Electrocortical Correlates of Value-Based Decisions

Thesis submitted in accordance with the requirements of the University of Liverpool for the degree of Doctor in Philosophy by John Tyson-Carr

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Frequent Abbreviations

AIC	Anterior Insula Cortex
BOLD	Blood-Oxygen-Level-Dependent
CLARA	Classical LORETA Recursively Applied
ECD	Equivalent Current Dipole
EEG	Electroencephalography
EFRP	Eye-Fixation Related Potentials
ERN	Event Related Negativity
ERP	Event-Related Potential
fMRI	Functional Magnetic Resonance Imaging
FRN	Feedback Related Negativity
I2MC	Identification by Two-Means Clustering
IC	Independent Component
ICA	Independent Component Analysis
I-DT	Identification by Dispersion-Threshold
LG	Lingual Gyrus
LORETA	Low Resolution Electromagnetic Tomography
LPP	Late Positive Potential
MEG	Magnetoencephalography
OFC	Orbitofrontal Cortex
PCC	Posterior Cingulate Cortex
PFC	Prefrontal Cortex
PHG	Parahippocampal Gyrus
SD	Standard Deviation
vmPFC	Ventromedial Prefrontal Cortex
VS	Ventral Striatum

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Declaration

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Abstract

Choice behaviour is characterised by a calculation of subjective value of all choice options followed by the selection of the most subjectively valuable option. Neuroeconomics was developed to unify the fields of economics, psychology and neuroscience to describe neurobiological processes underpinning observed preferences. However, many aspects of the neural computations required to compute subjective value are yet to be illuminated. The current thesis aimed to describe the spatiotemporal dynamics of subjective valuation within the context of an auction paradigm.

Brain processes related to subjective valuation were investigated using the incentive compatible Becker-DeGroot-Marschak auction task, revealing willingness-to-pay values for a variety of stimuli. Brain responses in response to stimulus onset and eye-fixations were extracted to highlight the electrophysiological response during value-based decisions, revealing the temporal evolution of brain processes on a scale of milliseconds. Analyses were accompanied by source dipole localisation methods to identify possible neural generators of observed responses.

Data from four experimental chapters implicated the automatic encoding of various magnitudes of subjective willingness-to-pay within multiple cortical activation patterns during value-relevant and value-irrelevant contexts. Low value items were encoded most prominently by a brain activation component represented over the right frontal scalp region, possibly originating from the insula. In contrast, a cortical activation pattern with a spatial maximum over the left hemisphere was strongest for high value items. Brain components specific to value were present immediately following stimulus presentation and persisted throughout an extended time interval during free viewing. Further to this, value encoding brain responses were observed for both products and product bundles.

The current thesis demonstrated the explicit representation of willingness-to-pay within neural activity recorded by means of EEG. Moreover, low and high subjective value was encoded by separate and lateralised brain responses in a coarse manner, in contrast to the linear encoding of subjective value within a single brain response. The early representation of value within EEG signals, prior to conscious deliberation, reiterates the automaticity of the initial valuation process.

Chapter 1

1.1. Introduction

A large proportion of human behaviour is characterised by higher-order decision making processes, requiring individuals to make the most subjectively useful option when presented with a variety of alternatives (Rangel, Camerer, & Montague, 2008). Over several decades, many theories have been put forward to explain choice behaviour, with each new theory accounting for scenarios not explainable by its predecessor (Glimcher & Fehr, 2014). Expected utility theory (von Neumann & Morgenstern, 1944) posited that adherence to their axiomatic principles meant that an individual behaves as if they are aiming to maximise some underlying utility function. Later, prospect theory (Kahneman & Tversky, 1979) superseded expected utility theory, emphasising the variety of scenarios not explainable by expected utility theory. First and foremost, prospect theory highlighted the influence of framing on choice behaviour, in that the way in which information is presented to an individual often influences the choice they make.

The relatively new field of neuroeconomics is concerned with describing the underlying neural computations governing value-based decision making (Rangel et al., 2008). Neuroeconomics utilises the wealth of experimental paradigms from economic research, the psychological theories of choice processes, the methods for investigating brain processes from neuroscience, and the computational models from the field of computer science that can describe decision making. Neuroeconomics has produced a wealth of research highlighting how individuals make choices and the neural systems governing them, frequently through the use of auction tasks to elicit subjective valuations within brain imaging contexts (Peters & Büchel, 2010).

From a marketing perspective, organisations are becoming increasingly sceptical in the use of self-report for revealing individuals' opinions of their products. The affect that individuals experience when presented with a stimulus is difficult to measure using self-report methods due to its complexity (Davidson, 2004). Additionally, subjects are more likely to give socially acceptable answers (Nighswonger & Martin, 1981). Hence, research has aimed to utilise neuroscientific

methods to learn about preferences, since neural responses are not influenced by subsequent willingness to disclose (Ohme, Reykowska, Wiener, & Choromanska, 2010). Although the description of a brain valuation system is of great relevance to researchers in the field of neuromarketing (Hakim & Levy, 2019), a dysfunctional reward system and an altered ability to evaluate stimuli being prevalent across several medical disorders gives decision making a clinical relevance. For example, reward dysfunctions resulting in impulsive choices are frequently expressed in those suffering from attention-deficit hyperactivity disorder (Stoy et al., 2011). Similarly, reductions in ventral striatal volume, a primary component of the brain valuation system (Bartra, McGuire, & Kable, 2013; Clithero & Rangel, 2014), were found in those suffering from attention-deficit hyperactivity disorder (Carmona et al., 2009), which was also independent of attentional processes (Scheres, Lee, & Sumiya, 2008).

Neuroeconomic research primarily utilises fMRI methods in the aim of revealing the brain processes utilised in economic decision-making tasks, highlighting the importance of the ventromedial prefrontal cortex, ventral striatum and the posterior cingulate cortex (Bartra et al., 2013; Clithero & Rangel, 2014). However, the use of electrophysiological methods allows the investigation of neural processes on a very fine time scale of milliseconds. In doing so, it is possible to observe the engagement of brain processes very early on in information processing during the interval immediately following stimulus presentation, although research utilising electroencephalography (EEG) is sparse. Thus, the current thesis aims to capitalise on the excellent temporal resolution of EEG methods to further understand the temporal characteristics of value-based decision making in the brain. Additionally, through the utilisation of modern source dipole analysis methods, the extent to which brain processes are engaged at distinct time intervals will be investigated.

1.2. Value in Economic Theory

1.2.1. Auction theory

Auction tasks are commonplace in modern society. Practically speaking, commercial organisations utilise auctions to sell a wide variety of commodities, and

government agencies frequently use auctions to assign government contracts, or for the privatisation of government firms (Klemperer, 2004). The popularity of eBay, and other internet auction websites offering similar services, demonstrate the prevalence of auctions in our day-to-day life. Importantly, auction tasks offer an incredibly simple tool for testing economic theories. The ability for auction tasks to elicit subjective valuations makes them a valuable instrument in the investigation of human decision-making processes, giving auctions huge empirical implications.

Various auction forms have been put forward and built upon, each having its own theoretical foundation governing optimal bidding mechanisms. The oldest and most prevalent auction form is an English auction (McCabe, Rassenti, & Smith, 1990). Here, a low price is raised incrementally until only a single bidder is interested in purchasing the item being auctioned. At this point, the final bidder purchases the item for a price equal to the increment at which the second-to-last bidder dropped out. In contrast, a Dutch auction is the descending price complement of the English auction (Li, Yue, & Kuo, 2018). Typically, a price is called out that is much higher than what anyone should be willing-to-pay for the item. The price is then subsequently lowered in small increments until someone is interested in making the purchase, at which point this bidder purchases the item for the given price. Other common auctions come in the form of sealed-bid designs (Coppinger, Smith, & Titus, 1980). In sealed-bid designs, a single bid is put forward by each bidder interested in making a purchase. In first-price auctions, the highest bidder wins the auction and pays a price equal to their bid. In second-price auctions, the highest bidder wins, but pays a price equal to the second-highest bid. The second-price sealed bid auction was first discussed formally by Vickrey (1961) and is therefore often referred to as the Vickrey auction. Similar to the Vickrey auction, we also have the Becker-DeGroot-Marschak (BDM) auction mechanism (Becker, Degroot, & Marschak, 1964). However, rather than having a sale price based on the bids submitted for the object, as is the case for the Vickrey auction, the sale price is drawn randomly from a distribution of prices encompassing the entire range of values that are expected to be put forward. In the BDM mechanism, all bidders who bid greater than (or equal to) the randomly selected value will receive the object being auctioned and pay a price equal to this value.

Although auctions can vary in their format, they all have one thing in common. That is, they are used by a seller to reveal willingness-to-pay (WTP) for the object being sold when the seller is not aware of the prices that bidders attach to the object, WTP being defined as the maximum amount of resources an individual is willing to give up in order to obtain an object (Noussair, Ruffieux, & Robin, 2004). This uncertainty regarding subjective valuations, for sellers and bidders alike, is an intrinsic feature of auction tasks. In situations wherein the subjective value of an object is known to the bidder, which is usually the case when it is valued based on its consumption or use by the bidder alone, this is known as a situation of privately known values. In theory, these situations imply that knowledge of the valuations that other bidders maintain would have no bearing on the personal valuation, since values are assigned for personal use. However, it is often the case that valuations are made based on several other assumptions. For example, if a bidder intends to resell an object upon winning an auction, then the valuations made are now dependent on predictions of valuations that other bidders would make.

The various auction formats also give rise to different bidding strategies (Klemperer, 2004). However, many of the differences between auctions are only superficial when it comes to defining strategies, and therefore, these strategies can overlap. For example, the Dutch auction is strategically equivalent to the first price sealed-bid auction (McCabe et al., 1990). Since these two auction types do not provide any feedback to bidders regarding the valuations that other bidders have made, the only option is to show interest at your own subjective valuation in a Dutch auction, providing the object is still available, or to submit your own subjective valuation in a first-price sealed-bid auction. Similarly, bidding strategies overlap between the English auction and the Vickrey auction, but only if the assumption of private values holds. In an English auction, it is clearly not beneficially to show interest after your own subjective valuation has been exceeded since it will only result in a loss, just as submitting a bid larger than your subjective valuation in a Vickrey auction would likely result in a loss. However, the feedback obtained in an English auction in the form of other bidder's behaviour may influence your own valuations if the assumption of private values is not held, in that your perceptions of the value of the object may be influenced by observing the behaviour of other

bidders. Therefore, the English auction and Vickrey are not strategically equivalent if there is inter-dependency of valuation between bidders (Klemperer, 2004).

Experimental economics primarily utilise the Vickrey and the BDM auction mechanisms to reveal WTP for goods and prospects (Noussair et al., 2004). Second price sealed-bid auction tasks such as the Vickrey auction, and other sealed-bid auction paradigms such as the BDM auction, by design, aim to reveal the true value that bidders assign to an object, and the optimal strategy should be to submit your exact WTP. In second-price auction designs, a winning bidder will always get the object for either their bid or less, but never more. Overbidding is obviously counter-productive since overbidding produces a chance of paying a price that exceeds the objects true subjective value. However, underbidding not only produces the possibility of missing out on a purchase at a price equal to its true subjective value, it also results in a chance of missing out on purchasing an object for less than its true value. Despite this, over and underbidding is frequently observed (Georganas, Levin, & McGee, 2017).

The irrational decision maker is often blamed as being the cause of bids that deviate from the true value of the object to the bidder (Kaas & Ruprecht, 2006). Note that rationality in the economic sense refers to an individual holding consistent preferences (Glimcher & Fehr, 2014). Although it is tempting to categorize individuals who violate the optimal strategy as being irrational, these decisions may not necessarily be a result of irrationality. Plott and Zeiler (2005) discussed the role of subject misconceptions in eliciting behaviour not in alignment with optimal decision making, utilising the commonly observed disparity between WTP and willingness-to-accept (WTA; Tunçel & Hammitt, 2014). WTA is the value that an individual is willing to sell something for and it should theoretically be similar to WTP for the same item (Yao-ji, Qian, & Cai-mei, 2007). The endowment effect, which is the tendency for an individual to value something more when it is in their possession in comparison to when valuing it to make a purchase (Thaler, 1980), has been put forward as a possible explanation for the WTP-WTA disparity in previous studies. In contrast, Plott and Zeiler (2005) argue that the WTP-WTA discrepancy is not a reflection of subjective preferences and theory underpinning the endowment effect does not explain these observed discrepancies. Rather, misconceptions that subjects hold regarding preference revealing tasks can account for violations of

optimal decision making (Cason & Plott, 2014; Chou, McConnell, Nagel, & Plott, 2008). For example, Plott and Zeiler (2005) conjecture that ill-conceived motivations to report a value other than their true subjective valuation may result from a lack of understanding of the task at hand. Critically, when these motivations are controlled for via procedural measures, WTP-WTA gaps are not observed. These procedures include providing training regarding the rules of the mechanism being used, allowing practice rounds to be carried out, provide anonymity in decisions so that bidders are not influenced by how others perceive them, and finally, utilising incentive-compatible measures such as the BDM mechanism.

For the purpose of empirical testing, measures revealing subjective value need to be incentive compatible, in that the dominant strategy reveals truthful valuations (Plott & Zeiler, 2005). Both the Vickrey auction and BDM auction mechanisms are frequently described as being incentive compatible (Kahneman, Knetsch, & Thaler, 1990; Rutstrom, 1998; Shogren et al., 2001), though this assumption has been questioned (Horowitz, 2006; Karni & Safra, 1987). For instance, Karni and Safra (1987) described how the BDM mechanism is not incentive compatible during the valuation of lotteries, i.e. for uncertain outcomes. Additionally, Horowitz (2006) suggested that this non-incentive compatibility also extends to non-random goods in context of both the BDM and Vickrey auction mechanisms, reasoning that since the price to be paid following an auction is random, a bid is likely to be influenced by the distribution of prices. Thus, the dominant strategy is no longer to bid their true valuation. Kaas and Ruprecht (2006) indeed highlighted how the optimal bidding strategy for risk-averse but rational bidders is to underestimate their WTP, possibly explaining underbidding in certain scenarios. Importantly, Horowitz (2006) explained that further research is needed to confirm the extent to which this compromised incentive compatibility can influence observed effects.

1.2.2. Prospect theory

Until 1979, the expected utility theory, originally described by von Neumann and Morgenstern (1944), dominated research of decision making under risk. Prior to the development of this theory, models explaining economic decisions could not account for probabilistic choices, such as is the case when decisions involve lottery

tickets with a limited chance of obtaining a gain or loss (Glimcher & Fehr, 2014). The expected utility theory implemented three principles to explain choice under uncertainty. Firstly, they defined the concept of “lotteries” as an outcome defined by a probability and a value, for example, a 25% chance of gaining £5. Secondly, the model implied the presence of an underlying continuous utility function whereby two choices in a lottery will have equal subjective value with specific gain probabilities. Lastly, the concept of independence was described. This states that if an individual is indifferent between two lotteries, then this indifference should extend beyond the context and indifference should be observed when the lotteries are placed within different lotteries indicating the same outcome. Put simply, the model implies that subjective utility is obtained by multiplying probability by the utility of the outcome (Glimcher & Fehr, 2014).

Prospect theory was developed to explain choice behaviour that cannot be explained by expected utility theory. Developed in 1979 by Kahneman and Tversky (1979), and expanded on in 1992 (Tversky & Kahneman, 1992), prospect theory proposes a utility function that is concave for gains, convex for losses, and steeper for losses than for gains. Here, individuals frame gains and losses relative to a reference point, indicative of their current wealth level. The shape of the utility function described results in increased sensitivity to losses than for gains of an equal amount, resulting in loss-aversion. Additionally, individuals tend to be risk-seeking when dealing with perceived losses, and risk-averse when dealing with perceived gains (Grinblatt & Han, 2005). Loss-aversion invokes that preferences are impacted much more by losses and disadvantages than they are to gains and disadvantages of an equal amount (Kahneman & Tversky, 1984; Tversky & Kahneman, 1991). The utility function described by Kahneman and Tversky (1979) is summarised in Figure 1.1. This utility function is concave in the gains region but convex in the loss region, highlighting the increased sensitivity to losses. This effect, known as loss aversion, has been observed across many fields, including within stock trading (Haigh & List, 2005), politics (Mercer, 2005), organ donation rates (Johnson & Goldstein, 2003) and also within animal studies (Chen, Lakshminarayanan, & Santos, 2006). Interestingly, loss aversion has been observed when individuals missed out on options that they deliberated over, but never actually obtained them in the first place (Carmon, Wertenbroch, & Zeelenberg, 2003).

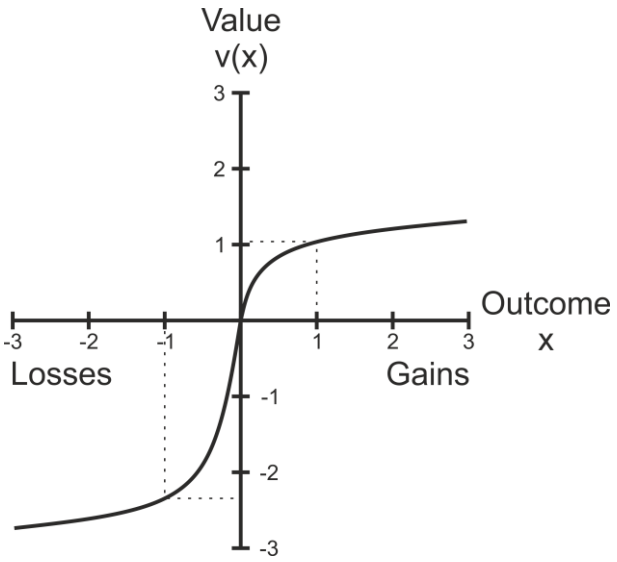

Figure 1.1. Utility function described by prospect theory, adapted from Kahneman and Tversky (1979). The dotted lines illustrate how losses have a much larger impact on perceived value than gains of an equal amount, an effect known as loss aversion.

Prospect theory describes choices as a two-phase process – editing and evaluation. During the editing phase, a preliminary analysis takes place that aims to simplify the prospects which will facilitate the decision-making process (Wilkinson & Klaes, 2012). Multiple operations can be applied here to create a representation that will be passed onto the next phase. For example, different prospects with common outcomes are combined, sure outcomes are segregated from prospects, shared components between prospects are cancelled out, prospects are simplified, and irrelevant prospects are rejected (Glimcher & Fehr, 2014). The second phase is the evaluation phase whereby all prospects are evaluated and the prospect offering the highest value is assumed to be selected.

1.2.3. Framing and editing

The limited capacity for a decision maker to process information has long been established, and this limited capacity can be detrimental to the quality of the decision made (Boettcher, 2004; Simon, 1956). However, the presence of complete information can lead to optimal decision making (Edwards, 1954). Framing refers to how inconsistent preferences are shown when identical information, either positive or negative, is displayed in different ways (Tversky & Kahneman, 1981). Framing effects have been across fields such as politics (Bizer, Larsen, & Petty, 2011),

healthcare (Gallagher & Updegraff, 2012; Krishnamurthy, Carter, & Blair, 2001; Meyerowitz & Chaiken, 1987; Peters, Hart, & Fraenkel, 2011; Van 't Riet, Ruiter, Werrij, & De Vries, 2010) and marketing (Chen et al., 2006; Gamliel & Herstein, 2012; Ganzach & Karsahi, 1995; McKechnie, Devlin, Ennew, & Smith, 2012; Raghubir, 2005; Wu & Cheng, 2011; Zhang & Han, 2012). A central principle of game theory is the invariance of choices regardless of the way in which the options are presented (von Neumann & Morgenstern, 1944), though this is challenged empirically (Kahneman & Tversky, 1984). Framing effects are a key component of prospect theory, explaining deviations from rationality as being most likely due to the simplification of the decision at hand to account for incomplete information (Kahneman & Tversky, 1979). Further work has suggested the potential impact of the emotional system on decision making processes. For example, De Martino, Kumaran, Seymour, and Dolan (2006) revealed how framing effects may be underpinned by the incorporation of emotional information into the decision-making process, reflected by increased amygdala activity and its integration in the prefrontal cortices. Additionally, a study by Sokol-Hessner et al. (2009) linked emotion to decision-making processes by way of emphasising the relationship between affective physiological responses, such as skin-conductance, and magnitude of loss outcomes.

As previously mentioned, Kahneman and Tversky (1979) described choice behaviour as a two-stage process comprised of editing and evaluation. However, how an option is framed is a way of influencing the representation that individuals form before any processing has taken place. Although framing undoubtedly influences perceptions, there is debate as to whether positive or negative framing is more successful in introducing cognitive bias. A study by Wu and Cheng (2011) found that framing product attributes positively produced more favourable responses in contrast to negative frames. However, prospect theory makes interesting predictions regarding how savings should be framed when a price reduction is presented. For example, Gamliel and Herstein (2012) found that presenting a deal framed in terms of potential losses increased purchase intent more so than when presented relative to its potential gains. This may stem from the increased sensitivity to losses, i.e. loss aversion, that prospect theory poses individuals have. Similarly, Ganzach and Karsahi (1995) found that framing messages in terms of potential

losses increased credit card use in contrast to messages that highlighted the benefits of using a credit card.

There are also scenarios wherein negative framing is more beneficial for introducing attitude change, most prolifically in healthcare. Meyerowitz and Chaiken (1987) revealed that pamphlets framing the importance of breast self-examination in terms of the potential losses had a much larger impact on attitudes and behaviours. However, a meta-analysis by Gallagher and Updegraff (2012) found that framing messages relative to the potential gains was more beneficial to encourage preventative behaviours regarding healthcare than framing them relative to losses. Finally, Shiv, Edell Britton, and Payne (2004) reported that the extent to which positive and negative framing influences attitudes depends on motivation. When motivation is high, negative framing is more effective than positive, when opportunity for processing is either high or low. When motivation is low, negative framing is more effective when processing opportunity is low, but less effective when processing opportunity is high.

For marketing, another important factor to consider is whether discounts should be framed in absolute or relative amounts (McKechnie et al., 2012). Chen, Monroe, and Lou (1998) found that indicating absolute monetary discount was perceived as being much more significant for high value products, whereas percentage discounts were perceived as more significant for low value products. This finding is reiterated by Zhang and Han (2012) who observed higher coupon redemption rate for products of a high value when coupons indicated absolute discounts.

In line with the limited cognitive resources for processing framed information (Boettcher, 2004; Simon, 1956), there are also methods for counteracting this induced cognitive bias. Framing effects are diminished when weak warning signals are given during a product valuation task and eliminated when strong warnings are given (Cheng & Wu, 2010). Additionally, this research found that these effects were dependent on the level of involvement of the subject. Weak warnings did not deter those who were less involved, whereas weak and strong warnings deterred those who were highly involved in the task. A second study elaborated on this “debiasing” effect using “elaboration” and “consider the opposite”, demonstrating that

encouraging subjects to take time to consider the decision can remove framing effects (Cheng, Wu, & Lin, 2014).

