of Finance*, *16*(1), 8–37.

Vigârio, R., Särelä, J., Jousmäki, V., Hämäläinen, M., & Oja, E. (2000). Independent component approach to the analysis of EEG and MEG recordings. *IEEE Transactions on Biomedical Engineering*, *47*(5), 589–593. https://doi.org/10.1109/10.841330

Von Neumann, J., & Morgenstern, O. (1944). *Theory of games and economic behavior.* Princeton University Press.

Wagner, J., Solis-Escalante, T., Grieshofer, P., Neuper, C., Müller-Putz, G., & Scherer, R. (2012). Level of participation in robotic-assisted treadmill walking modulates midline sensorimotor EEG rhythms in able-bodied subjects. *NeuroImage*, *63*(3), 1203–1211.

https://doi.org/10.1016/j.neuroimage.2012.08.019

Wallis, J. D., & Miller, E. K. (2003). Neuronal activity in primate dorsolateral and orbital prefrontal cortex during performance of a reward preference task. *European Journal of Neuroscience*, *18*(7), 2069–2081. https://doi.org/10.1046/j.1460-9568.2003.02922.x

Wallis, J. D., & Rich, E. L. (2011). Challenges of interpreting frontal neurons during value-based decision-making. *Frontiers in Neuroscience*, *5*, 1–12. https://doi.org/10.3389/fnins.2011.00124

Walton, M. E., Behrens, T. E. J., Noonan, M. P., & Rushworth, M. F. S. (2011). Giving credit where credit is due: Orbitofrontal cortex and valuation in an uncertain world. *Annals of the New York Academy of Sciences*, *1239*(1), 14–24. https://doi.org/10.1111/j.1749-6632.2011.06257.x

Walton, M. E., Croxson, P. L., Behrens, T. E. J., Kennerley, S. W., & Rushworth, M. F. S. (2007). Adaptive decision making and value in the anterior cingulate cortex. *NeuroImage*, *36*(SUPPL. 2), T142–T154. https://doi.org/10.1016/j.neuroimage.2007.03.029

Wang, J., & Han, W. (2014). The impact of perceived quality on online buying decisions. *NeuroReport*, *25*(14), 1091–1098. https://doi.org/10.1097/WNR.0000000000000233

Wang, L., Kuroiwa, Y., Kamitani, T., Takahashi, T., Suzuki, Y., & Hasegawa, O. (1999). Effect of interstimulus interval on visual P300 in Parkinson's disease. *Journal of Neurology Neurosurgery and Psychiatry*, *67*(4), 497–503. https://doi.org/10.1136/jnnp.67.4.497

Wang, X., Huang, Y., Ma, Q., & Li, N. (2012). Event-related potential P2 correlates of implicit aesthetic experience. *NeuroReport*, *23*(14), 862–866. https://doi.org/10.1097/WNR.0b013e3283587161

Wascher, E., Heppner, H., & Hoffmann, S. (2014). Towards the measurement of event-related EEG activity in real-life working environments. *International Journal of Psychophysiology*, *91*(1), 3–9. https://doi.org/10.1016/j.ijpsycho.2013.10.006

Wenzel, M. A., Golenia, J. E., & Blankertz, B. (2016). Classification of eye fixation related potentials for variable stimulus saliency. *Frontiers in Neuroscience*, *10*(FEB), 1–14. https://doi.org/10.3389/fnins.2016.00023

Wertenbroch, K., & Skiera, B. (2002). Measuring consumers’ willingness to pay at the point of purchase. *Journal of Marketing Research*, *39*(2), 228–241. https://doi.org/10.1509/jmkr.39.2.228.19086

Wessel, J. R. (2012). Error awareness and the error-related negativity: Evaluating the first decade of evidence. *Frontiers in Human Neuroscience*, *6*, 1–16. https://doi.org/10.3389/fnhum.2012.00088

Westbrook, A., Lamichhane, B., & Braver, T. (2019). The subjective value of cognitive effort is encoded by a domain-general valuation network. *Journal of Neuroscience, 39*(20), 3934–3947. https://doi.org/10.1523/JNEUROSCI.3071-18.2019

Wilkinson, N., & Klaes, M. (2012). An Introduction to Behavioral Economics. In *Basingstoke, GB: Palgrave Macmillan*. https://doi.org/10.1037/026600

Williams, L. M., Palmer, D., Liddell, B. J., Song, L., & Gordon, E. (2006). The “when” and “where” of perceiving signals of threat versus non-threat. *NeuroImage, 31*(1), 458–467. https://doi.org/10.1016/j.neuroimage.2005.12.009

Woodman, G. F. (2010). A brief introduction to the use of event-related potentials (ERPs) in studies of perception and attention. *Attention and Perceptual Psychophysiology, 72*(8), 1–29. https://doi.org/10.3758/APP.72.8.2031

Wright, N. D., Morris, L. S., Guitart-Masip, M., & Dolan, R. J. (2013). Manipulating the contribution of approach-avoidance to the perturbation of economic choice by valence. *Frontiers in Neuroscience, 7,* 1–8. https://doi.org/10.3389/fnins.2013.00228