1.2.4. Bundle valuation

Price bundling is a popular marketing strategy employed by organisations involving the combination of multiple products for a set price (Johnson, Herrmann, & Bauer, 1999). Price bundling is a strategy designed to benefit prospective buyers, in that it reduces transaction costs through the pairing of complementary products, as well as benefiting the seller through the reduction of their own transaction costs (Dansby & Conrad, 1984). Multiple pricing strategies are utilised in the field of bundle pricing to facilitate purchase intent (Olderog & Skiera, 2000). The simplest strategy is pure bundling in which products can be sold together for a single, consolidated price. Other strategies, described as mixed bundling, involve providing the opportunity to purchase two or more products together as a bundle or separately if desired. The inclusion of multiple products introduces an important dimension to the decision-making process. As posed by prospect theory (Kahneman & Tversky, 1979), the integration of losses should be perceived as more beneficial than the segregation of losses. Therefore, the inclusion of multiple products into a singly priced option will integrate the individual losses from purchasing each product within the bundle separately. A discount is often offered if the product bundle is purchased rather than the products individually, although this discount is not a necessary precursor (Simon & Fassnacht, 1993). For example, products within a bundle may offer little benefit if owned individually, yet they may offer benefit if used in conjunction. In turn, subsequent valuations of a bundle may be larger than the sum of the individual product valuations.

An important decision for organisations is to decide what products to bundle together for marketing. A wealth of research has revealed that products within a bundle should be complementary, in that the function of either product is facilitated by the other. Guiltinan (1987) poses that bundle valuations are enhanced in contrast to the individual products due to decreased effort from obtaining the products separately, enhanced customer satisfaction from obtaining products that enhance each other, or the enhancement of the image of obtaining all the products. This is in

contrast to bundles comprised of substitute products, i.e. two or more products performing the same function. In this scenario, bundle valuations may fall short of the sum of the individual valuations for each product due to overlapping benefits, an effect referred to as sub-additivity. Yan and Bandyopadhyay (2011) proposed a framework for bundle pricing and reported that increased product complementarity was always beneficial to the marketer, especially when the magnitude of a discount was larger. Empirical research of the influence of product complementarity was reported by Sheng, Parker, and Nakamoto (2014) who revealed that high product complementarity paired with small price discounts produced the greatest perception of quality.

Price framing also extends to product bundling strategies wherein two or more products are sold in conjunction. When using mixed bundling, there are tactics that organisations use to improve perceptions of the deal at hand. For example, they may wish to offer a main product at a given price and offer a discounted price for a second, tie-in product. Additionally, they may wish to simply provide a second, tie-in product for free if the main product is purchased (Hüttel, Schumann, Mende, Scott, & Wagner, 2018; Shampanier, Mazar, & Ariely, 2007). Another method used infrequently is offering a second, tie-in product for a token price such as £0.01, but only if the main product is purchased (Mao, 2016). Research has aimed to reveal the impact that these strategies can have on a consumers' perceptions of the deal presented to them. A study by Harlam, Krishna, Lehmann, and Mela (1995) revealed increased purchase intent when a single consolidated price is given for two products in comparison to the zero-pricing and discounted tie-in product strategy. Note here that each strategy was equal in cost to the consumer, but the framing of the message to the consumer is what influences subsequent cognitive bias. However, presenting products for free in a bundle can decrease subjective valuations for that product when presented individually (Raghubir, 2005).

1.3. The Decision-Making Process

The decision-making process is dynamic, involving the accumulation of evidence over time until the individual is ready to declare a choice. The decision-maker may consider the consequences of each action they can take, driven by shifts

of attention between each option (Busemeyer & Johnson, 2004). Rangel et al. (2008) presented a framework to help study the neurobiology of decision-making and to unify the multiple disciplines that neuroeconomics employs (see Figure 1.2). This framework describes the discrete phases that each decision goes through, from the initial representation formation to the evaluation of the outcome, and any subsequent learning that takes place as a result of the outcome.

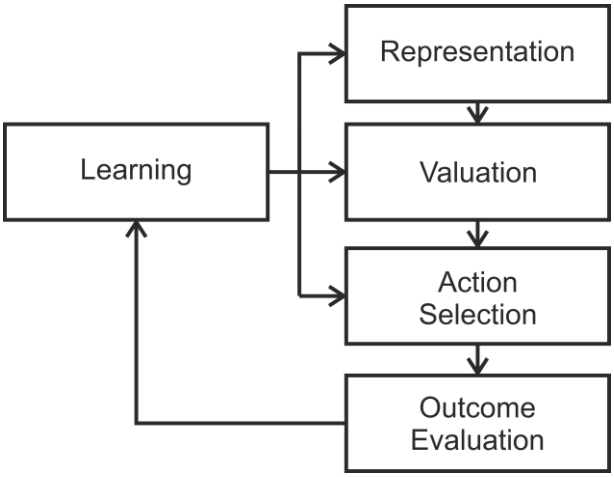

Figure 1.2. Framework for studying the neurobiology of decision making, adapted from (Rangel et al., 2008).

According to the decision-making framework (Rangel et al., 2008), the first stage of any decision involves forming an initial representation of the available options. It is here that we identify possible courses of action and evaluate internal and external factors that will inform the assignment of subjective values later in the process. As mentioned previously, the way in which the information is framed may be an influence at this stage (Glimcher & Fehr, 2014). The second and most critical stage is the valuation stage. This stage refers to the ability of the decision maker to assign a subjective value to each available option. Rangel et al. (2008) describe three hypothetical systems, each system assigning value to options based on their function. Firstly, a Pavlovian system that assigns value to evolutionarily relevant actions such as approach and avoidance behaviours regarding the consumption of food (Balleine, Daw, & O'Doherty, 2009). Secondly, a habit system that assigns values based on previous experience, such as waking up and automatically having a cup of coffee (Balleine et al., 2009).Thirdly, a goal-directed system that assigns value based on action-outcome associations that are updated as a result of outcome

evaluation (Balleine et al., 2009). This valuation stage is strongly modulated by other factors such as temporal discounting (Ballard & Knutson, 2009) and risk and uncertainty (Trepel, Fox, & Poldrack, 2005). The third stage outlined by Rangel et al. (2008) is the action selection stage. Here, individuals need to compare the subjective values that are assigned to each option and select the most subjectively useful option. The fourth stage includes the evaluation of the outcome whereby we evaluate the experienced utility of receiving the outcome and assign values to the actions that we selected. In the final stage of the process, we must feedback the information regarding outcome evaluation into the preceding representation, valuation and action selection stages to inform future decisions. The formalisation of the decision-making process in these five stages allows researchers to focus on understanding each of the computations we must complete in order to reach a decision, as well as how future decisions are informed regarding past experience.

1.4. Neuroeconomics

Neuroeconomics is a relatively new field of study, emerging only in recent decades, that aims to discover the origins of preferences and their calculation within the brain (Glimcher, 2003, 2011). Over decades, research regarding choice behaviour was dominated by economic theories, beginning with the work of von Neumann and Morgenstern (1944), and culminating in prospect theory (Kahneman & Tversky, 1979), and eventually cumulative prospect theory (Tversky & Kahneman, 1992). Regardless of the description, all theories aimed to describe an underlying value function that could summarise an individuals' tendency to maximise subjective utility.

With the advent of modern brain imaging techniques such as functional magnetic resonance imaging (fMRI), it followed that researchers were interested in revealing the underlying biology that could represent theories of choice, if they existed. Essentially, the field of neuroeconomics was born from the desire to understand the neural structures that underpinned choice behaviour (Bossaerts & Murawski, 2015). The aim of neuroeconomic research is summarised concisely by Fehr and Rangel (2011), with the authors stating that neuroeconomics is interested in describing the variables that the brain computes to make decisions, how neural

structures implement these computations, and the implications of this knowledge in real world contexts. Research has been very successful in this endeavour, highlighting a brain valuation system that may represent what we know to be subjective utility (Bartra et al., 2013; Clithero & Rangel, 2014). Other work has described the possible neural substrate of loss aversion (Canessa et al., 2017; Canessa et al., 2013; De Martino, Camerer, & Adolphs, 2010; Kokmotou et al., 2017; Sokol-Hessner, Camerer, & Phelps, 2013; Tom, Fox, Trepel, & Poldrack, 2007), risk and uncertainty (Hsu, Bhatt, Adolphs, Tranel, & Camerer, 2005; Mohr, Biele, & Heekeren, 2010; Singer, Critchley, & Preuschoff, 2009; Trepel et al., 2005), intertemporal choice (Albrecht, Volz, Sutter, Laibson, & Von Cramon, 2011; Kable & Glimcher, 2007; Kalenscher & Pennartz, 2008; McClure, 2004) and social preferences (Baumgartner, Götte, Gügler, & Fehr, 2012; Fehr & Camerer, 2007; Hare, Camerer, Knoepfle, O'Doherty, & Rangel, 2010).

Although the decision-making process is complicated, involving the discrete stages of valuation, action selection and feedback loops to update future decision making (Rangel et al., 2008), studying choice behaviour can be reduced down and research can be carried out on simple choices, involving the choice between a small number of goods with no informational asymmetries or considerations of optimal strategies (Fehr & Rangel, 2011). Fehr and Rangel (2011) also described a computational model that the neuroeconomic literature is outlining, whereby choices are made by computing and comparing a series of decision and outcome values to maximize experienced utility. Firstly, the model posits that the brain computes a "decision value" signal for each of the available options at the onset of the decision which forecasts the utility of selecting each option. Secondly, the brain must compute the experienced utility when the option selected is obtained. Importantly, this allows for feedback to be obtained to inform future choices. Thirdly, decisions are reached by comparing decision values as is described by models which are referred to as drift-diffusion models. Drift-diffusion models posit that choices are made via a noisy accumulation of evidence until a decision threshold is reached and a choice is made (Krajbich, Armel, & Rangel, 2010; Krajbich, Lu, Camerer, & Rangel, 2012; Krajbich & Rangel, 2011). Next, the model suggests that information is integrated regarding option attributes and their corresponding attractiveness in order to decide the decision value. Lastly, attention modulates the computation and comparison of

decision values, either by giving a different weighting to attributes of the options when deciding the decision value, or by affecting how decision values are compared when making a choice.

1.5. The Brain Valuation System

Neuroeconomics has aimed to discover and describe a system of neural structures that are responsible for human decision making, with research largely governed by the five phases of the decision-making process outlined by Rangel et al. (2008). The localisation of these regions in the brain has been pioneered through the use of high spatial resolution brain imaging methods such as fMRI. For example, Plassmann, O'Doherty, and Rangel (2007, 2010) observed the computation of decision values in the ventromedial prefrontal cortex in an fMRI auction task for both appetitive and aversive stimuli. Similarly, Grabenhorst and Rolls (2009) observed the possible neural substrate of outcome value in an odour experiment whereby the orbitofrontal cortex (OFC) tracked relative and absolute pleasantness of a stimuli, whereas the anterior insula cortex (AIC) tracked the relative unpleasantness (for a review of research investigating decision and outcome values, see Peters & Büchel, 2010).

A wealth of research has highlighted the central tenants of a brain valuation system, responsible for various aspects of value-based decision making. This work has revealed the prefrontal cortex (PFC) and its various sub-structures as being of central importance. The ventromedial portion of the PFC has been found to be responsible for the encoding of reward value (Knutson, Fong, Bennett, Adams, & Hommer, 2003; Knutson, Taylor, Kaufman, Peterson, & Glover, 2005) and anticipated gain probability (Kuhnen & Knutson, 2005), as well as the encoding of subjective pleasantness (Grabenhorst & Rolls, 2011) and confidence in choice behaviour (De Martino, Fleming, Garrett, & Dolan, 2013). In addition to this encoding of value, a previous study has described the role of the medial PFC in encoding the happiness of getting a product for free, suggesting the role of the PFC in affective valuations (Votinov, Aso, Fukuyama, & Mima, 2016). In addition to the medial PFC, Kable and Glimcher (2007) implicated in their study the role of the ventral striatum (VS) in delayed rewards, whereby activation in these regions increased as a reward

increases but decreases as the delay to the reward increases. The importance of both the ventromedial PFC and VS in subjective valuation was emphasised in a meta-analysis by Bartra et al. (2013), in that each demonstrated the encoding of positive subjective value. Critically, the signals in these two regions were prevalent at the onset of the decision as well as the outcome of the decision, and also for monetary rewards and primary rewards such as food. This work demonstrated a domain-general system in the brain responsible for the encoding of subjective value across multiple decision stages and reward types, i.e. a brain valuation system.

Although the ventromedial PFC and VS are likely to dominate what we refer to as a brain valuation system, there are several other brain structures revealed as showing some relevance. Despite confusion regarding the function of the posterior cingulate cortex (PCC), its role as a central connection hub linking multiple neural systems has been established, meaning it is involved in higher cognition (Leech, Braga, & Sharp, 2012). Votinov et al. (2016) also implicated the PCC in a choice brain circuit wherein the PCC was likely responsible for the integration of information in their binary decision task comparing various price conditions. A further meta-analysis by Clithero and Rangel (2014) not only pointed to the ventromedial PFC and VS in the computation of subjective value, but also the PCC. Additionally, the authors defined two distinct functional networks, one involving the central ventromedial PFC, dorsal PCC and VS, and a second involving the anterior ventromedial PFC, left angular gyrus and ventral PCC, each showing co-activation within their corresponding network.

The OFC is frequently highlighted in the literature regarding subjective valuation processes, and its functional parcellation has been the question of many studies (Kahnt, Chang, Park, Heinzle, & Haynes, 2012; Kringelbach & Rolls, 2004; Mackey & Petrides, 2010; Ongur, Ferry, & Price, 2003; Zald et al., 2014). Regarding its role in valuation, OFC signals have been shown to represent reward, affective value and subjective pleasantness on a continuous scale (Rolls, Grabenhorst, & Franco, 2009; Rolls, McCabe, & Redoute, 2008), and also to encode value across multiple sensory modalities (Chikazoe, Lee, Kriegeskorte, & Anderson, 2014). An animal study by McGinty, Rangel, and Newsome (2016) provided strong evidence for this function of the OFC, demonstrating amplified value encoding when fixations were made near cues associated with rewards. Grabenhorst and Rolls (2009)

revealed complementary roles of the OFC and the anterior insula cortex (AIC), whereby the OFC tracked relative subjective (and absolute) pleasantness, and the AIC tracked relative subjective unpleasantness. The insula is of great interest in neuroeconomic research, specifically prospect theory research, as it is frequently described as representing loss aversion processes and risky decision making (see Weller, Levin, Shiv & Bechara, 2009). For example, AIC activation has been shown to precede riskless choices and risk-aversion mistakes (Kuhnen & Knutson, 2005), and following unfair offers in the Ultimatum game (Sanfey, Rilling, Aronson, Nystrom, & Cohen, 2003). This is reiterated in animal studies showing insula dysfunction producing risk-taking behaviours (Mizoguchi et al., 2015), and maintained activation being observed in the AIC following negative outcomes (Jo & Jung, 2016). Regarding valuation specifically, a study by Rolls et al. (2008) revealed negative correlations between expected value in a decision task and AIC activity, and also revealed a relationship between AIC activation and uncertainty.

Bartra et al. (2013) highlighted in their meta-analysis the importance of two distinct patterns of activation – a linear function and a non-linear, “U-shaped” function. The authors argue that subjective valuation is a process whereby choices are placed on a common scale to facilitate the selection of a choice giving the greatest utility to the individual. Therefore, a neural system representing a domain-general valuation system must encode value in a positive, linear manner. In contrast, a structure demonstrating both positive and negative effects would indicate the encoding of salience or arousal. Whilst the ventromedial PFC and VS demonstrated positive encoding, regions including the AIC, dorsomedial PFC, dorsal and posterior striatum and thalamus each demonstrated a U-shaped response to valuation tasks, indicating the encoding of salience or arousal.

1.6. Electrophysiological Correlates of Value

Although localising the neural origins of information encoding during economic valuation is critical, fMRI methods severely lack in their ability to describe the temporal characteristics of the same information encoding. Studies utilising electrophysiological methods such as EEG have aimed to describe the temporal dynamics of valuation and the latencies at which various information is encoded, as

well as the oscillatory patterns elicited during decision making. Research has shown that the brain has the ability to categorise stimulus as being positive or negative very rapidly, as early as 120 ms (Smith, Cacioppo, Larsen, & Chartrand, 2003). Smith et al. also reported a negativity bias whereby negative stimuli were classified more rapidly, indicating increased attention allocation towards negative stimuli. Further research has reiterated the rapid encoding of stimulus attributes, extending to more complex information such as signals relating to valuation as early as 150 ms (Harris, Adolphs, Camerer, & Rangel, 2011). A later study observed post-decision value signals 200 ms following stimulus onset over a posterior region of the scalp, before moving to an anterior region at approximately 850 ms (Larsen & O'Doherty, 2014). An excellent feature of this study by Larsen and O'Doherty was the simultaneous recording of fMRI data, allowing the authors to reveal the neural generator of these signals. The intraparietal sulcus was the origin of the earlier, posterior signal, whereas the ventromedial prefrontal cortex was the origin of the later, anterior signal. Finally, Tzovara, Chavarriaga, and De Lucia (2015) demonstrated the ability to predict decision outcomes depending on decision difficulty wherein easy decisions can be decoded at approximately 500 ms whereas hard decisions at 700 ms.

1.6.1. N2

The N2 event-related potential (ERP) component is a negative wave occurring between 200 and 350 ms post-stimulus onset (Folstein & Van Petten, 2008), originating from the anterior cingulate cortex (Nieuwenhuis, Yeung, Van Den Wildenberg, & Ridderinkhof, 2003). The N2 is commonly observed over an anterior region of the scalp (Folstein & Van Petten, 2008), though sub-components of the N2 vary between posterior and anterior representation (Luck, 2005; Naatanen & Picton, 1986). In decision making research, investigations into the N2 have described the ability of the N2 to encode a variety of information. For example, Telpaz, Webb, and Levy (2015) revealed an increased N2 amplitude for more preferred products, and Kiss, Driver, and Eimer (2009) revealed an earlier and larger N2 for high reward targets. Additionally, Gajewski, Drizinsky, Zulch, and Falkenstein (2016) found increased N2 for counter-conformity decisions whereby a product was purchased for higher than the average price, or not purchased for a price below the average price. The implication of the N2 in counter-conformity decisions implies the role of N2 in

conflict processing, a finding that is repeatedly reported (Larson, Clayson, & Baldwin, 2012; Ma, Pei, & Wang, 2015; Ma, Wang, Dai, & Shu, 2007; Wang, Meng, Liu, Wang, & Ma, 2016). The N2 is also reported to be responsible for automatic preference encoding (Goto et al., 2017), suggesting the role of the N2 in attentional driven processes. In support of this, Folstein and Van Petten (2008) highlight how the majority of N2 investigations are focussed on cognitive control, detection of novel stimuli and visual attention. Therefore, as Hakim and Levy (2019) point out, despite its frequent appearance in valuation studies, it may simply reflect attentional processes rather than valuation specific processes, but the direction of attention to high and low value targets may make it an indirect measure of valuation processes.

1.6.2. P2

The P2 corresponds to a positive wave occurring between approximately 150 and 250 ms (Ma, Wang, & Wang, 2014), most likely originating from the orbitofrontal cortex (Polezzi, Lotto, Daum, Sartori, & Rumiati, 2008) and is observed at anterior regions of the scalp, as well as over the vertex (Luck, 2005). Although not frequently appearing in economic decision-making literature, its importance has been demonstrated. The P2 has been reported to be larger for negative stimuli, indicating an increased allocation of attentional resources to stimuli that need to be processed more rapidly (Carretié, Martín-Loeches, Hinojosa, & Mercado, 2001; Correll, Urland, & Ito, 2006; Huang & Luo, 2006; Jin, Zhang, & Chen, 2017; Wang, Huang, Ma, & Li, 2012). Similarly, Ma et al. (2014) found that a larger P2 reflected an early classification of stimuli via allocation of attentional resources, allowing individuals to classify product category membership semantically. In addition to their source localisation of the P2, Polezzi et al. (2008) found that the P2 distinguished between the predictability of outcomes in an economic decision-making task. Hence, it appears that the P2 may be indicative of attentional allocation, similar to the N2 component, but for the early processing of negative stimuli, and possibly for the categorisation of stimuli into general categories.

1.6.3. P3

The P3 wave is a positive deflection occurring over frontal midline electrode sites, followed later by a maximum over midline parietal sites (Luck, 2005), approximately 300 ms after stimulus onset (Nieuwenhuis, Aston-Jones, & Cohen, 2005) and is of great relevance in economic decision making research (see Hakim & Levy, 2019). The P3 is a component highly sensitive to the motivational significance of the stimulus eliciting the response, for example, target stimuli in visual search tasks elicited a greater P3 amplitude (Duncan-Johnson & Donchin, 1977). Here, motivational significance is task-specific, whereas stimuli can be inherently more motivationally significant. For example, regardless of being positive or negative, emotionally valent stimuli elicited larger P3 amplitudes (Johnston, Miller, & Burleson, 1986; Keil et al., 2002). The P3 is also relevant to the processing of outcomes indicating monetary gains and losses. Irrespective of a gain or loss, one study revealed that the P3 encoded the absolute magnitude of the feedback (Yeung & Sanfey, 2004). Similarly, Hajcak, Holroyd, Moser, and Simons (2005) observed increased P3 amplitude when individuals received unexpected outcomes in comparison to neutral and expected outcomes, and also in response to infrequent feedback. However, the authors also revealed increased P3 amplitude to positive feedback in comparison to negative feedback, similar to Johnson and Donchin (1985), but contrasting with the findings from Yeung and Sanfey (2004) who revealed valence-independence of the P3, and other studies demonstrating a negativity bias within the P3 (Ito & Cacioppo, 2000; Ito, Larsen, Smith, & Cacioppo, 1998). The contrasting findings make it difficult to utilise the P3 component in preference prediction and it may simply reflect the allocation of attentional resources to tasks, making it only an indirect measure of valuation behaviour (Hakim & Levy, 2019).

1.6.4. LPP

The late positive potential (LPP) is a positive component occurring after the P3 component, i.e. after 300 ms (Chen et al., 2010), and thus has been referred to as a maintained or late P3 response (Cacioppo, Crites, Gardner, & Berntson, 1994; Hajcak & Olvet, 2008). The similarity of the P3 to the LPP extends to their scalp

distribution, with both showing prevalence over a central parietal region (Cacioppo et al., 1994). The LPP is thought to be involved in the categorization of stimuli (Crites & Cacioppo, 1996; Ito & Cacioppo, 2000) and is strongly involved in emotional processing (Cuthbert, Schupp, Bradley, Birbaumer, & Lang, 2000; Hajcak, Moser, & Simons, 2006; Hajcak & Nieuwenhuis, 2006; Keil et al., 2002; Schupp et al., 2000). For example, a study by Schupp et al. (2004a) observed larger LPP amplitudes for threatening faces in contrast to neutral and friendly faces, and Hajcak and Olvet (2008) reported enhanced LPP for emotional stimuli (both positive and negative), suggesting a facilitated processing of emotional stimuli which is indexed by the LPP. The LPP has also been implicated in purchase decisions, specifically in consumer herding, whereby the magnitude of the LPP response reflected the tendency of a consumer to choose an option that other consumers have rated as being positive, despite having no information regarding the product themselves (Chen et al., 2010). Other studies have emphasised the potential use of the LPP as an index of purchase intent whereby increased LPP was found for more subjectively preferred products (Goto et al., 2019; Goto et al., 2017). The role of the LPP in emotional processes suggest the LPP is of great use in economic decision making, allowing researchers to use it as an index of product perception.