Wu, Y., & Zhou, X. (2009). The P300 and reward valence, magnitude, and expectancy in outcome evaluation. *Brain Research, 1286*, 114–122. https://doi.org/10.1016/j.brainres.2009.06.032

Xie, J., & Padoa-Schioppa, C. (2016). Neuronal remapping and circuit persistence in economic decisions. *Nature Neuroscience, 19*(6). https://doi.org/10.1038/nn.4300

Xu, Q., Shen, Q., Chen, P., Ma, Q., Sun, D., & Pan, Y. (2011). How an uncertain cue modulates subsequent monetary outcome evaluation: An ERP study. *Neuroscience Letters*, *505*(2), 200–204.

https://doi.org/10.1016/j.neulet.2011.10.024

Yagi, A. (1979a). Lambda waves associated with offset of saccades: A subject with large lambda waves. *Biological Psychology*, *8*(3), 235–238. https://doi.org/10.1016/0301-0511(79)90051-6

Yagi, A. (1979b). Saccade size and lambda complex in man. *Physiological Psychology*, *7*(4), 370–376. https://doi.org/10.3758/BF03326658

Yagi, A. (1981a). Averaged cortical potentials (lambda responses) time-locked to onset an offset of saccades. *Physiological Psychology*, *9*(3), 318–320. https://doi.org/10.3758/BF03326985

Yagi, A. (1981b). Visual signal detection and lambda responses. *Electroencephalography and Clinical Neurophysiology*, *52*(6), 604–610. https://doi.org/10.1016/0013-4694(81)91434-6

Yalch, R., & Brunel, F. (1996). Need Hierarchies in Consumer Judgments of Product Designs: Is It Time to Reconsider Maslow’s Theory? In K. P. Corfman & J. G. Lynch (Eds.), *NA - Advances in Consumer Research Volume 23* (pp. 405-410.). Association for Consumer Research.

Yao, D., Qin, Y., Hu, S., Dong, L., Bringas Vega, M. L., & Valdés Sosa, P. A. (2019). Which Reference Should We Use for EEG and ERP practice? *Brain Topography*, *32*(4), 530–549. https://doi.org/10.1007/s10548-019-00707-x

Yeung, N., & Sanfey, A. (2004). Independent Coding of Reward Magnitude and Valence in the Human Brain. *Journal of Neuroscience*, *24*(28), 6258–6264. https://doi.org/10.1523/JNEUROSCI.4537-03.2004

Yiend, J. (2010). The effects of emotion on attention: A review of attentional processing of emotional information. *Cognition and Emotion*, *24*(1), 3–47. https://doi.org/10.1080/02699930903205698

Yuan, J., Ju, E., Meng, X., Chen, X., Zhu, S., Yang, J., & Li, H. (2015). Enhanced brain susceptibility to negative stimuli in adolescents: ERP evidences. *Frontiers in Behavioral Neuroscience*, *9*, 1–13. https://doi.org/10.3389/fnbeh.2015.00098

Zamm, A., Palmer, C., Bauer, A. K. R., Bleichner, M. G., Demos, A. P., & Debener, S. (2019). Synchronizing MIDI and wireless EEG measurements during natural piano performance. *Brain Research*, *1716*, 27–38. https://doi.org/10.1016/j.brainres.2017.07.001

Zander, T. O., Andreessen, L. M., Berg, A., Bleuel, M., Pawlitzki, J., Zawallich, L., Krol, L. R., & Gramann, K. (2017). Evaluation of a dry EEG system for application of passive brain-computer interfaces in autonomous driving. *Frontiers in Human Neuroscience*, *11*, 1–16. https://doi.org/10.3389/fnhum.2017.00078

Zeeman, E. (1976). Catastrophe theory. *Scientiific American*, *31*(9), 65–83. https://doi.org/10.1063/1.2995174

Zeng, J., Zou, Y., & Zhang, Q. (2013). Social competition factor influences the neural response to rewards: An ERP study. *Brain Research*, *1501*, 12–20. https://doi.org/10.1016/j.brainres.2013.01.030

Zha, H., Ding, C., Gu, M., He, X., & Simon, H. (2001). Spectral relaxation for k-means clustering. *Advances in Neural Information Processing Systems*, *14*, 1057–1064. papers2://publication/uuid/16FFAB42-9D62-4F7D-889E-9A63C19B5A10

Zhuang, G., Tsang, A. S. L., Zhou, N., Li, F., & Nicholls, J. A. F. (2006). Impacts of situational factors on buying decisions in shopping malls: An empirical study with multinational data. *European Journal of Marketing*, *40*(1–2), 17–43. https://doi.org/10.1108/03090560610637293

Zink, R., Hunyadi, B., Huffel, S. Van, & Vos, M. De. (2016). Mobile EEG on the bike: Disentangling attentional and physical contributions to auditory attention tasks. *Journal of Neural Engineering*, *13*(4). https://doi.org/10.1088/1741-2560/13/4/046017