1.6.5. ERN/FRN

Two further components are critical in the understanding of the electrophysiological correlates of valuation behaviour – the error-related negativity (ERN) and feedback-related negativity (FRN). The ERN is a response normally observed in speeded response tasks, typically over frontal and central scalp regions (Luck, 2005). For example, ERN amplitude increased when a higher frequency of error correction was observed, representing a signal relating to error detection and compensation (Gehring, Goss, Coles, Meyer, & Donchin, 1993). Conversely, the nature of some tasks require that errors are not known until feedback is provided. Hence the FRN is a component observed in response to negative feedback (Miltner, Braun, & Coles, 1997). It is believed that the ERN and the FRN are produced by the same neural system but in different circumstances (Gentsch, Ullsperger, & Ullsperger, 2009; Walsh & Anderson, 2012).

The ERN has been described as an index of both error magnitude (Bernstein, Scheffers, & Coles, 1995) and monetary loss (Gehring & Willoughby, 2002). Similarly, a wealth of research has identified the role of the FRN as an index of loss aversion in humans. For example, Kokmotou et al. (2017) revealed a correlation between loss aversion and FRN amplitude when evaluating choice outcome. The FRN has also been posited as being an index of reward prediction errors, i.e. receiving feedback indicating an unfavourable outcome. Hakim and Levy (2019) argued that this reward prediction error cannot be used as a direct indication of subjective valuations, but it may be an important proxy in indicating the subjective value an individual assigns to an outcome. For example, by using reverse inference, a marketer may infer the value of a product by the magnitude of a reward prediction error response. If a large FRN is indicative of differences between expectation and the outcome itself, then this could be interpreted as either effective advertising or an inadequate product.

Chapter 2

2.1. Electroencephalography

2.1.1. Physiological basis of EEG

Signals in the brain are conducted along billions of neurons (Lent, Azevedo, Andrade-Moraes, & Pinto, 2012). Each neuron produces a small change in electrical potential as it activates, resulting in observable changes outside of the central nervous system in the form of local field potentials in the extracellular space surrounding neurons (Herreras, 2016) and also on the scalp as measured by electroencephalography (EEG) (Speckmann, Elger, & Gorji, 2011). Signals are propagated along the axon of a neuron, made possible due to the ability of the axon membrane to alter its permeability to cations such as sodium (Na^+) and potassium (K^+).

The current view in EEG research is that EEG measures the postsynaptic currents resulting from synchronised firing of clusters of neurons (Nunez & Srinivasan, 2006), in contrast to the earlier belief that EEG measures the action potential. Action potentials produce a high-frequency signal, and the ability of cortical tissue to act as a filter to high-frequency data means this signal is attenuated greatly by distance (Bédard, Kröger, & Destexhe, 2006). This is not the case for postsynaptic potentials which, in contrast, are low frequency in nature and can be propagated across the scalp. Hence, it is considered that EEG is a much more direct measure of neuronal activity than other tools (Teplan, 2002). The measuring of synaptic currents resulting from neural activity is a direct measure of the neural activity that produced it, albeit a measurement from a relatively large number of neurons. In comparison, tools such fMRI only indirectly measure neural activity from the resulting haemodynamic responses, though the correlation is strong (Logothetis, 2003).

2.1.2. EEG acquisition

Electroencephalographic methods measure the electrical potentials across the scalp by positioning electrodes across the head according to an internationally

recognised placement system, such as the 10-20 electrode system (Klem, Luders, Jasper, & Elger, 1999) or 10-5 system (Oostenveld & Praamstra, 2001). The standardization of electrode placement system allows for the comparison of data between labs utilising different EEG acquisition systems.

For all research studies outlined in the current thesis, a 128-electrode sponge-based sensor net was used (Royal Philips, Eugene, Oregon, USA). Figure 1.1 illustrates the locations of electrodes across the head using this system. This high-density system gives enhanced coverage of the head, with electrodes positioned over the face and other regions not covered by systems utilising fewer electrodes. Modern placement schemes for high-density electrode caps benefit from the placement of electrodes over the inferior head region, allowing for the recording of neural activity from medial and basal temporal regions (Feng et al., 2016; Song et al., 2015). Larger spatial sampling also benefits from reducing the aliasing of spatial frequency (Tucker, 1993). A saline solution is used as the conducting medium and the net is positioned on the head according to three anatomical landmarks – the nasion and the left and right pre-auricular points. The Cz electrode was used as an initial reference and data was recorded at 1000 Hz with a filter of 0.1 to 200 Hz.

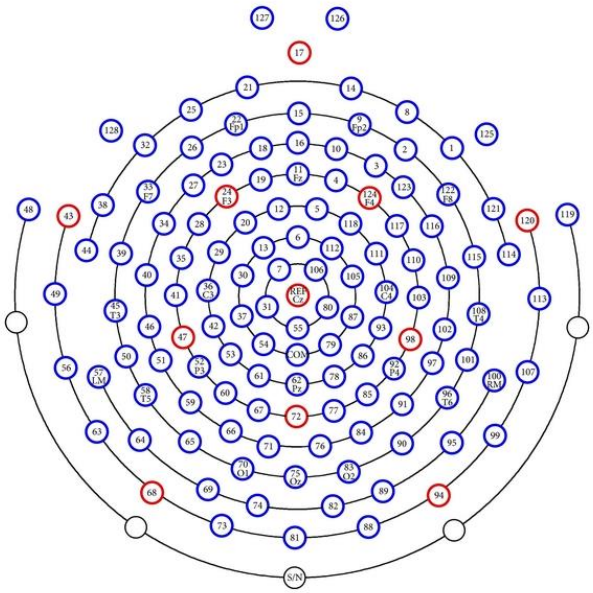

Figure 1.1. Distribution of the 128 electrodes across the scalp for the Geodesic sensor net.

Whilst each electrode is recording activity across the scalp, the amplitude is miniscule and must be amplified and digitized so that they can be visualized on a computer. An important step in this amplification process is the use of grounding and reference electrodes. In an EEG amplification system, the activity at a given site is established using a differential amplifier, whereby activity at an active electrode site is the amplified difference between active-ground voltage and the reference-ground voltage (Luck, 2005).

2.1.3. EEG data processing

Following the completion of data collection, the continuous EEG data must be inspected for the presence of artifactual data. A chief issue with EEG methods is the ease at which data can be contaminated by electrical potentials from non-cerebral sources. Physiological artifacts can arise from eye-blinks (Hoffmann & Falkenstein, 2008), head movements (O' Regan, Faul, & Marnane, 2010), eye-movements (Nikolaev, Meghanathan, & van Leeuwen, 2016) and heartbeat (Viola et al., 2009). Muscle movements involving the face and neck can also have a variety of effects on EEG data, producing different spectral profiles with various peak frequencies (Goncharova, McFarland, Vaughan, & Wolpaw, 2003). Non-physiological artifacts are also detrimental to EEG recordings, for example, electrical devices produce a 50/60 Hz noise that greatly contaminates data (Puce & Hämäläinen, 2017).

Although artifacts are minimised at the acquisition stage, there are several methods to account for the artifacts at the pre-processing stage. In the present thesis, all data was corrected using the adaptive artifact correction method described by Ille, Berg, and Scherg (2002) implemented in Brain Electrical Source Analysis (BESA, GmbH). This method utilises a spatial filter approach for artifact correction, separating artifact and brain activity to avoid distortion of the continuous EEG data. The method is limited primarily by the researcher being able to accurately define an artifact topography with a high signal-to-noise ratio. After correcting the continuous data using this method, all data is visually inspected and data epochs containing artifacts not characterised by a systematic topography, and not subject to correction via spatial filtering, are discarded.

2.1.4. ICA

Independent component analysis (ICA) was first utilised by Makeig, Bell, Jung, and Sejnowski (1996) in the processing of EEG data. ICA works by separating summed independent source signals into the original independent signal without any prior knowledge of the source processes, i.e. blind separation of source signals (Makeig & Onton, 2011). When visualising EEG data, the data is assumed to be a mix of signals from independent brain sources. ICA separates the recorded data into a set of maximally independent components. Since the continuous data is explained by overlapping but unique brain source activations over a period of time, the independent components identified must represent the source signals from unique brain sources. Similar to the spatial filtering process discussed previously, ICA creates what is essentially a set of spatial filters, whereby a single component removes variance accounted for by all but one of the unique source signals that contribute to the continuous data across all channels (Makeig & Onton, 2011). For each of these components, this leaves us with a time series indicating polarity and relative amplitude at each time point, along with a single scalp map representing the projection of the component onto the scalp. ICA is most useful when applied to datasets comprising 128 or more channels (Delorme & Makeig, 2004), but it has been shown to be of use with datasets utilising 32 channels (Makeig, 2002).

The application of ICA is most frequent in the process of artifact correction (Puce & Hämäläinen, 2017), but is also critical in the identification of important brain processes to make inferences about cognitive processes (Makeig et al., 1999). Artifacts within continuous EEG data can have very stereotypical scalp patterns and time courses, making them very easily identifiable using ICA. For example, eye-blinks produce a strong anterior pattern over frontal electrodes, and horizontal eye-movements produce two clusters of activation over a left and right anterior region with opposite polarity. Similarly, electrocardiographic artifacts arising from heartbeat produce easily discernible components due to their distinct temporal and spatial patterns, usually observed over posterior regions corresponding to pulses from the neck. However, there are some artifacts that ICA struggles to separate. For example, 50/60 Hz line noise can vary as a result of changing electrode impedance over the course of an experiment, producing a spatial pattern that is inconsistent over the

recording. Myoelectric responses originating from muscle movement, i.e. electromyographic signals, also produce highly variable signals in terms of both frequency and spatial distribution, and they can even contaminate signals in the alpha and beta frequency ranges wherein brain data is typically observed (Goncharova et al., 2003).

2.1.5. Source dipole analysis

EEG methods excel in their ability to investigate the temporal dynamics of the process that it is investigating, something which methods such as fMRI do not have the ability to do due to the nature of haemodynamic responses. When an electrical signal is produced inside of a medium, such as the brain, the signal is conducted across the medium, diminishing in strength with distance. If we have a dipole in the brain with a known location and orientation, as well as the distribution of conductance across the brain, then it is possible to predict the distribution of electrical propagation across the scalp when that dipole is active (Luck, 2005). This is referred to as the “forward problem”, referring to the prediction of observed potentials at given electrodes with a known source generator (Hallez et al., 2007).

Solving the forward problem requires a head model characterising the conduction of electrical potentials within the human head. The first head models were comprised of conduction through a homogenous sphere (Frank, 1952), but it was soon realised that the different tissues in the head result in different conductivities depending on the medium (Hallez et al., 2007), resulting in more realistic head models such as the four-shell ellipsoid head model with different conductivities for brain tissue, scalp, bone and cerebrospinal fluid (Blimke, Myklebust, Volkmer, & Merrill, 2008).

In contrast to the forward problem, we may also be interested in localising the source of a given scalp distribution given only the pattern of this distribution. This is referred to as the “inverse problem” and is much more complicated than the reverse (Luck, 2005). The inverse problem was first described in 1853 (Von Helmholtz, 2004) and the author reported how the current distribution inside a conductor cannot be uniquely identified given only the distribution of electromagnetic field outside of the medium. This is due to the infinite number of unique solutions that produce any given

distribution. Nevertheless, there are several inverse solutions utilising parametric and non-parametric methods that are used to generate probabilistic solutions of source generators (Grech et al., 2008), utilising the same head models previously described. A commonly used method is the LORETA algorithm which produces a region of maximal activity in the brain, but with a degree of dispersion (Pascual-Marqui, Michel, & Lehmann, 1994). In the current thesis, data were analysed using classical LORETA analysis recursively applied (CLARA), which applies LORETA iteratively to reduce the source space and resolve closely neighbouring sources (Hyder, Kamel, Boon, & Reza, 2015). A second method used in the current thesis is the fitting of a dipole model using a sequential strategy, whereby dipoles were sequentially fitted to explain the three-dimensional source currents that contributed primarily to the data (Scherg & Berg, 1996; Stancak et al., 2002). Dipole orientations were determined based on the peak activation in specific time intervals.

2.1.6. Strengths & limitations of EEG methods

The main benefit of EEG research is the ability to investigate the temporal dynamics of brain processes on a scale of milliseconds (Luck, 2005), a feature that cannot be matched by many brain imaging methods utilised in neuroscience. Methods such as fMRI have a temporal resolution of 4 to 6 seconds, and other methods based on haemodynamic responses, such as positron emission tomography, can have temporal resolutions upwards of 40 seconds (Aine, 1995). The high temporal resolution of EEG stems from the nature of the neuronal responses, in that the postsynaptic responses are a direct measure of cortical activity, and also from the speed at which these electrical signals are conducted. The generation of these electrical potentials in the brain also produces a small electromagnetic field that is synchronised with the electrical potentials. These magnetic fields are able to be detected by magnetoencephalography (MEG), and MEG can therefore be used in a similar way to EEG with the added benefit of improved spatial resolution (Hämäläinen, Hari, Ilmoniemi, Knuutila, & Lounasmaa, 1993). However, the volume currents from electrical potentials and the resulting magnetic field are orthogonal in nature, in that they occur at right angles with each other. This means that the two methods are optimum in detecting specifically oriented dipoles in the brain. Whereas MEG is optimised for detecting tangential

sources, EEG can detect sources of all orientations (Cohen & Cuffin, 1991). Ahlfors, Han, Belliveau, and Hämäläinen (2010) reported in their study a source orientation for almost all cortical locations to which MEG was insensitive. This contrasted with EEG which was much more insensitive to source orientation.

The benefits of EEG extend to the ability to implement it in parallel with other complementary methods. Simultaneous EEG and MEG studies combine the improved spatial resolution of MEG with the ability to detect all source orientations with EEG (Chowdhury et al., 2015; Ding & Yuan, 2013; Ebersole & Ebersole, 2010; Henson, Mouchlianitis, & Friston, 2009) and concurrent EEG and fMRI studies combine the temporal and spatial resolution of the respective methods (Huster, Debener, Eichele, & Herrmann, 2012; Larsen & O'Doherty, 2014).

The prevailing limitation in EEG research is the inverse problem, i.e. the inability to be certain of the source of brain potentials observed across the scalp limits the spatial resolution of EEG techniques greatly. Although the temporal dynamics are often of great importance, research questions concerning the spatial aspects of a cognitive process are more suited to other functional imaging techniques. Although EEG can localise the origin of signals with an accuracy of 1 cm (Luck, 2005), making it acceptable to localise general regions of activation, neural structures have many sub-divisions, each corresponding to unique functions. For example, the importance of the OFC is emphasised across several fields, including decision making (Padoa-Schioppa & Assad, 2006), and very fine functional divisions of the OFC region have been reported (Kahnt et al., 2012; Zald et al., 2014). The inability to estimate with enough degree of certainty the source of signals results in the inability to discern the origin of signals from functional sub-regions of neural structures.

2.2. Eye-Tracking

2.2.1. General principles

Eye-tracking entails the monitoring of gaze position relative to the subjects' environment, allowing researchers to identify the nature of how attention is being allocated during any given task. In recent years, several eye-tracking systems have been developed, including head-mounted eye-trackers, tower-mounted systems,

remote eye-trackers allowing free movement within a small distance. Although these systems are much less invasive than typical scleral coil eye-tracking techniques (van der Geest & Frens, 2002), they tend to compromise on spatial and temporal resolution. As is the case with video-based eye-tracking systems, the sampling rate of pupil data is restricted to the sampling rate of the cameras utilised by the system.

The primary function of eye-tracking methods is to determine periods of eye-movements, referred to as saccades, and periods of eye-fixations. In general, a set of parameters are defined that determine thresholds for characterising a gaze point as belonging to a saccade or an eye-fixation. For example, a saccade being defined as having a minimum velocity of 30 degrees/sec, acceleration of 8000 degrees/sec^2, and a minimum deflection of 1 degree (Plochl, Ossandon, & Konig, 2012). In contrast, any values that fall short of these thresholds may be attributed as belonging to a period of fixation. Periods of fixations must also be of a minimum length, typically between 80 and 150 ms (Nyström & Holmqvist, 2010).

In the current thesis, the Pupil Labs head-mounted eye-tracker was used (Pupil Labs, Berlin, Germany). This system detects the pupil position(s) from a video stream of the eye(s) and maps the gaze position onto a video stream representing the subjects' field of view. The native software detects pupil location using a video stream of the eye(s). This is done firstly by estimating the pupil region based on the strongest response for a centre-surround feature (Swirski, Bulling, & Dodgson, 2012) and then finding the edges of the eye (Canny, 1986). The darkest regions and reflections on the eye are detected next, before being extracted and converted to contours. Candidate pupil ellipses are fitted using ellipse fitting (Fitzgibbon & Fisher, 1995) before fitting a final ellipse defining the edges of the pupil. Gaze positions are mapped using a nine-point calibration procedure and gaze position can be calculated relevant to a surface defined with a pre-defined set of surface markers placed in the field of view. The sampling rate of the Pupil Labs eye-tracker varied with video resolution, in that a 200×200 pixel recording could sample pupil data at 200 Hz, whereas a 400×400 pixel recording could sample at 120 Hz. The world view camera sampled at 60 Hz.

2.2.2. Eye-movement detection

Eye-trackers produce a vector of raw data comprised of the x and y-coordinates of the gaze position at any point in time. However, this data needs to be analysed further to determine the onset and offset of distinct eye-movement related events. For example, the gaze position at any given time point may belong to a period of fixation, saccadic eye-movement, period of smooth-pursuit or a blink. Less frequently, research identifies the presence of glissades, a period of eye-movement following a saccade that is unreliably assigned to either the preceding saccade or the following fixation (Nyström & Holmqvist, 2010). Though the distinct types of events are well defined qualitatively, the detection of these events within raw data largely depends on the algorithm utilised and its corresponding parameters. For example, the method that is used to filter the gaze data can have a great influence on the detection of events. Event-detection algorithms can be defined broadly based on two classes – dispersion-based algorithms and velocity-based algorithms.

2.2.2.1. Dispersion-based thresholds

One way of classifying events in gaze position data is using dispersion-based algorithms. These algorithms define a fixation based on gaze data being restricted to a certain region (i.e. a dispersion threshold), typically of less than 0.5° of visual angle, for a minimum duration of time, typically 80 – 150 ms (Nyström & Holmqvist, 2010). The most commonly used dispersion-based algorithm used, which is also utilised in the native software of the Pupil Labs eye-tracking system, is the dispersion-threshold identification (I-DT) algorithm (Salvucci & Goldberg, 2000). This method begins by using a sliding window encompassing a number of data points representing the minimum fixation duration. The window begins at the beginning of the gaze data and transitions through the data, one data point at a time, calculating the dispersion of the data points in the window by summing the difference between the minimum and maximum x-coordinate and the difference between the minimum and maximum y-coordinate. If this dispersion is greater than the threshold, it is not a fixation. However, if the dispersion is less than the threshold, it is counted as a fixation and the window is expanded until the dispersion of the data points exceeds

the threshold, at which point a full fixation is defined at the centroid of x and y coordinates in the time window.

Despite the need for only the two parameters of minimum duration and dispersion threshold, inconsistencies can arise in dispersion-based algorithms based on how the dispersion is calculated, which can in turn yield significantly different fixation durations and the number of fixations extracted (Blignaut, 2009). Similarly, algorithms may have their own rules for accepting or rejecting fixation candidates, and even for merging two or more subsequent fixations, resulting in more possible inconsistencies between algorithms (Hessels, Niehorster, Kemner, & Hooge, 2017).

2.2.2.2. Velocity-based thresholds

Gaze data comprised of x and y coordinates, as well as time course, allows for the calculation of gaze velocity. Using this gaze velocity, velocity-based algorithms define fixation candidates based on a predefined velocity threshold, often 30°/s, wherein a period is labelled as a fixation candidate if the gaze velocity does not exceed this threshold. Additional parameters can be utilised to help characterise a fixation. For example, the EyeLink system (SR Research Ltd., Mississauga, Ontario, Canada) includes acceleration data and motion to make sure a saccade is being made, ensuring the eye has moved a significant enough distance to define a new fixation. Similar to the dispersion-based algorithms, parameter definitions will have a large influence on the events subsequently extracted. However, defining a velocity threshold to identify fixation candidates is based on “rules of thumb” (Nyström & Holmqvist, 2010), and comparable results between research is difficult due to this.

The collection of eye-tracking data can sometimes be problematic due to the presence of noise. For example, when collecting data from young children. To account for this, Hessels et al. (2017) developed a noise-robust algorithm that is able to extract fixation events in noisy data, referred to as the identification by two means clustering (I2MC) algorithm. The first step in this method is the maximising of eye-tracking data by interpolating missing data. Secondly, it uses the k-means clustering method utilising 2 means, i.e. k = 2 (Jain, 2010), wherein data within a sliding window are forced into two clusters. The authors reason that if the current data

window encompasses a saccade, there will be few cluster membership transitions concentrated at a fixed point. Alternatively, if the current data window encompasses a fixation, the transitions of cluster membership will be driven by the noise in the data alone and, in turn, will be sporadic. These points of cluster membership transitions will subsequently be used to identify fixation onsets and offsets. This algorithm was utilised in chapter 7 of the current thesis as an alternative to the I-DT algorithm of the native Pupil Labs software.

2.3. Co-registration of EEG and Eye-Tracking

Typical EEG experiments are usually very constrained, in that participants are often discouraged from making eye-movements during task due to the impact that eye-movements can have on brain potential recordings (Plochl et al., 2012). However, the synchronisation of brain responses to fixations allows researchers to investigate cognitive processes at the point of information processing. The implementation of eye-tracking in EEG research is frequently seen in research investigating attentional processes (Fischer, Graupner, Velichkovsky, & Pannasch, 2013), granted that fixations are an important index of attentional allocation. Visual search paradigms frequently utilise combined EEG and eye-tracking to investigate word predictability (Dimigen, Sommer, Hohlfeld, Jacobs, & Kliegl, 2011) and target detection (Dias, Sajda, Dmochowski, & Parra, 2013).

2.3.1. Advantages of co-registration

Real-world neuroimaging applications are becoming more prevalent in recent years with the improving EEG technology, and other mobile brain imaging techniques such as functional near-infrared spectroscopy (McDowell et al., 2013). In laboratory experiments, events can easily be synchronised within the brain imaging data, such as image presentation on a computer screen. In mobile brain imaging, however, it is much more difficult to label events to investigate brain potentials. The implementation of eye-tracking allows researchers to investigate brain responses at the point of fixation, providing an event trigger critical for highlighting relevant portions of EEG data. This allows research to take the well-established findings from laboratory experiments and investigate whether the same is observed in realistic

scenarios as the context in which a task is completed may influence the cognitive processes utilised.

Although the influence of eye-movements on brain potentials is well established (Plochl et al., 2012), there are several methods and procedures to account for this. It is standard procedure to simply discard epochs contaminated by eye-blinks or eye-movements. A consequence of this is the possibly detrimental loss of data, reducing the signal-to-noise ratio and the extent to which we are detecting the underlying neural activity. However, there are multiple tools to reduce this data loss. ICA is a strong tool to account for blinks and certain eye-movements (Makeig et al., 1996), as well as spatial filtering (Ille et al., 2002), regression (Schlogl et al., 2007) and dipole modelling (Berg & Scherg, 1991).

A notable method for accounting for eye-movements and the linear and non-linear effects that eye-movements can induce is the Unfold toolbox (Ehinger & Dimigen, 2019). This method explains the continuous data in a single regression model to account for the inevitable overlap of EEG data epochs in free-viewing scenarios. Importantly, it can use regression to account for the linear and non-linear effects that eye-movements can have on brain potentials. For example, the size of the saccade that precedes a fixation has a non-linear effect on the visual lambda response observed approximately 100 ms after fixation onset (Nikolaev et al., 2016). However, spline regression implemented in Unfold can remove variance specific to the differing saccade sizes.

2.3.2. Limitations of co-registration

The myoelectric nature of eye-movements means that the electrical potentials observed when an eye-movement is initiated is magnitudes larger than cortical potentials researchers are interested in measuring. Despite efforts to control for the influence of eye-movements on brain potentials, the data will inherently have some remaining bias from these eye-movements (Nikolaev et al., 2016). Nikolaev et al. outlined the impact of eye-movements on brain data, emphasising the saccadic spike potential and the lambda response. The saccadic spike potential is a response observed at the onset of a saccade, representing a myoelectric response from the rotation of the eye. This response scales with the size of the saccade that produced

it (Boylan & Doig, 1989; Keren, Yuval-Greenberg, & Deouell, 2010; Riemslag, Van der Heijde, Van Dongen, & Ottenhoff, 1988), and is also influenced by the direction of that saccade (Keren et al., 2010; Thickbroom & Mastaglia, 1986). The lambda response is considered as the eye-fixation related potential (EFRP) equivalent of the P1 visual response. Similar to the saccadic spike potential, its amplitude is dependent on the size of the saccade that preceded it (Dimigen et al., 2011; Nikolaev et al., 2016; Ries, Slayback, & Touryan, 2018; Yagi, 1979), as well as the difference in contrast and luminance between the two fixation locations (Kazai & Yagi, 2005; Szirtes, Marton, & Breuer, 1982). The influence of eye-movements on not only the myoelectric response, but also the brain potentials that are required to be investigated, make it much more difficult to interpret the resulting findings. Any condition-wise differences in eye-movements, such as a larger saccade amplitude in one condition, may induce differences that are wrongly interpreted as being due to experimental manipulations.

Chapter 3

3.1. Research Problems

The brain structures underpinning the brain valuation system have been well characterised through meta-analytic analyses of fMRI data (Bartra et al., 2013; Clithero & Rangel, 2014). However, the temporal dynamics of brain valuation processes are less clearly defined. Little is known about the temporal features of valuation processes during incentive compatible auction tasks due to few electrophysiological investigations. Research has revealed that subjective value can be discerned as early as 150 ms following stimulus onset (Harris et al., 2011; Larsen & O'Doherty, 2014; Tzovara et al., 2015), though these never utilised an incentive compatible auction design. Furthermore, although the brain valuation system has been described well, the poor temporal resolution of fMRI methods results in a deprived understanding of when these neural structures are engaged on a fine temporal scale of milliseconds.

Several questions regarding neural computations for subjective valuation remain unanswered. Firstly, it remains undecided whether brain components can reflect subjective value by indexing WTP. Moreover, if brain components measured by EEG reflect WTP, it is unclear whether a single brain component reflects the entire subjective valuation process, or whether multiple components explain the full extent of subjective valuation. Secondly, the extent to which subjective valuation is an automatic process is unclear. Although the automaticity of valuation processes has been suggested using fMRI methods (Lebreton, Jorge, Michel, Thirion, & Pessiglione, 2009), the degree to which value-related signals were manifested in early brain components prior to conscious elaboration is not known. Consequently, the use of high-temporal resolution methods such as EEG would allow for the elaboration on the automaticity of valuation processes. Thirdly, stimulus-response paradigms allow researchers to investigate brain responses immediately following the presentation of a stimuli. However, it is unclear how value is computed and built in free-viewing situations whereby more elaborate processing takes place in the time period extending beyond the immediate post-stimulus interval. Lastly, there is a wealth of literature describing the benefits of price bundling to a seller and the

potential mechanisms governing the valuation of product bundles (Fang, Sun, & Gao, 2017). However, there is limited research investigating the brain processes governing the valuation of bundled goods which may shed light on the potential mechanisms of bundle valuation. For example, both sub-additivity and super-additivity are observed with different bundling strategies, such as the pairing of disparately priced products to produce a sub-additive effect (Popkowski Leszczyc, Pracejus, & Shen, 2008), or the pairing of complementary products to produce an additive effect (Harlam et al., 1995), yet the neural computations of such processing remains unclear.

The current thesis investigated brain responses at the point of stimulus presentation to reveal brain components for subjective valuation. Extending on this, the use of simultaneous EEG and eye-tracking recordings allowed for the investigation of brain responses at the point of eye-fixation in free viewing situations. To our knowledge, this is the first attempt to reveal the electrophysiological correlates of WTP within a BDM auction paradigm. Additionally, the EEG methods employed benefited from the temporal resolution to assess the automaticity of subjective valuation, as well as the subtleties of bundle valuation.

3.2. Hypotheses

H_1 Subjective values of objects in an auction experiment will be encoded by distinct spatiotemporal cortical activation patterns.

H_2 Subjective value will be encoded in specific cortical activation components equally in different contexts due to the automaticity of valuation processes.

H_3 The spatiotemporal activation patterns sub-serving subjective values will be determined early on during free viewing period and maintained throughout the viewing period.

H_4 Pairing a low and high value object into a single product bundle will produce a sub-additive effect. The sub-additive effect related to product

bundling will be indexed by a spatiotemporal cortical activation component showing sensitivity to subjective values.

3.3. Thesis chapters

Chapter 4 describes an ERP study utilising EEG which investigated the spatiotemporal characteristics of value-based decision making in the brain (H_1). A source dipole model was developed to describe the computation of low and high WTP in different source regions in the brain. The paradigm also employed two different rating tasks, only one of which required a computation of subjective value, thus allowing the investigation of the automaticity of value-based decision-making processes (H_2).

Chapter 5 examines the time-course of economic decisions in a combined EEG and eye-tracking experiment. Through the use of ICA techniques, clusters of brain components across subjects were revealed to emphasise the computation of subjective value in the brain for low, medium and high value products in a free viewing paradigm (H_1). The study also describes the evolution of neural processes unique to subjective valuation over time by investigating eye-fixation related potentials (EFRPs) at distinct time points throughout an extended decision period (H_3).

Chapter 6 is comprised of a further analysis of the data described in Chapter 5. Through the utilisation of a mostly identical analysis pipeline to Chapter 5, Chapter 6 aimed to determine whether comparable brain components reflecting subjective value were present immediately following stimulus onset (H_1, H_2). This was achieved by analysing brain responses synchronised to stimulus onset. The varying temporal overlap between brain responses synchronised to fixation onset acts as a low-pass filter. Thus, an investigation into the neural response at stimulus onset will reveal more information regarding the high-frequency components relevant to value encoding.

Chapter 7 extended the combined EEG and eye-tracking method to investigate the valuation of product bundles. The brain components encoding

subjective value for product bundles were investigated (H_1). Additionally, the sub-additivity from bundling two disparately priced products was examined, as well as investigating the neural representation of the sub-additive effect (H_4). With the addition of varying product complementarity within bundles, the influence of complementarity on bundle valuation was also studied.

Chapter 8 comprises a general discussion of all experimental findings. The implications of the findings are discussed in the context of the current opinions in the field of neuroeconomics, and future directions are deliberated.

Chapter 4

The neural correlates of economic value and valuation context: An event-related potentials study

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This experiment investigated the spatial and temporal dynamics of brain processes during the subjective valuation of products and product bundles.

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The roles of the co-authors are summarised below:
I designed the study in collaboration with Andrej Stancak and collected the data. Katerina Kokmotou, Vicente Soto and Stephanie Cook and assisted with the collection of data and contributed useful comments whilst preparing the manuscript for publication. Andrej Stancak, Nicholas Fallon and Timo Giesbrecht contributed to the experimental design as well as the large-scale planning of this project. Andrej Stancak and Timo Giesbrecht secured funding for project.

4.1. Neural correlates of economic value and valuation context: an event-related potential study

4.1.1. Abstract

The value of environmental cues and internal states is continuously evaluated by the human brain and it is this subjective value that largely guides decision-making. The present study aimed to investigate the initial value attribution process, specifically the spatio-temporal activation patterns associated with values and valuation context using electroencephalographic event-related potentials (ERPs). Participants completed a stimulus rating task in which everyday household items marketed up to a price of £4 were evaluated with respect to their desirability or material properties. The subjective values of items were evaluated as willingness-to-pay (WTP) in a Becker-DeGroot-Marschak auction. Based on the individual's subjective WTP values, the stimuli were divided into high and low value items. Source dipole modelling was applied to estimate the cortical sources underlying ERP components modulated by subjective values (high vs. low WTP) and the evaluation condition (value-relevant vs. value-irrelevant judgments).

Low WTP items and value-relevant judgements both led to a more pronounced N2 visual evoked potential at right frontal scalp electrodes. Source activity in right anterior insula and left orbitofrontal cortex was larger for low vs. high WTP at around 200 ms. At a similar latency, source activity in right anterior insula and right parahippocampal gyrus was larger for value-relevant vs. value irrelevant judgements. A stronger response for low- than high-value items in anterior insula and orbitofrontal cortex appears to reflect aversion to low-valued item acquisition which, in an auction experiment, would be perceived as a relative loss. This initial low-value bias occurs automatically irrespective of the valuation context.

4.1.2. Introduction

Economic values of stimuli are continuously and automatically encoded in the human brain. Previous brain imaging studies show that valuation occurs predominantly in the orbitofrontal cortex (OFC), ventromedial prefrontal cortex (vmPFC) and the ventral striatum (Bartra et al., 2013; Clithero & Rangel, 2014; Padoa-Schioppa, 2007; Raghuraman & Padoa-Schioppa, 2014). Value attribution is one of the first stages of any value-based decision (Rangel et al., 2008). Previous studies investigated the modulation of event-related potential (ERP) components by hedonic aspects of visual stimuli (for a review, see Hajcak et al. 2012). For example, a negativity bias reflecting preferential processing of unpleasant stimuli may result in greater ERP responses (Delplanque, Silvert, Hot, Rigoulot, & Sequeira, 2006; Huang & Luo, 2006; Smith et al., 2003). Some studies identified the role of the late positive potential in the encoding of emotional stimulus valence (Foti, Hajcak, & Dien, 2009; Macnamara, Foti, & Hajcak, 2009; Moser, Hajcak, Bukay, & Simons, 2006), however, the late positive potential also varies as a function of motivational significance (i.e., salience; Weinberg & Hajcak 2010). Although the subjective pleasantness of a stimulus may contribute to the value of perceived goods, economic value is not identical to emotional valence.

Electrophysiological studies have highlighted that value-related signals appear as early as 200 ms post-stimulus presentation in binary decision tasks where a choice between two options is required (Larsen & O'Doherty, 2014; Tzovara et al., 2015). Differences in ERPs were also observed across multiple time windows ranging from 150 to 800 ms (Harris et al., 2011). However, ERPs were not investigated in relation to behavioural measures concerning economic value directly. Other investigations of the value-encoding phase were focussed within specific brain regions (Hunt et al., 2012). A common finding in previous ERP studies investigating the representation of value-based preferences in binary reaction time tasks was a progression of activations from the occipito-temporal cortical regions to frontal and prefrontal sites over the course of the ERP (Harris et al., 2011; Larsen & O'Doherty, 2014). However, the involvement of a reaction time response in experiments investigating the representation of value also adds a motor readiness component to ERPs which may interact with activations related to the automatic valuation process

occurring in absence of decision making (Gluth, Rieskamp, & Büchel, 2013; Polania, Krajbich, Grueschow, & Ruff, 2014). Further, binary decision making as compared to reporting hedonic ratings has been found to involve different brain regions, such as anterior cingulate cortex (Rolls, Grabenhorst, & Parris, 2010).

Several ERP components relevant to value-based decision making have been revealed in previous literature. The event-related negativity (ERN) and feedback-related negativity (FRN) are two ERP components that, due to their nature, allow us to investigate decision making processes (Walsh & Anderson, 2012). These two components are elicited by feedback following decision tasks and are relevant to reward-prediction errors (Gehring, Liu, Orr, & Carp, 2012; Nieuwenhuis, Holroyd, Mol, & Coles, 2004; Yu & Huang, 2013). Additionally, the P300 ERP component is often implicated in which the P300 encodes outcome valence (San Martin, 2012; Yeung & Sanfey, 2004). It is generally found that these ERP components are specific to outcome processing, though it has been revealed that the eliciting stimuli can modulate the ERP magnitude at the outcome stage (Yeung & Cohen, 2006).

A common method for estimating the economic value of goods is via auction tasks such as the Becker-DeGroot-Marschak (BDM) mechanism (Becker et al., 1964). The BDM mechanism is an incentive compatible method for estimating a subject's willingness-to-pay (WTP) for goods and prospects (Wilkinson & Klaes, 2012). Previous fMRI studies have established that the brain valuation system activates during the BDM mechanism (Chib, Rangel, Shimojo, & O'Doherty, 2009; Plassmann et al., 2007, 2010).

The context in which economic decisions are made can also influence the neural activations within the brain valuation system. For example, neural responses within valuation regions can be modulated during an auction task in which bids may be forced (Plassmann et al., 2007, 2010), passive viewing tasks (Levy, Lazzaro, Rutledge, & Glimcher, 2011) and tasks in which value is irrelevant (Grueschow, Polania, Hare, & Ruff, 2015; Polania et al., 2014) or where outcomes are uncertain (Payzan-LeNestour, Dunne, Bossaerts, & O'Doherty, 2013). Activation of the brain valuation system during tasks in which it was not required demonstrates the automaticity of valuation processes (Lebreton et al., 2009).

The aim of the present study was to investigate the spatio-temporal aspects of brain economic evaluation of everyday household items during a task in which value was either task-relevant or irrelevant. Subjects viewed each item but were not requested to make a speeded response, rather, they rated the likeability or the material features of the item. A BDM auction experiment was used to evaluate WTP in a separate session, and the WTP values were correlated with ERPs and subjective ratings.

4.1.3. Methods

4.1.3.1. Participants

Twenty-five healthy participants (14 females) with a mean age of 24 ± 4.67 (mean ± SD) years took part in the study. The experimental procedures were approved by the Research Ethics Committee of the University of Liverpool. All participants gave written informed consent in accordance with the declaration of Helsinki. Participants were reimbursed for their time and travel expenses.

4.1.3.2. Procedure

All experimental procedures were carried out in a dimly lit, sound attenuated room. Participants sat in front of a 19-inch LCD monitor. The study was carried out in two sessions approximately 2-5 days apart. During the first session, participants completed the auction task. During the second session, participants completed the rating task. The stimuli comprised 90 everyday household items varying in value from £0.75 to £4.00 with a mean value of £2.52 ± £1.01 (mean ± SD) obtained from a shopping catalogue. Food items were excluded to avoid confounds arising from difference in the appetitive value of stimuli between session 1 and 2 of the study. Stimuli were presented in random order. Presentation of stimuli was controlled using Cogent 2000 (UCL, London, UK) in MATLAB 7.8 (MathWorks, Inc., USA). Experimental protocols and stimulus timings are illustrated in Figure 4.1.

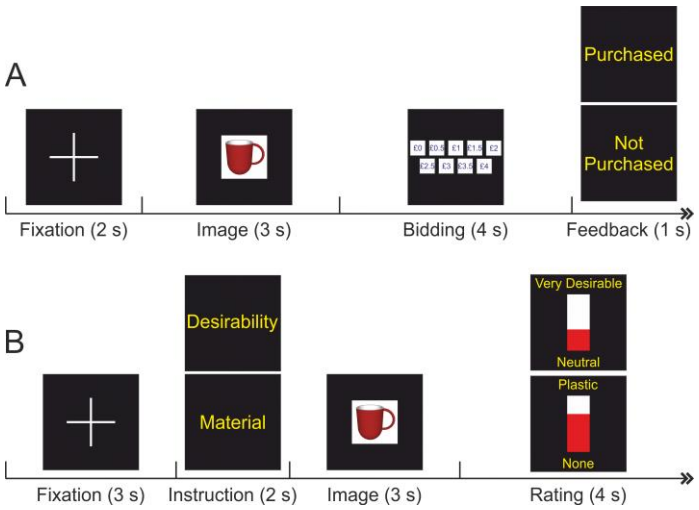

Figure 4.1. Experimental protocol. A. Timeline of auction task. A fixation cross was presented at the beginning of each trial for 2 s. Following offset of the fixation cross, an image was presented for 3 s followed by the bidding options for 4 s. A total of nine options were available between £0 and £4 in increments of £0.50. Following the selection of a bid, feedback was presented for 1 s to indicate the outcome of that auction. B. Timeline of EEG task. A fixation cross was presented at the beginning of each trial for 3 s. Next, an instruction was presented for 2 s to indicate the demands of the trial, followed by an image for 3 s. Following image offset, a VAS was presented for 4 s to allow either a desirability rating or material estimation depending on the preceding instruction.

4.1.3.3. Auction task

The protocol for the auction task was adapted from previous studies (Plassmann et al. 2007, 2010) and employed the BDM mechanism (Becker et al., 1964; Wilkinson & Klaes, 2012). Each stimulus was presented once resulting in a total of 90 auctions.

Each auction consisted of a fixation cross followed by an evaluation stage, a bidding period and then feedback. During the evaluation stage, participants appraised the stimulus that was presented on-screen. The bidding period required the participants to bid on the item. Here, participants were asked to bid between £0 and £4 in increments of £0.50 giving a total of nine options. During the feedback stage, participants were notified as to whether or not the item was won. The outcome of an auction was dependent on the bid and a randomly generated number, in which the item was purchased when $b \geq r$, where *b* represents the bid and *r* represents the randomly generated number for that auction. At the end of the experiment, three auctions resulting in a purchase were selected at random. For each auction selected, a price equal to *r* was subtracted from an initial endowment of £12. Therefore, the

actual endowment could vary between £0 and £12. The participant could pick up the items won within a few days of completion of the full experiment.

4.1.3.4. Rating task

Approximately 2-5 days following completion of the auction task, participants returned to take part in session 2. EEG was recorded continuously using the 128-channel Geodesics EGI system (Electrical Geodesics, Inc., Eugene, Oregon, USA) with the sponge-based HydroCel Sensor Net. The sensor net was aligned with respect to three anatomical landmarks (two pre-auricular points and the nasion). Electrode-to-skin impedances were kept below 50kΩ and at equal levels across all electrodes as recommended for the system (Ferree, Luu, Russell, & Tucker, 2001; Luu, Tucker, Derryberry, Reed, & Poulsen, 2003; Picton et al., 2000). The sampling rate was 1000 Hz and Cz was used as the initial reference. Data was filtered online using a 0.1-200 Hz bandpass filter.

After fitting the EEG cap, participants completed a computerized rating task. Each trial began with a fixation cross followed by an instruction stage, evaluation period and then rating. During the instruction stage, participants were presented with either the word ‘DESIRABILITY’ or ‘MATERIAL’, which served to cue the participant to the required type of evaluation. The evaluation stage began with the presentation of one of the visual stimuli, followed by the presentation of a visual analogue scale (VAS) for the rating stage. In the value-relevant condition, the participant would have to rate the desirability of the preceding stimulus (anchors: “neutral”-“very desirable”), while in the value-irrelevant condition, the participant would rate the proportion of the preceding stimulus composed of a certain material (for example, “none”-“plastic”). Here, the proportion of the scale that is shaded indicated the percentage of plastic composition. Desirability and material estimation trials were randomly intermixed within blocks.

Investigating the neural basis of subjective value is complicated by the multiple non-specific neural processes elicited during experimental paradigms used to reveal subjective value. During the rating task, the only difference between these two conditions was the calculation of subjective value for the trials in which desirability was rated. Any differences in ERPs between these two trials can,

therefore, be attributed to computation required to report subjective value. Of course, automatic processes involved in valuation would still be present. Each stimulus was presented in both conditions, yielding a total of 180 trials, split into three blocks.

4.1.3.5. Median split of WTP values

The stimulus set was divided into high and low WTP items using a median split of subjective values. In the case of items with identical value on both sides of the split, the items with that value were removed in such a manner that there was no overlap in value between the two sides and there was an equal number of stimuli in each category. For an unequal number of stimuli of identical value on each side of the split, stimuli of that value were removed randomly from the side with more. This produced two categories of stimuli (high and low value) of equal size for each participant, with a mean of 38.48 ± 5.02 (mean ± SD) items remaining in each condition.

4.1.3.6. ERP analysis

EEG data were pre-processed using BESA v. 6.0 program (MEGIS GmbH, Munich, Germany). Oculographic artefacts and electrocardiographic artefacts were removed using principle component analysis based on averaged eye-blinks and artefact topographies (Berg & Scherg, 1994). Data were also visually inspected for the presence of atypical electrode artefacts due to muscle movement. Data were filtered from 1-45 Hz and epochs contaminated with artefacts were excluded manually.

ERPs in response to stimulus presentation were computed separately for each level within conditions (High Value Item & Desirability Rating; High Value Item & Material Estimation; Low Value Item & Desirability Rating; Low Value Item & Material Estimation) by averaging respective epochs in the intervals ranging from 300 ms before image onset to 1000 ms following image onset. Epochs were baseline corrected using a time window of -300 to 0 ms relative to stimulus onset. The mean number of accepted trials in each condition (following the median split and artefact rejection) was 32.4 ± 5.8 (mean ± SD).

4.1.3.7. Source dipole reconstruction

Grand average potentials were computed by combining all conditions. The grand average waveform was used to define a source dipole model in BESA v. 6.0 program. Using a sequential strategy (Hoechstetter et al., 2001; 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). Six ECDs were consecutively seeded until the source model explained 91.6% of the variance. This amount of explained variance is comparable to previous ERP source dipole localisation studies (Hämäläinen et al., 1993; Schlereth, Baumgärtner, Magerl, Stoeter, & Treede, 2003; Stancak, Johnstone, & Fallon, 2012; Vrana, Polacek, & Stancak, 2005), and suggests that the six-dipole model explained all major ERP components. Classical LORETA analysis recursively applied (CLARA) method, which is an iterative application of the LORETA algorithm (Pascual-Marqui et al., 1994), was used as an independent source localisation method to confirm the locations of the ECDs (Wright et al., 2015). The orientations of ECDs were fitted with the constraint of fixed dipole locations and determined at the maximum of the source strength. A 4-shell ellipsoid head volume conductor model was employed, using the following conductivities (S/m = Siemens per meter): brain = 0.33 S/m; scalp = 0.33 S/m; bone = 0.0042 S/m; cerebrospinal fluid = 1 S/m.

Source waveforms for each condition were exported and analysed using the EEGLab toolbox (Delorme and Makeig 2004). Due to the large number of statistical tests that this requires, P values were corrected using permutation-based repeated-measures ANOVA utilising 5000 permutations (Maris & Oostenveld, 2007). For each latency identified, mean activation over a 10 ms period was calculated, centred on the peak of the observed effect and for each participant. The data were exported to SPSS Statistics version 22.0 (IBM Corp, 2013) for further analysis.

It is important to note the limitations of source analysis techniques due to the inverse problem manifesting in the possibility to generate a number of plausible source dipole models (Michel & Murray, 2012). Therefore, a priori information, such as constraining the source dipole locations to the cortical mantle, has been implemented in source dipole localisation methods to reduce the number of possible solutions (Michel et al., 2004). To build a plausible source dipole model, we applied

two different source dipole modelling methods. Firstly, the sequential method consisting of fitting equivalent current dipoles sequentially, and secondly, a distributed source dipole modelling method (CLARA). Both methods yielded highly convergent source dipole models which mitigates but does not completely overcome the limitations associated with the large number of potential source dipole solutions given the mathematical features of the inverse problem.

4.1.4. Results

4.1.4.1. Behavioural data

The high value items had a mean WTP of 2.1 ± 0.87 (mean ± SD) and desirability rating of 50.4 ± 29.7, whereas the low value items had a mean WTP of 0.66 ± 0.62 and desirability rating of 27 ± 25.3. To ensure this finding was not confounded by individual differences, a regression model for each participant was created with WTP as a predictor and desirability as a dependent variable. This produced a mean unstandardized coefficient of 15.5 ± 9.37; a one-sample t-test revealed this to be significantly different from zero, $t(24) = 8.27$, $P < .001$. A mean adjusted R^2 of 0.23 ± 0.17 (mean ± SD) was also found across subjects. Therefore, desirability of objects was linearly related to WTP (see Figure 4.2).

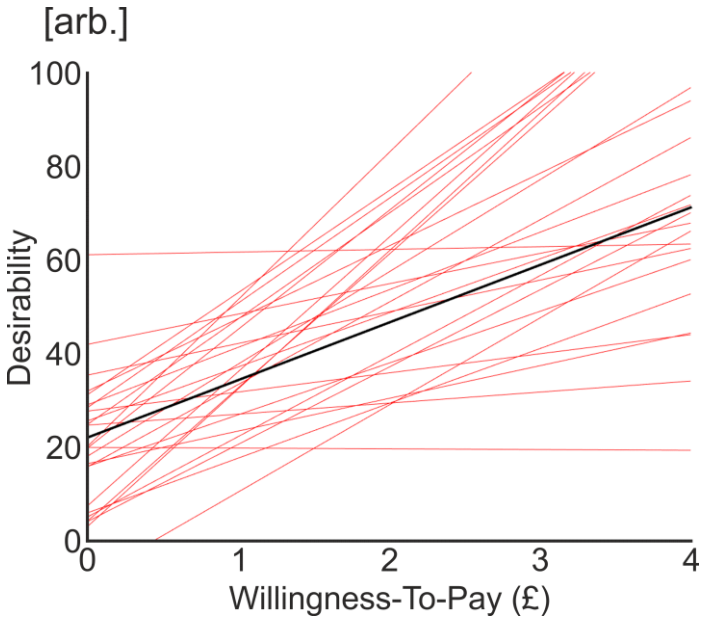

Figure 4.2. Regression lines for each subject predicting desirability from WTP. Grand average regression line is shown in black.

4.1.4.2. Source dipole model

Figure 4.3 illustrates the ERPs at each electrode site in response to stimulus presentation across all conditions in the form of a butterfly plot; ERP components and their corresponding latencies and topographies are labelled. Four distinct ERP components were observed across the epoch beginning with the visually evoked P1 component peaking at 99 ms, a component related to the early processing of visual stimuli (Hopf et al. 2002) and characterised by the strong positivity over the central occipital electrodes with reversed polarity over the frontal electrodes. A P2 component peaked at 209 ms with bilateral positivity over the occipital electrodes but with negativity restricted over a frontal region on the right side of the head (Freunberger, Klimesch, Doppelmayr, & Holler, 2007; Luck, 2005). Although clearly overlapping with the P2, the N2 component peaking at 243 ms can be differentiated by the additional negativity over a frontal region (Folstein & Van Petten, 2008). The P3 component (Polich, 2007) emerges at approximately 316 ms in a parietal region on the right side of the scalp, before reaching a positive maximum at 354 ms over the midline frontal electrodes.

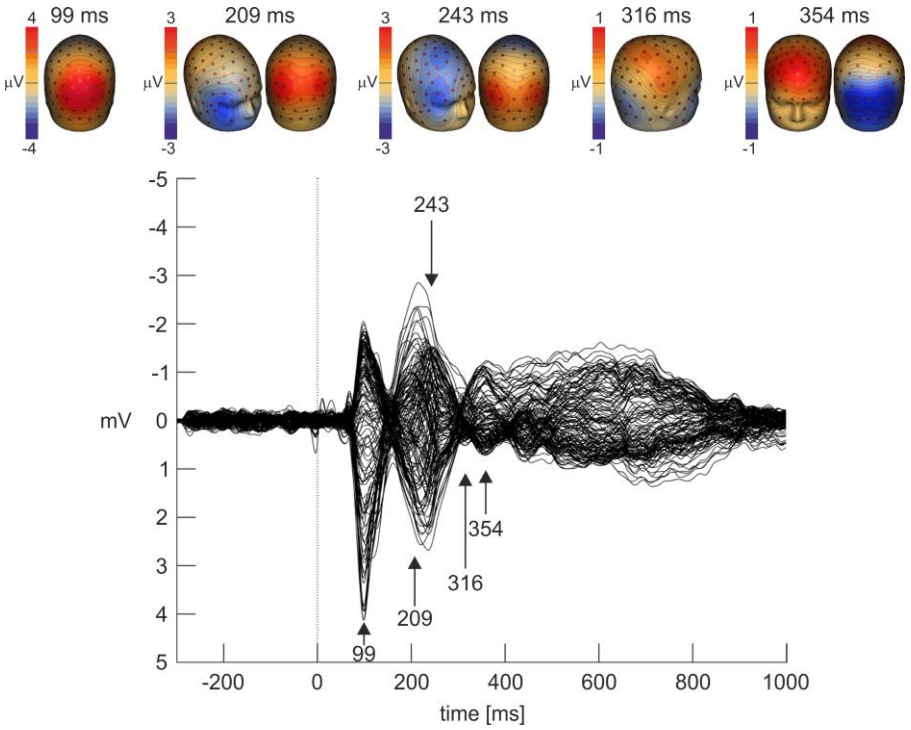

Figure 4.3. Butterfly plot of grand average ERPs in response to stimulus presentation. Distinct ERP components are highlighted with arrows (99, 209, 243, 316 and 354 ms). The topographic map for each ERP component is also displayed.

Figure 4.4A shows the source waveforms and the appropriate topographic maps for different ECDs and Figure 4.4B illustrates the spatial localisation of the ECDs. ECD 1 was located in the right lingual gyrus (Brodmann area 18; approximate Talairach coordinates: x = 18 mm, y = -59 mm, z = 9 mm) with a peak latency at 95 ms and again at 121ms. ECD 2 showed similar characteristics being located in the left lingual gyrus (Brodmann area 18; x = -17 mm, y = -59 mm, z = 9 mm) with a peak latency at both 100 ms and 215 ms. Both ECD 1 and 2 showed a positive maximum over the medial occipital electrodes and a negative potential over a frontal region of the scalp. The latency and the topographical pattern indicate that these two sources were equivalent to the visual P1 component. ECD 3 was located in the right anterior insula cortex (Brodmann area 13; x = 32 mm, y = 15 mm, z = 0 mm), peaking at 233 ms and showing maximum negativity over a frontal region on the right side of the scalp. This spatial map corresponds to the frontal portion of the N2 component. ECD 4 was located in the left orbitofrontal cortex (Brodmann area 11; x = -26 mm, y = 34 mm, z = -2 mm) showing a small peak at 230 ms. ECD 4 projected positivity over a frontal region localised marginally on the left side. However, this was masked by the N2 component. ECD 5 was located in the right parahippocampal gyrus (Brodmann area 28; x = 19 mm, y = -17 mm, z = -21 mm), showing two peak latencies of 215 ms and 316 ms corresponding to both the P2 and the early P3 component. ECD 5 accounted for positivity over a posterior region, localised primarily on the right side of the scalp. ECD 6 was fitted in the posterior cingulate cortex (bordering closely with the anterior cingulate cortex; Brodmann area 31; x = 3 mm, y = -18 mm, z = 42 mm). The source peaked at 248 ms and 431 ms with negativity being distributed across a frontal region of the scalp at 248 ms (contributing to the N2 component at the vertex) and positivity at 431 ms. The final source dipole model accounted for 91.6% of the total variance. CLARA method was used to verify the origins of the fitted ECDs. A mean discrepancy of approximately 15 mm was found between the location of each ECD and the maxima of the nearest cluster.

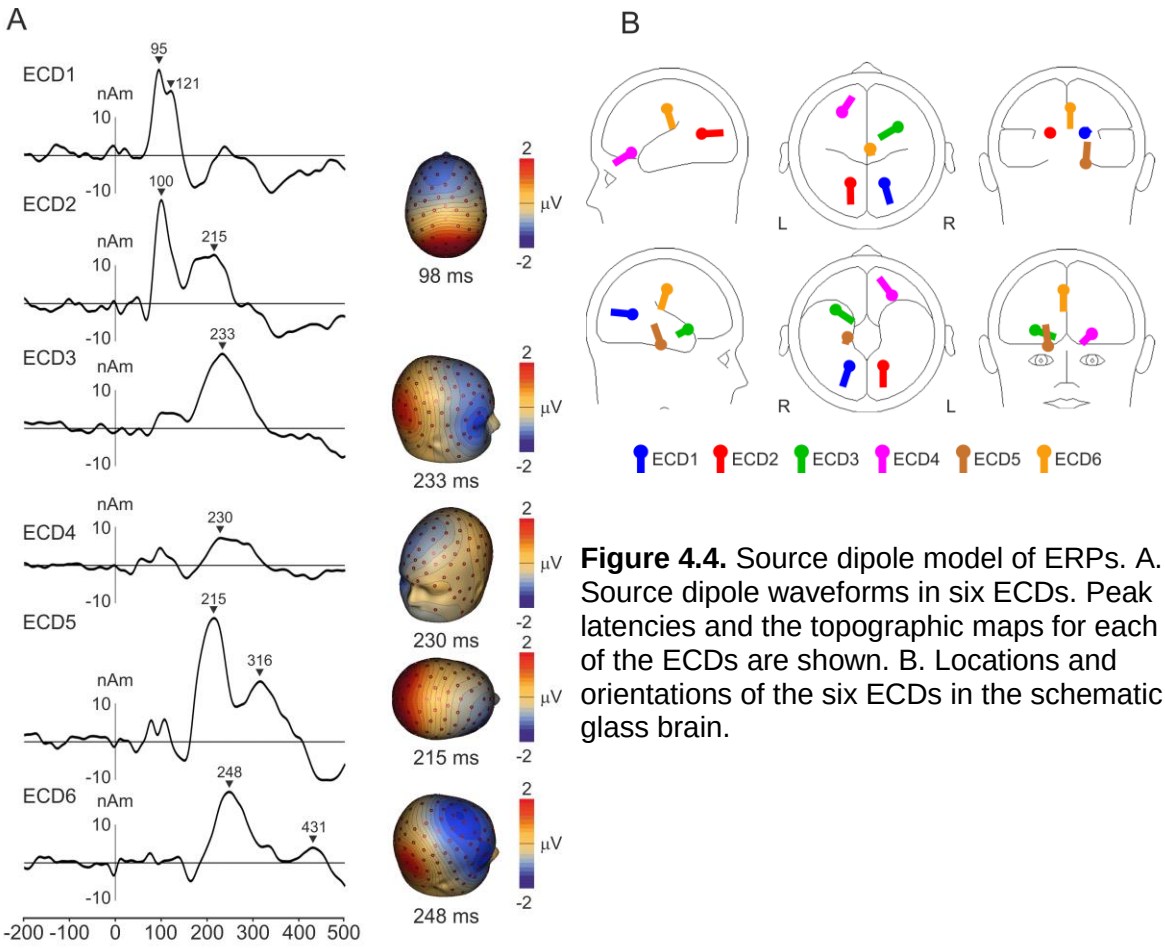

Figure 4.4. Source dipole model of ERPs. A. Source dipole waveforms in six ECDs. Peak latencies and the topographic maps for each of the ECDs are shown. B. Locations and orientations of the six ECDs in the schematic glass brain.

4.1.4.3. Effects of rating task and WTP

To test the effect of rating task and value on ERPs, a two-way ANOVA for repeated measures was carried out over the latency interval ranging from -200 ms to 450 ms using permutation analysis (Maris & Oostenveld, 2007) with 5000 permutations. The F value waveforms were masked inclusively to highlight significant latencies that extended beyond three standard deviations of the source's mean baseline amplitude. Figure 4.5 shows the topographies at the peak significance of each observed main effect with the corresponding source waveform. Activity over a 10 ms interval centred on the peak significance for each effect (indicated by the shaded region on the source waveform) was exported for further analysis. Table 4.1 and 4.2 summarise the mean amplitude and test statistics for each condition over the stated time interval for the main effects of rating task

(desirability vs. material) and value (high vs. low); significant interactions are highlighted in Table 4.3.

Table 4.1
Mean source amplitude ± SDs for both desirability and material estimation conditions over the stated time interval for each significant latency and the corresponding ECD. F and P values for the relevant ANOVA are also displayed.

ECD	Time Interval [ms]	Desirability	Material	$F_{(24)}$	P
ECD2	172 – 182	14.2 ± 23.2	9.32 ± 22.3	9.93	0.004
ECD3	201 – 211	19.28 ± 14.51	12.04 ± 12.2	17.6	< 0.001
ECD5	204 – 214	37.26 ± 20.81	27.49 ± 20.09	8.34	0.008

Table 4.2
Mean source amplitude ± SDs for both high and low value conditions over the stated time interval for each significant latency and the corresponding ECD. F and P values for the relevant ANOVA are also displayed.

ECD	Time Interval [ms]	High Value	Low Value	$F_{(24)}$	P
ECD3	195 – 205	10.07 ± 12.85	17.81 ± 15.31	9.19	0.006
ECD4	228 – 238	5.09 ± 8.07	9.36 ± 8.89	12.57	0.002

Table 4.3
Mean source amplitude for desirability ratings of high value (HD) and low value (LD) items and for material estimation ratings of high value (HM) and low value (LM) items for each significant latency and the corresponding ECD over the stated time interval. F and P values for the relevant ANOVA are also displayed.

ECD	Time Interval [ms]	HD	HM	LD	LM	$F_{(24)}$	P
ECD6	424 – 434	7.44 ± 12.76	1.85 ± 10.13	1.47 ± 10.32	5.05 ± 15.2	8.25	0.008

Figure 4.5A indicates three significant main effects of rating task on the activity from ECD 2, 3 and 5. The waveforms for these ECDs all demonstrate larger activation for desirability ratings than for material estimation ratings. Figure 4.5B illustrates the two significant main effects of value on the activity from ECD 3 and 4, each displaying greater activation for low value items. Despite the main effect of value at 233ms in ECD 4, it is important to note the difficulty in discerning the differences on scalp topographies due to the dominance of the negativity originating from ECD 3 which peaked at approximately the same time. Only one significant interaction between rating task and value was observed (ECD 6) which is visualised in Figure 4.5C. During the value rating condition, source activation for a desirability rating of a high value item was higher than in other conditions. Pairwise comparisons indicate that this activation was significantly stronger than during the material estimation and high value condition, $t(24) = 2.23$, $P = 0.035$, and also the desirability rating and low value condition, $t(24) = 2.1$, $P = 0.046$, but not the material estimation and low value condition, $t(24) = 0.65$, $P = 0.524$. No other significant differences were found ($P > 0.05$).

A possible explanation for this interaction could be a result of task-switching. For example, upon presentation of a high value item, participants would need to suppress their response if the task required material estimation with a low composition of the given material, with the same going for a low value item in the material estimation task in which composition was high. To test this, a regression model was produced for each subject with desirability as the independent variable and material composition as the dependent variable. This produced a mean unstandardized coefficient of -0.063 which was not significantly different from zero, $t(24) = -1.51$, $P = .145$, thus suggesting that task-switching does not adequately explain the interaction effect in PCC.

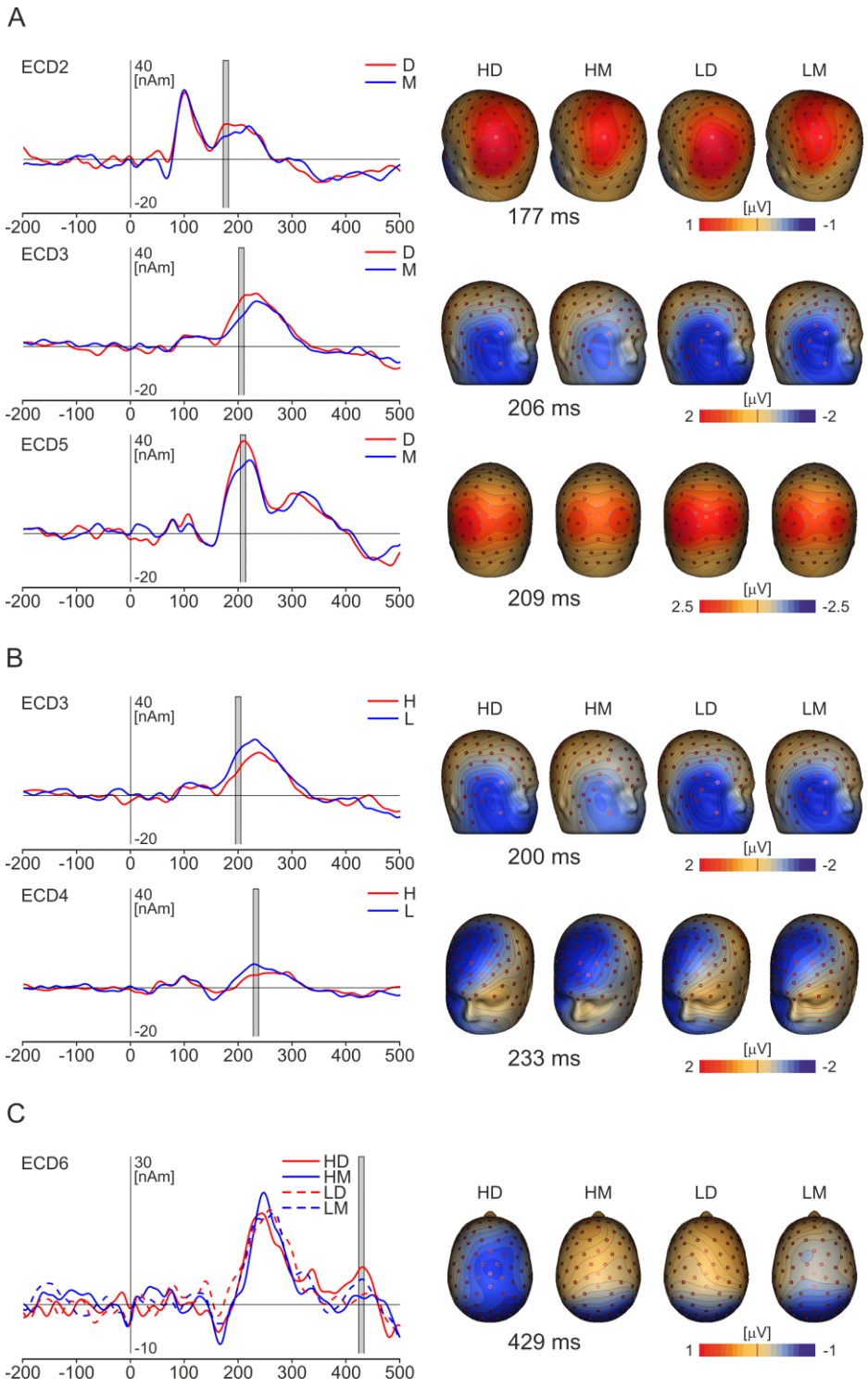

Figure 4.5. Effects of subjective value and context on source dipole waveforms. Each line represents the source dipole waveform for each condition (D = desirability rating; M = material estimation; H = high value items; L = low value items; desirability of high [HD] and low [LD] value items; material estimation of high [HM] and low [LM] value items). The shaded grey region on the source dipole waveforms indicates a 10 ms latency period in which a main effect or interaction was revealed, centred on the peak significance. Topographic maps for each condition are displayed. A. ECDs demonstrating a main effect of rating task (ECD 2, 3 and 5). B. ECDs demonstrating a main effect of value (ECD 3 and 4). C. ECD demonstrating significant interaction between rating task and value (ECD 6).

4.1.5. Discussion

This study explored the cortical representation of value by comparing items associated with high or low WTP, and recorded ERPs during passive viewing of items in two different valuation contexts, allowing us to disentangle the automatic and the elaborate and conscious valuation processes. Results showed increased cortical activity following the presentation of low value stimuli at the latency of approximately 200 ms, corresponding to the N2 and P2 components of ERPs. Although multiple sources contributed to ERP data at this latency, the economic value of items only modulated the activation in the right AIC and the left OFC. The effects of valuation context were seen in the left LG, right AIC and right PHG.

Modulation of source activity within the right AIC peaked at 200 ms, and activity was the strongest for rating of low value items. Although overlapping with the P2 component, source dipole orientation and topographical differences in the negativity over the forehead indicated that the N2 component that demonstrated an effect of value was distinct from the P2 component. The N2 potential was previously reported as being related to aspects of attentional selection (Codispoti, Ferrari, Junghofer, & Schupp, 2006; Naatanen & Picton, 1986; Patel & Azzam, 2005), or emotional content of visual stimuli (Olofsson & Polich, 2007). The anterior N2 component has been related more specifically to novelty detection and cognitive control (Folstein & Van Petten, 2008). The present study shows that the right AIC, a region known to be involved together with the OFC and amygdala in loss aversion (Canessa et al., 2017; Canessa et al., 2013; Markett, Heeren, Montag, Weber, & Reuter, 2016; Tom et al., 2007), contributed to effects of economic value on the amplitude of the N2 component. Therefore, it is possible that the bias towards low value items reflects a loss averse response as low value items could represent possible sources of financial loss. However, without more experimental control, it is difficult to speculate on the underlying cognitive processes.

The low-value bias seen in the N2 component might have been boosted in the present study by the relatively limited range of value among the items on offer. Bartra et al. (2013) report a quadratic pattern within the AIC showing increased BOLD signal in response to extreme outcomes, positive or negative, and decreased BOLD for neutral stimuli. With a relatively small range of values in the current study

(£0 - £4), the low value items may well have been negatively encoded (high arousal). In contrast, the high-value items may not have passed a threshold in order to be perceived as truly rewarding thus eliciting no arousal response.

A similar low-value bias was also seen in left OFC at a latency of 233 ms; despite falling within the N2 component latency, this effect was characterised by increased positivity over the left frontal region but masked by the negativity of the N2. The modulation of source activity for this ECD by stimulus value exhibits an automatic valuation, independent of the valuation context. Modulation of BOLD signal by subjective value has been observed frequently, often within the OFC (Clithero & Rangel, 2014). Interestingly, this modulation has been observed for various paradigms utilising several measures of value such as hedonicity ratings (Grabenhorst & Rolls, 2009; Lebreton et al., 2009), binary choice tasks (FitzGerald, Seymour, & Dolan, 2009) and importantly, BDM auctions (Plassmann et al., 2007, 2010). The same modulation is also found for multiple reward types and across multiple stages of the decision-making process (for a review, see Peters and Büchel, 2010). Further to this, animal research utilising electrophysiological methods have highlighted the encoding of subjective value within the OFC (Padoa-Schioppa, 2013; Padoa-Schioppa & Assad, 2006). Similar conclusions have been drawn regarding the vmPFC (Bartra et al., 2013; Clithero & Rangel, 2014), however given the limitations to spatial resolution that EEG presents, the current findings may not differentiate the activation of the OFC from the neighbouring vmPFC. The emergence of value-based signals in electrophysiological animal research has been observed in OFC at latencies as early as 150 ms (Padoa-Schioppa, 2013). Thus, formation of subjective value occurs automatically at an early stage and aids subsequent decision, regardless of whether this signal is an accurate depiction of the ultimate value assigned to the stimulus after further deliberation.

The cortical activity in the 200 ms latency range was also modulated by the valuation context. Given that the only computational difference between the two rating tasks is the presence of valuation, any differences in ERPs between the two contexts likely represent the cortical responses associated with attribution of value. The first modulation by the context was observed within the latency of the P2 component at 177 ms; the source activity in the LG was stronger when subjects focused on desirability of items, rather than the material compositions. It has been

suggested that the P2 is involved in working memory processes (Finnigan, O'Connell, Cummins, Broughton, & Robertson, 2011; Lefebvre, Marchand, Eskes, & Connolly, 2005; Taylor, Smith, & Iron, 1990; Wolach & Pratt, 2001), visual feature recognition (Hillyard and Münte 1984), and attention allocation (Martin-Loeches, Schweinberger, & Sommer, 1997). Federmeier and Kutas (2002) reported context-dependent modulations of the P2 in the left hemisphere which finding accords the present study.

An effect of the valuation context was also observed in the P2 component at a slightly later latency of 209 ms. This modulation was related to an increase in source activity in right PHG when evaluating the desirability of items compared to evaluating materials. Given the role of the PHG in memory processes (Aminoff, Kveraga, & Bar, 2013), it is likely here that focusing on the desirability of a stimulus has elicited working memory processes to a greater extent or required a greater magnitude of attentional allocation. This may be due to the more complex analysis required to reach a decision about value rather than a simpler perceptual evaluation. Assuming value-based decisions require an in-depth analysis of the stimuli, in contrast to the perceptual decision requiring estimation of a single material, this modulation may simply be a result of visual feature recognition regarding multiple aspects of the stimuli (Hillyard & Munte, 1984).

Finally, the right AIC also showed an increased source activity for the rating of desirability resulting in greater negativity over the right forehead. Augmentation of anterior N2 components have been attributed to attentional processes (Codispoti et al., 2006; Naatanen & Picton, 1986; Patel & Azzam, 2005) and it seems the differing computational demands of the value-based and perceptual decisions augmented the observed N2 in the current study. The additional requirement of value-computation for the value-based decision could be the contributing factor to this increased amplitude. Indeed, Naatanen and Picton (1986) highlight that the N2 component can be modulated by conscious processing of stimuli, and thus, this processing may well be value specific.

A final modulation of ERPs by the valuation context was observed at approximately 429 ms in PCC. The source activity in PCC, manifested as the negativity potential at vertex electrodes, was prominent for the rating of desirability of

high value items, indicating this activation to be specific to highly valued stimuli in an economically relevant context. However, this finding should be interpreted with caution due to the lack of statistically significant differences between the desirability rating of high value items condition, and the material estimation of low value items at the same latency.

To conclude, we show that the subjective value of simple household items, measured as WTP in an auction experiment, manifests in ERPs in the latency window and electrodes corresponding to the N2 component. The value-related cortical response, purportedly originating in right AIC and left OFC, is enhanced for low-value items possibly by eliciting loss aversion. The low-value bias in these cortical regions occurred across two different valuation contexts suggesting that this response is a part of an automatic valuation process. In contrast to the subjective value, the valuation context modulates the P2 and N2 components with stronger cortical responses in left LG, right AIC and right PHG occurring whilst subjects focused on desirability than on material aspects of items.

Chapter 5

Neural underpinnings of value-guided choice during auction tasks: An eye-fixation related potential study

Tyson-Carr, J. [1], Soto, V. [1], Kokmotou, K. [1], Roberts, H. [1], Fallon, N. [1], Byrne, A. [1], Giesbrecht, T. [2], Stancak, A. [1]

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This experiment investigated the brain components in response to eye-fixations, extracted from independent component analysis, that represent economic valuation over the full time course of a decision.

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The roles of the co-authors are summarised below:
I designed the study in collaboration with Andrej Stancak and collected the data. Vicente Soto, Katerina Kokmotou, Hannah Roberts and Adam Byrne assisted with the collection of data and contributed useful comments whilst preparing the manuscript for publication. Andrej Stancak, Nicholas Fallon and Timo Giesbrecht contributed to the experimental design as well as the large-scale planning of this project. Andrej Stancak and Timo Giesbrecht secured funding for project.

5.1. Neural underpinnings of value-guided choice during auction tasks: an eye-fixation related potentials study

5.1.1. Abstract

Values are attributed to goods during free viewing of objects which entails multi- and trans-saccadic cognitive processes. Using electroencephalographic eye-fixation related potentials, the present study investigated how neural signals related to value-guided choice evolved over time when viewing household and office products during an auction task.

Participants completed a Becker-DeGroot-Marschak auction task whereby half of the stimuli were presented in either a free or forced bid protocol to obtain willingness-to-pay. Stimuli were assigned to three value categories of low, medium and high value based on subjective willingness-to-pay. Eye fixations were organised into five 800 ms time-bins spanning the objects total viewing time. Independent component analysis was applied to eye-fixation related potentials.

One independent component (IC) was found to represent fixations for high value products with increased activation over the left parietal region of the scalp. An IC with a spatial maximum over a frontocentral region of the scalp coded the intermediate values. Finally, one IC displaying activity that extends over the right frontal scalp region responded to intermediate- and low-value items. Each of these components responded early on during viewing an object and remained active over the entire viewing period, both during free and forced bid trials.

Results suggest that the subjective value of goods are encoded using sets of brain activation patterns which are tuned to respond uniquely to either low, medium, or high values. Data indicates that the right frontal region of the brain responds to low and the left frontal region to high values. Values of goods are determined at an early point in the decision-making process and carried for the duration of the decision period via trans-saccadic processes.

5.1.2. Introduction

Selecting appropriate courses of action entails a value assignment process wherein the most subjectively beneficial action is selected (Rangel et al., 2008). Being a function of momentary needs, value itself is unique to the individual and is typically revealed via behavioural measures (Schultz, 2017), such as auction tasks. The Becker-DeGroot-Marschak (BDM) auction (Becker et al., 1964) is from a class of incentive compatible methods that reveal participant willingness-to-pay (WTP) for goods and prospects (Wilkinson & Klaes, 2012). BDM auctions have been often utilised in value-based decision making research (Chib et al., 2009; Grueschow et al., 2015; Hare, O'Doherty, Camerer, Schultz, & Rangel, 2008; Harris et al., 2011; Peters & Büchel, 2010; Plassmann et al., 2007, 2010; Weber et al., 2007), though a variety of methods for prompting unique valuations are employed (see Peters and Büchel, 2010).

Neuroeconomic research has posited the explicit representation of value signals in the brain (Glimcher & Fehr, 2014), with the ventromedial prefrontal cortex, orbitofrontal cortex (OFC) and ventral striatum playing prominent roles (Bartra et al., 2013; Chib et al., 2009; Clithero & Rangel, 2014; Lebreton et al., 2009; Levy & Glimcher, 2012). Valuation appears to be largely an automatic process which resolves values even if people focus on value-irrelevant aspects of objects such as perceptual features (Grueschow et al., 2015; Polania et al., 2014; Tyson-Carr et al., 2018), or when subjects are not required to valuate items (Plassmann et al., 2007, 2010). Although BOLD-fMRI methods excel in terms of spatial resolution to isolate brain regions responsible for economic valuation, these methods are limited by the temporal resolution which allows tracking brain activation on a scale of seconds (Shmuel & Maier, 2015).

Capitalising on the high temporal resolution of electrophysiological methods, electroencephalography (EEG) has aimed to show the temporal dynamics of value-based decisions, though research is sparse. Event-related potential (ERP) signals have been shown to represent value in binary decision tasks, even as early as 150 ms post-stimulus (Harris et al., 2011; Larsen & O'Doherty, 2014; Tzovara et al., 2015). It has also been demonstrated that activation may progress from occipito-temporal regions to frontal regions of the scalp over time following stimulus

presentation (Harris et al., 2011; Larsen & O'Doherty, 2014). Our recent study (Tyson-Carr et al., 2018) revealed that a visual evoked potential component within the latency of N2 and originating in the right anterior insula was preferentially activated with items having low subjective values. Moreover, Roberts et al. (2018) reported that the parietal P200 eye movement-related potential may index attention to low value products in a realistic setting. Similarly, magnetoencephalographic methods have also been used to classify the neural mechanism of value-guided choices (Hunt et al., 2012). In addition to the initial value attribution stage, outcome specific modulation of ERPs have also been observed in the P300, which may encode valence (San Martin, 2012; Yeung & Sanfey, 2004), and also the event- and feedback-related negativity which may be linked to reward-prediction errors (Gehring et al., 2012; Nieuwenhuis et al., 2004; Yu & Huang, 2013).

While previous fMRI and ERP studies shed light on spatial and temporal aspects of valuation during economic decision making, the detailed dynamics of the valuation process that evolve while an object is being viewed is poorly understood. When people evaluate objects to make economic decisions, their valuation evolves during free viewing of a visual scene. In free viewing, one or more objects in the visual field are explored in a series of saccades and fixations concatenated by trans-saccadic integration mechanisms (Melcher & Colby, 2008). Objects of greater value or those having a pleasant emotional connotation tend to be viewed for a longer time than objects of low value or aversive stimuli (Krajbich et al., 2010; van der Laan, Hooge, de Ridder, Viergever, & Smeets, 2015). If values are attributed to objects automatically, the assignment of an object to a high or low subjective value category would be captured by the brain early on during the viewing process and, once established, the value category would persist throughout the viewing period. In contrast, if values are attached to objects only after a careful exploration, purportedly involving volitional effort, objects would be assigned a provisional value, e.g., suggested initially by the automatic valuation process, but this value would be updated over a series of successive eye fixations. In such case, information about brain valuation while people are viewing objects before they decide to purchase would likely be encoded in the cortical responses to eye fixations, occurring just before a purchasing decision is made.

Eye-fixation related potentials (EFRPs) allow for the unveiling of neural processes at the point of fixation (Baccino & Manunta, 2005), and are often utilised during the free reading of words or viewing of scenes (Dimigen et al., 2011; Fischer et al., 2013; Hutzler et al., 2007; Nikolaev et al., 2016; Simola, Le Fevre, Torniainen, & Baccino, 2015). BOLD-fMRI lack the temporal resolution necessary to investigate the brain processes occurring on a scale of hundreds of milliseconds, and averaged ERPs only pick up information about the cortical activations occurring in the initial stage of valuation locked to the onset of visual stimulus. To overcome both of these shortcomings, EFRPs can provide a window into the cortical activations occurring over the entire period of free viewing accompanying the valuation.

Firstly, following up on our previous study (Tyson-Carr et al., 2018), we predicted that one activation component localised across the right frontal region of the scalp would encode low-value items. Since the range of products was expanded in the high-value interval in the present study (£0 - £8) compared to our previous study (£0 - £4) (Tyson-Carr et al., 2018), it was also hypothesised that other components would encode high- or medium-value items independently of the low-value sensitive component. Based on previous studies reporting the latency of value-based decision processes within the range of the N2 visual-evoked potential component (Harris et al., 2011; Kiss et al., 2009; Larsen & O'Doherty, 2014; Telpaz et al., 2015), we hypothesised that value encoding will occur in the latency of the N2 EEG component. Secondly, it was hypothesised that due to automaticity of valuation demonstrated in a number of previous studies (Grueschow et al., 2015; Lebreton et al., 2009; Plassmann et al., 2007, 2010; Polania et al., 2014), components would categorise the value of objects during initial eye fixations and maintain activations in subsequent eye fixations throughout the viewing period; the automaticity of value-based decision making would manifest in similarity of activation profiles over the viewing period for forced and free bids.

5.1.3. Methods

5.1.3.1. Participants

Twenty-four healthy participants (16 females) with a mean age of 25 ± 5.06 (mean ± SD) years took part in the study. The experimental procedures were

approved by the Research Ethics Committee of the University of Liverpool. All participants gave written informed consent in accordance with the declaration of Helsinki. Participants were reimbursed for their time and travel expenses. Due to technical issues with eye-tracking data, 6 participants were excluded, thus data from 18 participants were submitted for analysis.

5.1.3.2. Procedure

All experimental procedures were carried out in a dimly lit, sound attenuated room. Participants sat in front of a 19-inch LCD monitor. The study was carried out in a single experimental session involving the completion of an auction task. The stimuli included 180 everyday household items varying in value from £0.35 to £8.00 with a mean value of £4.30 ± 2.41 obtained from a shopping catalogue. Stimuli were presented in random order. Presentation of stimuli was controlled using Cogent 2000 (UCL, London, UK) in MATLAB 7.8 (MathWorks, Inc., USA).

5.1.3.3. EEG recordings

EEG was recorded continuously using the 128-channel Geodesics EGI system (Electrical Geodesics, Inc., Eugene, Oregon, USA) with the sponge-based HydroCel Sensor Net. The sensor net was aligned with respect to three anatomical landmarks (two pre-auricular points and the nasion). Electrode-to-skin impedances were kept below 50 kΩ across all electrodes as recommended for the system (Picton et al. 2000; Ferree et al. 2001; Luu et al. 2003). The sampling rate was 1000 Hz and electrode Cz was used as the initial reference. The recording bandpass filter was 0.1-200 Hz.

5.1.3.4. Eye-tracking recordings

Gaze positions were monitored using the Pupil head-mountable binocular eye-tracker (Kassner, Patera, & Bulling, 2014). Eye-cameras ran at a sampling rate of 120 Hz and the world camera at 60 Hz. Gaze tracking was calibrated using a 9-point manual marker calibration protocol in which calibration markers were presented sequentially on the stimulus presentation monitor. Following calibration, gaze

position accuracy was tested using a program that presented markers randomly on the screen for the participant to track. If gaze position was not easily discernible, calibration was repeated, otherwise the experiment was continued. Pupil Capture software v 0.8.1 was used for data collection. Pupil Player software v 0.8.6 running in Xubuntu was used for data visualisation and raw data exporting.

During the auction task, a series of digital fiducial surface markers were placed in each corner of the screen in order to define the surface of the monitor display. These markers were displayed continuously throughout the trials. Offline surface detection was carried out post data-collection but prior to fixation detection to allow fixations to be localised relative to the surface.

5.1.3.5. Auction task

The protocol (see Figure 5.1) for the auction task was adapted from previous studies (Plassmann et al., 2007, 2010) and employed the BDM mechanism (Becker et al. 1964; Wilkinson and Klaes 2012). Each stimulus was presented once in either a free bid or forced bid protocol, resulting in a total of 180 auctions.

Each auction consisted of a fixation cross followed by an evaluation stage, a bidding phase and then feedback. During the evaluation stage, participants appraised the stimulus. Afterwards, they were required to bid between £0 and £8 using a mouse to select the appropriate option on the screen. Bidding options were in increments of £0.50 between £0 and £2 and in increments of £1 between £2 and £8. This allowed more resolution at lower ends of the value scale, thus giving a total of 11 options. Participants clicked an orange square once satisfied with their bid. The screen had a horizontal size of 38.8º and vertical size of 34.7º when participants were viewing at a distance of 65 cm, stimuli had a horizontal and vertical size of 19.5º and the bidding scale had a horizontal size of 34.5º and vertical size of 2.3º. After bid selection, feedback was provided as to whether the item was purchased or not. The outcome of an auction was dependent on the bid and a randomly generated number, in which the item was purchased when $b \geq r$, where *b* represents the bid and *r* represents the randomly generated number for that auction. Following the experiment, one of the auctions that resulted in a purchase were selected at random and the outcome was implemented. Here, the participant's endowment of £8 was

reduced by an amount equal to *r* for the implemented auction. The item purchased could be picked up within a few days of completion of the experiment.

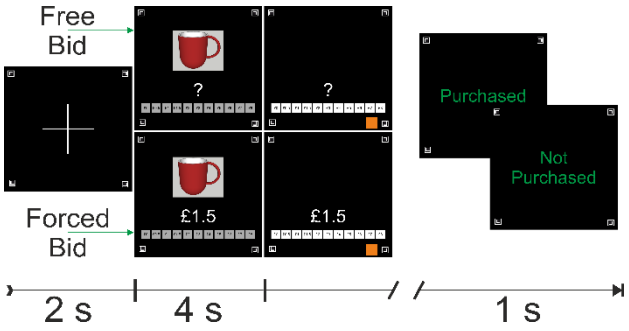

Figure 5.1. A timeline of the main auction task. A fixation cross was presented for 2 s followed by image presentation for 4 s, during which the trial type is indicated. If a '?' is presented below the image, individuals are allowed to bid freely after the image has offset. If a monetary amount is shown instead, the individuals must bid the reported amount. Following bidding, feedback was presented for 1 s to indicate the auction outcome.

Half of the stimuli were presented in the free bid condition whereas the other half were presented in the forced bid condition. In the free bid condition, participants were presented with a question mark above the bid amounts, indicating that they are free to bid whatever they like for the item. In the forced bid condition, participants were presented with a monetary amount above the bid amounts to indicate what they are required to bid for the item. Here, the participant cannot select any other option and cannot continue until they have selected that option. The only difference between these two conditions is the need for a computation of value.

After the main auction task, another auction task was conducted without recording EEG in order to obtain subjective WTP values for the items presented in the forced bid protocol. This is to allow categorisation of stimulus value that is not represented by a trivial forced bid procedure in which they have no influence over the reported value.

5.1.3.6. Split of WTP values

The stimulus set was divided into three groups of high, medium and low subjective value products for both the free bid and forced bid stimuli. To avoid overlapping values between these conditions, stimuli were removed randomly so that there were six groups of equal size (free bid and low / medium / high value; forced

bid and low / medium / high value), with each value category containing unique WTP values that did not overlap with any other value category. An average of 118 ± 17.3 trials were submitted for analysis for each subject, giving 19.7 ± 2.88 trials per condition.

The splitting of WTP into three categories was decided based on our previous study (Tyson-Carr et al., 2018) which included a stimulus set that was comprised of a relatively small range of subjective values (£0 to £4), split into two value categories of low and high value. The expansion of the stimulus value range to between £0 and £8 afforded us the ability to include a third value category comprised of products with intermediate WTP, increasing the ability to capture brain components for distinct increments of value. An increased number of value categories was not possible due to limited numbers of epochs.

5.1.3.7. EEG pre-processing

EEG data were pre-processed using BESA v. 6.1 program (MEGIS GmbH, Munich, Germany). EEG data were spatially transformed to reference-free data using common average reference method (Lehmann, 1984). Oculographic artefacts and electrocardiographic artefacts were removed using principle component analysis based on averaged eye-blinks and artefact topographies (Berg & Scherg, 1994). Data were also visually inspected for the presence of atypical electrode artefacts occurring due to muscle movement. Data were filtered from 0.5-45 Hz and exported to EEGLab (Delorme & Makeig, 2004) for further processing.

5.1.3.8. Detection of eye-fixations

Fixations were detected based on the given parameters of 150 ms minimum duration and a 1° dispersion threshold (Blignaut, 2009). Each subject made on average 3965 ± 792 (mean ± SD) fixations on the screen across the experiment. Next, only fixations occurring during image presentation were accepted, resulting in 1725 ± 299 fixations. Following the splitting of stimuli into three value categories and the required exclusion of overlapping stimuli, fixations occurring during trials of excluded stimuli were also removed, resulting in 1154 ± 222 fixations. Given the two trial types accompanying the three value conditions, this resulted in a mean of 192 ±

5.4 fixations for each of the six conditions. Fixations overlapping with artefacts within the EEG data were also removed, resulting in 171± 4.6 fixations per condition. In addition to the six conditions, fixations were also organised into five time bins. These time bins were classified based on five 800 ms intervals encompassing the 4000 ms of image presentation. This allowed the organisation of fixations into five discrete and equally spaced categories between image onset and offset. These categories will be referred to as TB1, TB2, TB3, TB4 and TB5 hereafter. Since the data was also split into five time bins, this further reduced the number of fixations per condition to 34 ± 2.44 fixations and 8.76 ± 1.5 fixations per trial for every subject submitted for analysis.

5.1.3.9. Eye-fixation related potential analysis

Since EEG and eye-tracking was recorded with separate systems, the data had to be synchronised. A TTL pulse inputted into the EEG data stream indicating image onset and the corresponding appearance of the image in the word-view camera of the eye-tracking allowed for synchronisation.

After synchronising eye-tracking and EEG data, EFRPs in response to fixation onset were computed separately for each level of value condition (low, medium, high), trial type (free, forced) and time bin (TB1, TB2, TB3, TB4, TB5) by averaging respective epochs in the intervals ranging from 200 ms before fixation onset to 400 ms following fixation onset. Epochs were baseline corrected using an individual baseline in the time window of -200 to -100 ms relative to fixation onset (Luck, 2005). This baseline was selected to mitigate effects of the saccadic spike potential (SP). Given the modulation of the SP by a variety of eye-movement characteristics, baselines encompassing the SP may induce differences between conditions due to condition specific eye-movements (Nikolaev et al., 2016).

5.1.3.10. Eye-movement characteristics

Since eye-movement characteristics can modulate the pre-saccadic activity, the SP and the lambda brain potentials, eye-movement characteristics were analysed (Boylan & Doig, 1989; Keren et al., 2010; Nikolaev et al., 2016; Riemslag et al., 1988; Thickbroom & Mastaglia, 1986). Saccade amplitude was defined as the

gaze distance between saccade initiation and fixation onset, expressed in degrees of visual angle, for each fixation. Saccade direction represented the angle between these two points for each fixation.

5.1.3.11. Component clustering

EFRPs were input into the EEGLab (Delorme & Makeig, 2004) STUDY structure to allow for the clustering of similar independent components (ICs) across subjects. Independent component analysis (ICA) was first carried out on the concatenated epochs for each subject to identify a set of ICs. Next, ERP and scalp map component measures were computed and used to build a pre-clustering array for clustering components into 18 clusters. Clustering into 18 clusters was chosen to reflect the number of participants submitted for analysis to allow independent components to be distributed amongst an appropriate number of clusters for a suitable separation of brain components. To restrict analysis to the most significant clusters, 95% confidence intervals were computed on the time course of each cluster. If the confidence intervals did not exceed zero, i.e. the interval overlaps with zero, the cluster was excluded.

5.1.3.12. Unfold toolbox

Free viewing in EEG paradigms allow us to examine neural processes over an extended period of time. However, the introduction of free viewing is accompanied by overlapping neural responses from subsequent fixation events. Thus, any value- or condition-related changes in EFRPs may be confounded by associated eye-movements. To control for the impacts of eye movements on EFRPs, the Unfold toolbox (Ehinger & Dimigen, 2019) was employed. This toolbox uses linear deconvolution to isolate the neural response from events with varying temporal overlap.

To ensure that the changes in IC clusters were not a result of saccadic eye-movements occurring within the latency of each epoch, each IC cluster was back projected onto the continuous EEG data and analysed using the Unfold toolbox to test for the influence of overlapping potentials on the data (see Supplementary materials). Firstly, a linear model was defined for the linear deconvolution procedure

to estimate potentials across all fixations. Since we were not interested in the potentials for each condition, but rather the grand average deconvolution, the potentials for each condition were not modelled here. Next, a regression analysis was applied to the continuous EEG data using the following formula:

$$EEG = X_{dc}b + e \quad \text{(Eq. 1)}$$

where X_{dc} encodes covariates for all time samples in the continuous EEG data, b contains the regression (beta) coefficients and e the residuals. Next, the regression formula was solved for the beta (b) coefficients, wherein these betas represented non-overlapping potentials. Since our model did not include terms for any condition, the intercept represented the de-convolved brain potentials for each IC cluster.

5.1.4. Results

5.1.4.1. Behavioural data

Mean WTP values were computed for each condition separately. In the free bid trials, a mean value of £0.71 ± £0.64 was observed for low value items, £2.23 ± £1.14 for medium value items and £5.02 ± £1.50 for high value items. In the forced bid trials, a mean WTP value of £0.76 ± £0.85 was observed for low value items, £1.99 ± £1.44 for medium value items and £4.31 ± £1.80 for high value items.

All value categories were significantly different from each other ($P < .001$). There was also a significant difference between free and forced bid trials, $F(1,17) = 8.84$, $P = .009$, $\eta_p^2 = .342$, as well as an interaction between value and trial type, $F(2,34) = 18.9$, $P < .001$, $\eta_p^2 = .526$. Pairwise comparisons reveal a significant difference between medium value items for free and forced bids, $t(17) = 2.31$, $P = .037$, $d = 0.19$, and also between high value items, $t(17) = 4.15$, $P < .001$, $d = 0.43$. Given that this could potentially confound results when interpreting any main effect or interaction including trial type, these analyses will have the addition of a covariate analysis with WTP values.

5.1.4.2. Fixation location data

The mean saccade amplitude for each condition was calculated and input into a 3 (values) × 2 (forced vs. free) × 5 (time bins) ANOVA for repeated measures.

There were no significant main effects or interactions between conditions for saccade amplitude.

The circular nature of saccade direction required statistical testing appropriate for circular statistics. The mean circular saccade direction for each subject and condition was calculated using the CircStat toolbox (Berens, 2009) before being analysed using the bpnreg package (Cremers & Klugkist, 2018) implemented in R (R Core Team, 2018). A mixed effects model was fitted to assess the interaction between value category, trial type and time bin regarding the circular outcome of saccade direction. This analysis produced the 95% highest posterior density (HPD) intervals, an interval allowing probability statements about the parameters, displayed in Figure 5.2. Inspection of the intervals reveal overlapping intervals between all value categories, within all time bins, for both free and forced bids, with the exception of TB2 for free bids wherein low value products elicited different saccade directions. We therefore conclude that saccade direction was only intermittently different between conditions, given the overlapping distributions of circular mean directions.

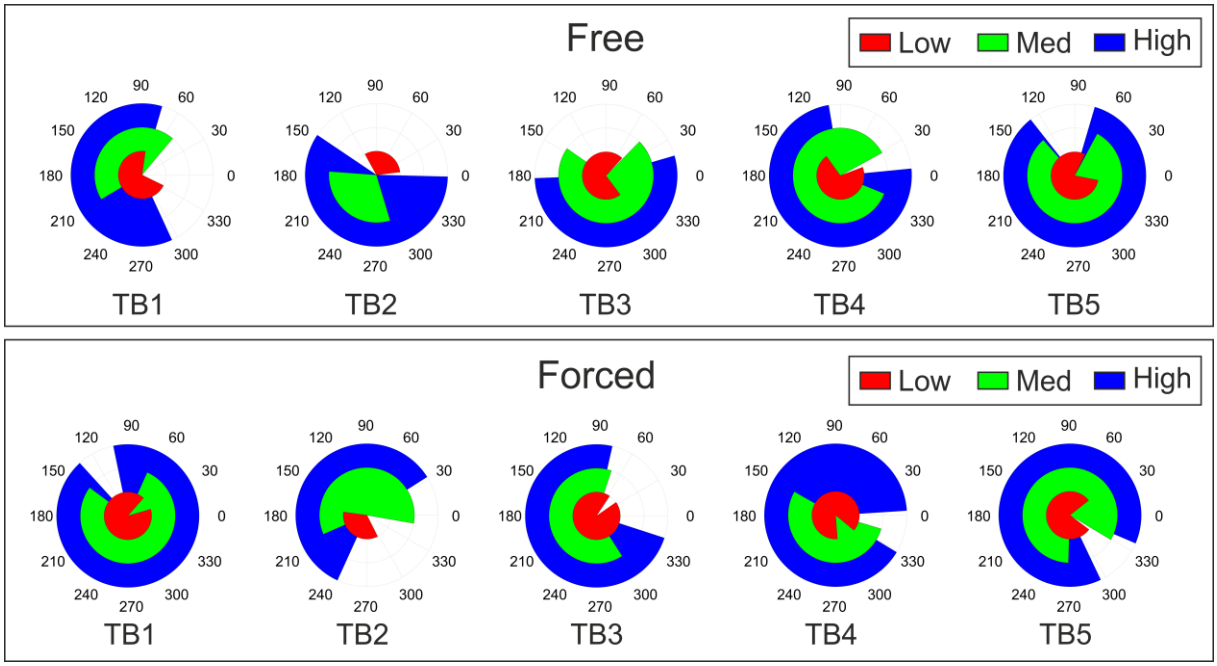

Figure 5.2. 95% HPD confidence intervals for saccade direction measured in degrees of visual angle for each condition.

To aid in the interpretation of EFRPs, fixation data across the screen was converted into a 40×40 bivariate histogram to visualise the locations of fixations for each condition. During the evaluation stage of the paradigm, a large part of the

screen had no relevance to the participant. Therefore, analysis was restricted to two regions of interest – the product region of interest (ROI) and the value scale ROI (green shaded area of Figure 5.3A-B). The fixation data, comprised of number of fixations per histogram bin, across the whole of each ROI were then submitted to a 3 (WTP categories) × 2 (free vs. forced) × 5 (time bins) repeated measures ANOVA to investigate the differences in fixation location between conditions. Given the large number of analyses from computing a three-way ANOVA on each histogram bin, P values were corrected using the Bonferroni-Holm (Holm, 1979) correction for multiple comparisons. Figure 3 summarises the results of all main effects. Firstly, three clusters of differences were observed across the product ROI, all indicating a significantly increased number of fixations for high value products. Secondly, a small cluster of significant differences was found on the left side of the value ROI, indicating an increased number of fixations for low value products. Thirdly, the cluster of significant differences indicated an increased number of fixations on the product ROI during forced bid trials, as well as an increased number of fixations on the value scale ROI during forced bid trials. Lastly, participants fixated progressively less on the product ROI and more so on the value scale ROI. Interaction effects did not indicate significant modulation and therefore did not require further investigation.

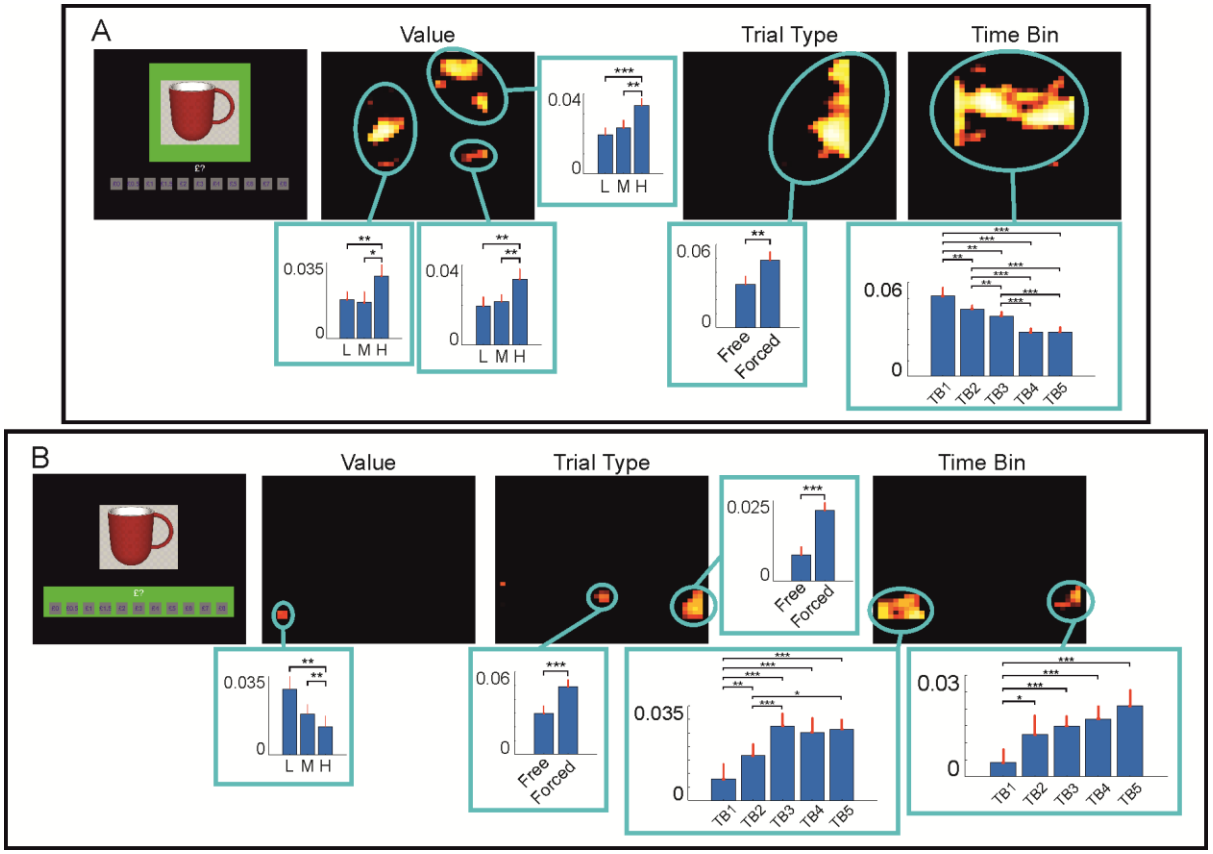

Figure 5.3. Fixation locations. Heatmaps indicating fixation location differences within conditions for the image region (A; green highlighted area) and the scale region (B; green highlighted area). Bar graphs showing mean number of fixations per histogram bin. Bar graphs also indicate direction of effects for each cluster of differences.

The same 40×40 bivariate histogram illustrating statistically significant differences between conditions was calculated with fixation duration parameters across the product and value scale ROI (Figure 5.4). Two major differences are observed between the number of fixations and corresponding fixation durations. Firstly, an increased number of fixations across the product ROI for high value products was paired with irregular differences in fixation duration. This suggests an increased number of fixations for high value products, independent of fixation duration, due to sporadic differences in fixation duration but a systematic increase in number of fixations. Secondly, an increased number of fixations on the product ROI during forced bid trials is paired with longer fixation durations during free bid trials on the product ROI. Hence, free bid trials elicited fewer but longer fixations, in contrast to forced bid trials eliciting many short fixations.

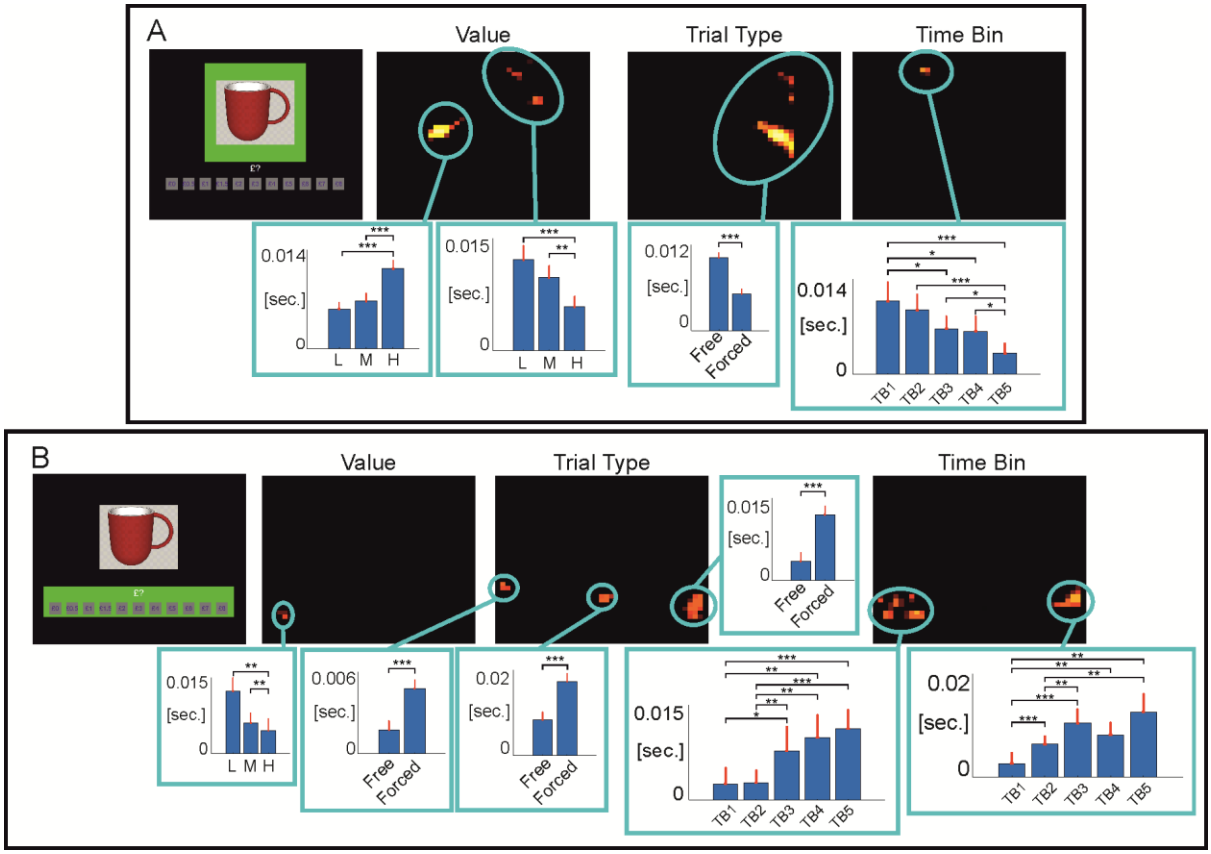

Figure 5.4. Fixation durations. Heatmaps indicating fixation duration differences within conditions for the image region (A; green highlighted area) and the scale region (B; green highlighted area). Bar graphs showing mean fixation duration in each histogram bin. Bar graphs also indicate direction of effects for each cluster of differences.

To further explore fixation data within the value scale ROI, fixations were extracted for each condition and the location of the fixations along the x-axis of the computer screen were normalised between -1 and 1. Transforming the time axis allowed for the visualisation of what set of values were being fixated during each time bin for each value category and trial type. Figure 5.5A demonstrates in the form of a bar graph how individuals were fixating in the centre of the value scale ROI regardless of value condition during TB1 for free bids. Fixating the centre of the screen during the initial viewing period was likely related to the indication of the type of condition (free vs forced) at this spot. However, in free bids, fixation location during TB2 was already predictive regarding low value items, with fixation location predicting their bid from TB3 onwards. This bias towards the left of the screen was reflected in the subjective WTP values in which the mean WTP for low and medium value items fall below the middle value of the scale. Figure 5.5B illustrates fixation

locations during each time bin and each value category for forced bid trials, though no significant relationships were found.

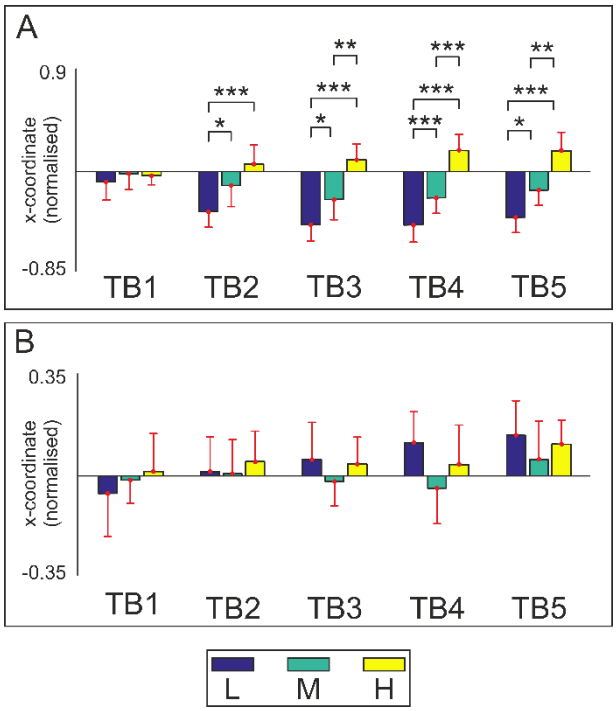

Figure 5.5. Scale fixations x-axis coordinates. Mean x-axis coordinates for fixations on the scale normalised between -1 and 1. Mean coordinates for each value category and time bin are shown for free bids (A) and forced bids (B). Post-hoc tests are shown: * = *P* < .05, ** = *P* < .01, *** = *P* < .001.

5.1.4.3. Eye-fixation related potentials

ICs were clustered into 18 clusters. To identify the most significant clusters, confidence intervals were computed across the waveform for each cluster. To be submitted for further analysis, 95% confidence intervals had to exceed zero at peak component amplitude. This check resulted in nine clusters being submitted for further analysis. Mean component amplitude across the whole time course and IC maps are summarised in Figure 5.6. The number of components, as well as the number of subjects included in the cluster, are also reported.

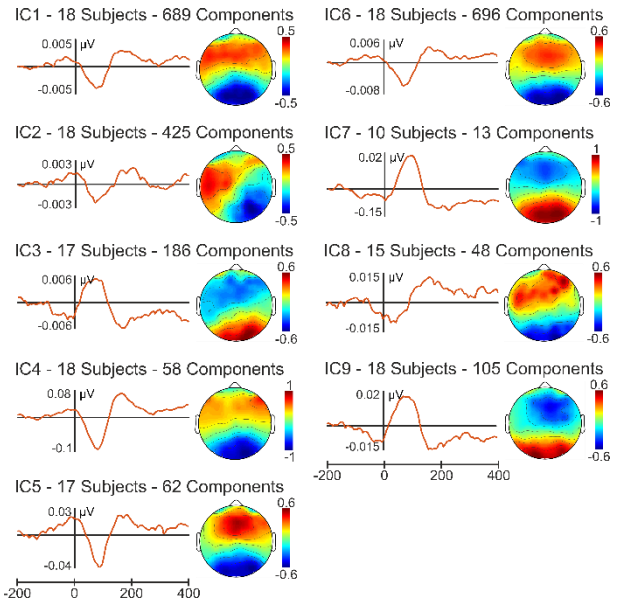

Figure 5.6. EFRP clusters. Independent component clusters for EFRP data that passed confidence intervals checks are illustrated with their corresponding waveforms and scalp maps.

The data from each of the nine clusters were submitted to a permutation-based repeated-measures ANOVA utilising 2500 permutations. Analysis was constrained to latencies between 50 ms and 270 ms to limit analysis to the latencies of brain potentials known to be involved in economic decisions (Tyson-Carr et al., 2018). A single cluster could contain a varying number of components belonging to different subjects, with subjects not necessarily contributing an equal number of components to any one cluster. Therefore, components belonging to the same subject were summated to produce a single component for each subject thus allowing for the preservation of the original null hypothesis. Consequently, statistical analysis on IC amplitude is in terms of summated component amplitude.

Firstly, an ANOVA with value category and trial type as independent variables was carried out to highlight the influence of these two factors on IC amplitude, either individually or interactively. Secondly, to investigate the interaction between value category and time bin, an ANOVA with value category and time bin as independent variables was carried out. Lastly, trial type and time bin were submitted to an ANOVA to investigate the interaction between these two variables. This resulted in a set of significant latencies for each cluster illustrating one of the above effects. Our method of permutation testing was limited to two factors which produced overlapping

factors between the three ANOVAs completed. Hence, these permutation tests were used to detect latencies of interest across the clusters. Following extraction of these significant latencies, the corresponding omnibus ANOVA was completed to ensure the results were robust to the appropriate statistical tests.

In order to further restrict analyses, significant latencies were excluded based on two criteria. Firstly, significant differences had to be observed for a minimum of 5 consecutive milliseconds to ensure that the differences were not the result of momentary spikes. Next, latencies demonstrating significant interactions were excluded if the cluster did not first demonstrate a main effect within one of the independent variables. Results are summarised in Figures 5.7A-C.

Figure 5.7A highlights all significant latencies that demonstrated a significant main effect of value category across clusters. A significant effect of value was revealed between 158 and 165 ms in IC1, $F(2,34) = 3.46$, $P = .046$, $\eta_p^2 = .17$. High value items produced significantly decreased amplitude in comparison to both low value items, $t(17) = 2.26$, $P = .033$, $d = 0.57$, and medium value items, $t(17) = 2.58$, $P = 0.02$, $d = 0.65$. Separation of value categories was also observed for IC2 between 50 and 70 ms, $F(2,34) = 6.49$, $P = .004$, $\eta_p^2 = .28$, in which significantly increased amplitude was demonstrated for high value items in comparison to low value items, $t(17) = 3.7$, $P < .001$, $d = 0.56$, and medium value items, $t(17) = 2.5$, $P = .024$, $d = 0.5$. A similar effect was also demonstrated in IC3 between 148 and 160 ms, $F(2,32) = 3.97$, $P = .028$, $\eta_p^2 = .2$, with medium value items eliciting greater activity in comparison to low value items, $t(16) = 2.34$, $P = .037$, $d = 0.61$, and high value items, $t(16) = 2.076$, $P = .041$, $d = 0.43$. However, the component was at its strongest over a frontocentral region of the scalp. A statistically significant effect was revealed between 85 and 103 ms for IC4, $F(2,34) = 3.42$, $P = .044$, $\eta_p^2 = .167$, with high value items eliciting significantly increased amplitude in comparison to low value items, $t(17) = 2.78$, $P = .015$, $d = 0.43$. A second statistically significant effect of value in IC4 was revealed between 155 and 214 ms, $F(2,34) = 3.7$, $P = .035$, $\eta_p^2 = .178$. Post-hoc testing revealed significantly increased amplitude for medium value items in comparison to low value items, $t(17) = 3.06$, $P = .004$, $d = 0.42$.

Figure 5.7. EFRP cluster effects. Clusters that demonstrate main effects of value category (A) or trial type (B) are shown, along with the time course of activations for the value relevant effects in IC1, IC2 and IC3 with corresponding effects (C). An interaction between value category and trial type (D) and an interaction between value category and time bin (E) are also illustrated.

Figure 5.7B demonstrates the main effects of trial type (free vs. forced bids). Three of the clusters demonstrated significantly increased activation during free bid trials. This effect was observed between 190 and 195 ms for IC1, $F(1,17) = 5.06$, $P = .038$, $\eta_p^2 = .23$, between 172 and 179 ms for IC2, $F(1,17) = 4.72$, $P = .044$, $\eta_p^2 = .22$, and lastly between 100 and 110 ms for IC5, $F(1,16) = 4.9$, $P = .041$, $\eta_p^2 = .23$. In contrast, two clusters demonstrated significantly increased activation during forced bid trials, firstly between 97 and 105 ms in IC4, $F(1,17) = 4.9$, $P = .04$, $\eta_p^2 = .22$, and also between 126 and 144 ms in IC6, $F(1,17) = 11.8$, $P = .003$, $\eta_p^2 = .41$.

As shown in Figure 5.7A, three significant effects separate different value categories. We therefore show in Figure 5.7C the corresponding time course of these activations across the 5 time bins in the same latencies. A main effect of time bin was observed for IC1 between 158 and 165 ms, $F(4,68) = 8.02$, $P < .001$, $\eta_p^2 = .32$. Post-hoc testing revealed significantly increased activation in TB1 in comparison to TB2, $t(17) = 4.66$, $P < .001$, $d = 1.25$, TB3, $t(17) = 4.95$, $P < 0.001$, $d = 1.47$, TB4, $t(17) = 4.39$, $P < 0.001$, $d = 1.37$, and TB5, $t(17) = 3.43$, $P = 0.007$, $d = 0.91$. For IC2 between 50 and 70 ms, no significant differences between time bins were found. A statistically significant effect of time bin was found for IC3 between 148 and 160 ms, $F(4,64) = 3.1$, $P = .021$, $\eta_p^2 = .16$. Post-hoc tests revealed significantly increased amplitude in TB1 in comparison to TB2, $t(16) = 2.34$, $P = 0.03$, $d = 0.81$, TB4, $t(16) = 2.78$, $P = 0.013$, $d = 0.91$, and TB5, $t(16) = 2.77$, $P = 0.014$, $d = 0.82$. It therefore appears that for clusters encoding low and medium value, activity is greatest early on during valuation, whereas it is maintained throughout the viewing period for high value brain components.

The interactions between value category and trial type are reported in Figure 5.7D. Here, only one significant effect was found for IC4 at a latency between 180 and 190 ms, $F(2,34) = 3.5$, $P = .041$, $\eta_p^2 = .17$. Following on from the main effect of value at a similar latency, this interaction appears to be a result of decreased amplitude for low value items in comparison to medium value items, $t(17) = 3.54$, $P = .002$, $d = 0.75$, and high value items, $t(17) = 2.7$, $P = .012$, $d = 0.51$, in the forced bid trials only.

Finally, the interactions between value and time bin are reported in Figure 5.7E. The only statistically significant interaction was found in IC2 in the epoch of 150 and 160 ms, $F(8,136) = 2.2$, $P = .035$, $\eta_p^2 = .11$. Post-hoc tests revealed significant differences in TB2, TB3 and TB4. In TB2, high value items elicited significantly increased amplitude in comparison to low value items, $t(17) = 2.19$, $P = .017$, $d = 0.84$. In TB3, medium values elicited increased amplitude in comparison to high value items, $t(17) = 2.35$, $P = .028$, $d = 0.75$. Finally, in TB4, high value items elicited significantly increased amplitude in comparison to low value items, $t(17) = 2.1$, $P = 0.048$, $d = 0.74$.

Since stimulus onset may have an influence on eye-fixation related potentials in the first time bin (Dimigen et al., 2011; Nikolaev et al., 2016), we carried out further analysis to account for any confounds. Firstly, we calculated the global field power based on the original grand average EFRP for each time bin and subject. Secondly, we averaged data across four separate latencies to summarise activity at the latency of the P1, P2, N2 and P3 components. Finally, we submitted this data to separate ANOVAs to determine whether the average amplitude of the corresponding components was influenced by time bin. Significant main effects of time bin were revealed for the P1 measured between 50 and 120 ms, $F(4,68) = 8.46$, $P < .001$, $\eta_p^2 = .33$, the P2 between 150 and 200 ms, $F(4,68) = 18.9$, $P < .001$, $\eta_p^2 = .53$, the N2 between 200 and 280 ms, $F(4,68) = 21.3$, $P < .001$, $\eta_p^2 = .56$, and the P3 between 280 and 350 ms, $F(4,68) = 23$, $P < .001$, $\eta_p^2 = .57$. All post-hoc tests revealed differences between time bin 1 and all other time bins ($P < .05$), with no other differences being present ($P \geq .05$). This suggests stimulus onset had a significant influence on the grand average EFRPs, and therefore, this may explain the differences observed between time bins in IC1 between 158 and 165 ms, and also between time bins in IC3 between 148 and 160 ms. However, the lack of differences between time bins in IC2 between 50 and 70 ms implies that this cluster is not influenced by stimulus onset, and therefore, may represent value-related activity. Lastly, although EFRPs have been shown to be modulated by fixation rank (Fischer et al., 2013; Kamienkowski, Varatharajah, Sigman, & Ison, 2018), the absence of differences between time bins after time bin 1 suggests brain data is not modulated by fixation rank in the current study.

5.1.5. Discussion

The present study postulated the presence of value-specific cortical activation components of which at least some would respond to a specific value category early on during the viewing period and maintain their activations throughout the viewing period both during free and forced bid trials. The findings largely support our predictions. Firstly, unique cortical activation components were observed for high, medium and low/medium value products. Additionally, a left, middle, right lateralisation effect was found for high, medium, low/medium value products, respectively. Secondly, effects were mostly observed within the latency of the N2

EEG component, emphasising the importance of this component in economic valuation processing. Lastly, the brain component specific to high value did not significantly vary throughout the valuation stage, although it was strongest during the initial and the final stage of valuation. The maintained component activation for high value products suggests the increased cognitive processing required for high value items in comparison to low and medium value items. The fixation heat maps indicating an increased number of fixations, independent of fixation duration, across the product for high value products provides further support for this increased cognitive processing, similar to previous studies (Anderson & Halpern, 2017; Anderson & Yantis, 2012).

Brain components encoding distinct categories of stimuli is prevalent across many domains. For example, the N170 EEG component has frequently been described as being an activation specific to face-processing (Calvo & Beltran, 2013; Cao, Jiang, Gaspar, & Li, 2014; Zhang, Luo, & Luo, 2013), as well as encoding the emotional valence of faces (Qiu, Wang, & Fu, 2017). Evidence for the encoding of emotional valence is also prevalent amongst several other brain components. For example, the P1, N1, P2 and N2 components have been shown to respond to stimuli with a negative valence (Huang & Luo, 2006; Lithari et al., 2010; Smith et al., 2003). It has also been demonstrated that the encoding of negative valence can persist into later components such as the LPP (Schupp et al., 2004b). Lithari et al. (2010) highlighted the role of the P3 component in the encoding of positive valence, however, also emphasised the role of the P2 component in positive valence encoding. A rapid categorisation of stimuli according to their economic value may encourage fast responses offering the best possible decision outcome (Brosch, Pourtois, & Sander, 2010). Results suggest a rapid and approximate categorisation of stimuli according to their subjective values in which low and high value items are clearly differentiated. Interestingly, a separate scalp pattern was associated with medium value products. The presence of a specific component featuring activation over the midline scalp regions may be a result of absence of either the left-hemisphere high-value or the right-hemisphere low-value value allocation.

Further to the categorisation of subjective value, lateralisation of cortical activation was also observed. IC2, which distinguished the processing of high value items, was most prominent over the left parietal region of the scalp, whereas IC1

demonstrated a spatial maximum that extended over a right frontal region of the scalp and responded to low/medium value products. Hemispheric asymmetry regarding the role of the left and right hemispheres, and their relatedness to approach and withdrawal behaviours respectively, has long been established (see Hakim and Levy, 2019). Similarly, this asymmetry has been observed concerning emotions, motivation and affect (Davidson, 1998b; Demaree, Everhart, Youngstrom, & Harrison, 2005; Harmon-Jones, Gable, & Peterson, 2010). The affective valence hypothesis (Alves, Fukusima, & Aznar-Casanova, 2008) and previous studies (Lawrence, Hinton, Parkinson, & Lawrence, 2012; Price & Harmon-Jones, 2011) also highlight the role of the left hemisphere in approach behaviour.

In the ERP domain, Aguado, Dieguez-Risco, Mendez-Bertolo, Pozo, and Hinojosa (2013) reported an increase in LPP amplitude over left temporal regions for positive facial expressions – also, the encoding of negative affect in the right hemisphere has been frequently observed (Ahern & Schwartz, 1985; Balconi & Mazza, 2009; Kokmotou et al., 2017; Windmann et al., 2006). Additionally, a left/right hemispheric lateralisation during the evaluation of pleasant/unpleasant odours has been reported (Cook et al., 2015; Henkin & Levy, 2001). Critically, Pizzagalli, Sherwood, Henriques, and Davidson (2005) link approach behaviour with the evaluation of rewards allowing us to speculate on hemispheric asymmetry in terms of valuation processes. In the time-frequency domain, increased slow-wave oscillations originating from the right prefrontal cortex were indicative of an increased inclination for risk (Gianotti et al., 2009). From a neuromarketing perspective, Ohme et al. (2010) posited that frontal asymmetry might be an important tool for evaluating the effectiveness of adverts. Further evidence for this comes from the increase of theta and alpha activity in the left and right hemisphere whilst observing pleasant and unpleasant adverts respectively (Vecchiato et al., 2014; Vecchiato et al., 2011).

The present finding of left frontal activations, represented by IC2, is in line with the valence hypothesis and suggest that goods with high economic value may share the same neural representation as positive affect and could possibly be indicative of motivation related processes, specifically approach behaviours. It could be argued that in a similar fashion to the bias towards low value items (Tyson-Carr et al., 2018), low value stimuli could induce withdrawal behaviours due to being potential sources of financial loss. For example, Shenhav, Dean Wolf, and

Karmarkar (2018) reported that choosing between low value items could induce anxiety since these items can be interpreted as aversive in certain situations.

From a functional brain imaging perspective, brain regions encoding value either positively or negatively have been reported (Bartra et al., 2013). In their meta-analysis, Bartra et al. pointed out that several brain regions demonstrated either positive or negative encoding of value, or even both positive and negative encoding together. Anatomically, the OFC specifically has been subject to a volume of research regarding the functions of its sub-regions. The discrimination of the lateral and medial aspects of the OFC is well documented (Kringelbach & Rolls, 2004; Zald et al., 2014), and even finer organisations have been suggested (Kahnt et al., 2012; Mackey & Petrides, 2010; Ongur et al., 2003). The distinct functional connectivity of multiple sub-regions demonstrates the ability of the OFC to encode a wide variety of values, such as both reward and punishment (Elliott, Dolan, & Frith, 2000; O'Doherty, Kringelbach, Rolls, Hornak, & Andrews, 2001), making it a candidate for the encoding of distinct value categories. Our data suggests that the valuation process occurring during free viewing of goods is based on sets of activation patterns which are employed in response to either low, medium or high value but none of these patterns encodes the value throughout the whole range of values.

A benefit of analysing cortical responses to individual successive eye fixations is the ability to highlight value encoding across the time course of a decision. A single interaction between value and time bin within IC2 is characterised by differences within TB2, TB3 and TB4, with the most linear encoding of value present in TB2. As is emphasised by the fixation location data, it was as early as 800-1600 ms post stimulus onset when individuals have most likely already decided the amount they are ultimately willing to bid. IC strength was also highest in this time bin for high value items, reiterating the link between this cluster and the valuation of high value products. However, an important finding was the activation cluster observed over subsequent time bins, specifically for the ICs that decode different value categories. The brain component encoding high value showed no significant variation throughout the time course, although confidence intervals did overlap with zero in the third time bin, suggesting the increased amount of cognitive processing that takes place when valuating high value options.

The reported fixation heat maps showed an increased number of fixations for high value items. This greater number of fixations is an indicator of an increased amount of time spent valuating the product and provides evidence for an increased amount of cognitive resources utilised during the valuation of high value products, something that has been observed in previous studies (Audrin, Brosch, Sander, & Chanal, 2018; McGinty et al., 2016; Simola et al., 2015). A wealth of research has highlighted how the emotional content of a scene can modulate the nature of eye-fixations. A previous study demonstrated increased attention towards both positive and negative stimuli, reflected in longer fixation durations and more rapid fixation onsets (Nummenmaa, Hyona, & Calvo, 2006). Similarly, eye-movements are more likely to be directed towards scenes that are affectively salient in comparison to scenes that are simply visually salient (Niu, Todd, & Anderson, 2012). Various eye-movement characteristics have also been shown to predict scene valence (Tavakoli et al., 2015) and eye-tracking can be used to infer cognitive processes such as attention (Hayhoe & Ballard, 2005). From an economic decision-making perspective, we are more likely to choose items that we fixate for longer (Cisek et al., 2014; McGinty et al., 2016), which is especially true for luxury products (Audrin et al., 2018). A study by Simola et al. (2015) reported enhanced fixation rates and longer gaze durations for unpleasant stimuli when they also had high arousal. However, gaze duration and fixation rates were increased for pleasant stimuli when they had low arousal. The increased number of fixations for high value products in the current study, as demonstrated in the fixation heat maps, may reflect the same processes as reported in this previous study by Simola et al., whereby the high value products are pleasant but not arousing, thus eliciting a larger number of fixations. Conversely, the fixation heat maps also demonstrate an increased number of fixations on the value scale for low value products, indicating that the value of low value products was decided rapidly and fixating on the product was no longer necessary given this quick categorisation.

Our data are relevant for evaluation of the drift-diffusion models of the valuation processing resting on accumulation of evidence during decision making tasks. Drift-diffusion models have been utilised to explain choices during binary decisions (Krajbich et al., 2010), trinary decisions (Krajbich & Rangel, 2011) and simple purchase decisions (Krajbich et al., 2012). Milosavljevic, Malmaud, Huth,

Koch, and Rangel (2010) employed the drift-diffusion model to demonstrate a fast, under 1000 ms, elaboration of decision value by accumulation of noisy information until a decision threshold is reached. Using single neuron recordings, much of this research revealed the role of the OFC, the lateral prefrontal cortex and the anterior cingulate cortex in value encoding in animals (Padoa-Schioppa, 2009; Padoa-Schioppa & Assad, 2006; Tremblay & Schultz, 1999; Wallis & Miller, 2003), with value differentiation observed at approximately 450 ms post stimulus (Kennerley, Dahmubed, Lara, & Wallis, 2009). Single neuron recordings in humans have also revealed the role of the amygdala in value encoding, and importantly, how the neuronal spike count differentiated value as early as 250 ms (Jenison, Rangel, Oya, Kawasaki, & Howard, 2011). ERP methods have also reiterated this and revealed rapid value encoding in the brain (Larsen & O'Doherty, 2014), even as early as 150 ms (Harris et al., 2011). Our results point to a rapid categorisation of stimuli according to their economic values occurring within an epoch comprising two 800-ms time bins and this finding is consistent with both the drift-diffusion model data (Milosavljevic et al., 2010) and single-neuron studies in animals.

The automaticity of the valuation process is captured in the differences between forced and free bids. Forced bidding trials allow for the disentanglement of valuation specific processes from generic, non-specific neural processes (Plassmann et al., 2007, 2010). IC1, IC2 and IC5 each demonstrated increased strength for free bids. It would, therefore, seem that brain component expressed in IC1 is responsible for the encoding of low value products, most prominently in free bidding procedures. IC5, though showing no segregation of value, is specific to deliberate valuation. IC4, a component that was reported to be unique to medium/high value items in the forced bidding condition, demonstrated increased strength during forced bidding along with IC6. The presence of an automatic valuation system in the brain has previously been demonstrated in which value appeared to be computed in value-irrelevant tasks (Grueschow et al., 2015; Lebreton et al., 2009). There is also a wealth of research investigating value-driven attentional capture, the process whereby value is used as a cue to capture attention, which highlights the automatic nature of valuation processes. For example, the presence of a distractor in a binary decision task will increase reaction times and reduce decision optimality as the learned value of the distractor increases (Itthipuripat, Cha,

Rangsipat, & Serences, 2015). Additionally, attention and eyes were captured during unconstrained viewing by task-irrelevant but previously rewarded stimuli (Anderson & Yantis, 2012), thus emphasising the ability to automatically evaluate stimuli within our visual field despite their lack of relevance to the current task.

An important consideration when using simultaneous EEG and eye-tracking recordings is the potential influence of eye-movement characteristics on EEG components. The SP, a potential observed at saccade onset, is modulated by saccade sizes and direction (Keren et al., 2010), and the visual lambda response can be modulated by fixation duration and saccade sizes (Nikolaev et al., 2016). In the present study, the varying temporal overlap between fixation events suggests that some effects could be explained by eye-movement related events alone. However, this is an inherent condition of free-viewing situations and several methods can be used to control for these factors. For example, we utilise here the method of linear deconvolution, using Unfold (Ehinger & Dimigen, 2019), to confirm our independent component clusters. Using this method, we revealed that saccade initiation was not likely to have had an influence on the cluster waveforms.

Traditional ERP experimental designs limit understanding to the initial cognitive processing that takes place within the first second following stimulus onset. However, although evidence suggests that value encoding occurs rapidly (Harris et al., 2011; Roberts et al., 2018; Tyson-Carr et al., 2018), further deliberation over time may influence the final evaluation. Past research indeed highlights how value-based decisions are guided by evidence accumulation until a decision point is ultimately reached (Krajbich et al., 2010; Krajbich et al., 2012; Krajbich & Rangel, 2011; Polania et al., 2014). Importantly, Melcher and Colby (2008) highlight in their framework how information between subsequent saccades is integrated to produce a more complex view of the world and it is this sequential remapping of sensory information that we speculate could underpin value-guided choice. It is these trans-saccadic processes that are of great relevance to the growing field of real-world neuroimaging. In real life, our conscious experience comprises a series of fixations to gather information and initiate motor behaviours. Not only can we disentangle the trans-saccadic gathering of information, the method also benefits from the outstanding temporal resolution of EEG, something which fMRI methods severely lack. The method described in this study is also easily applicable to real life settings

to help further our understanding of value-guided choice in a naturalistic setting (Roberts et al., 2018; Soto et al., 2018). A well-known drawback of this method is the contamination of EEG data with saccades. Any systematic difference in eye-movements between conditions can easily produce false-positives. However, recent advanced methods of analysis of eye fixation related potentials, such as the Unfold toolbox (Ehinger & Dimigen, 2019), can account for a large proportion of the confounds that eye-movements can introduce.

The present study aimed to reveal the brain components responsible for valuating specific value categories in the context of EEG. However, the treatment of WTP as a continuous factor may reveal, more generally, the dynamics of economic valuation in the brain. Future research would benefit from revealing correlations of brain components with WTP to emphasise the temporal characteristics of a more general subjective valuation system. A final consideration is the minimum effect duration in the current study. The current study implemented a minimum duration of 5 ms for effects to be interpreted. Although this avoids interpreting effects resulting from momentary differences spanning a few samples, it is uncertain to what extent differences being observed for 5 ms may reflect higher-order cognitive processes.

To conclude, we demonstrate for the first time that valuation processes can be tracked over the time course of a decision using combined eye-tracking and EEG recordings. Our study advances the knowledge of temporal dynamics of the valuation process which has been acquired using event-related potentials locked to the onset of fixations. A set of brain components were revealed that encoded distinct value categories, each with a unique presentation across the scalp that reiterated the encoding of positive and negative affect in the left and right hemispheres respectively. Value categorisation for products is achieved automatically as it also occurred during forced bid choices and economic valuation appears to be largely completed within 1600 ms after presenting a visual stimulus.

5.1.6. Supplementary materials

Results indicate the presence of ICs that encode high, medium and low value items with prevalence over the left, middle and right scalp regions respectively. Given that the value scale is present during item evaluation, it may be that these scalp patterns are the result of saccadic movements over the value scale rather than

value-related cerebral processing. Since epochs can expand beyond the fixation duration, it is likely that several saccades are initiated within a single epoch. Therefore, the initiation of saccades with systematic directions could explain the prevalence of, for example, an increased activation over the left frontocentral scalp region for high value items.

Supplementary Figure 5.8 illustrates data from the three clusters that demonstrated effects of value category; IC1, IC2 and IC3. For each cluster, global field power and individual electrode activity for both the original back projection and the deconvolved back projection is shown. Because we were interested in the latencies whereby effects of value-category were observed, the corresponding scalp maps averaged across the latencies of observed effects are shown. For each observed effect, the mean activity at each electrode site for the original back projection was compared to the corresponding de-convoluted scalp map using paired t-tests. P-values were corrected using the Bonferroni-Holm (Holm, 1979) correction for multiple comparisons and electrodes showing significant differences are highlighted.

Scalp maps at the latencies of the observed effects are highly similar after being analysed using linear deconvolution, with significant differences being observed sporadically (see Figure 5.8). To test this similarity, correlation coefficients were calculated to test the similarity between the original back projection and the de-convolved data for each cluster and latency interval of interest. Correlation coefficients were then transformed using the Fisher transform procedure to allow statistical testing (Fisher, 1921). This involved putting the coefficients into the inverse hyperbolic tangent function. The resulting Fisher Z values were submitted to one-sample t-tests which revealed significant differences from zero ($P < 0.05$), thus indicating similarity between the back-projected and de-convolved data (see Table 5.1).

Table 5.1

Mean Fisher Z values (±SD) indicating similarity between back-projected data and the de-convolved data. One-sample t-test results are also shown with the corresponding degrees of freedom (df), t-values and p-values.

	Fisher Z (Mean ± SD)	df	t	P
IC1 158 – 165 ms	1.34 ± 0.42	17	14.2	< .001
IC2 50 – 70 ms	1.81 ± 0.81	17	9.49	< .001
IC3 148 – 160 ms	1.55 ± 0.72	16	8.87	< .001

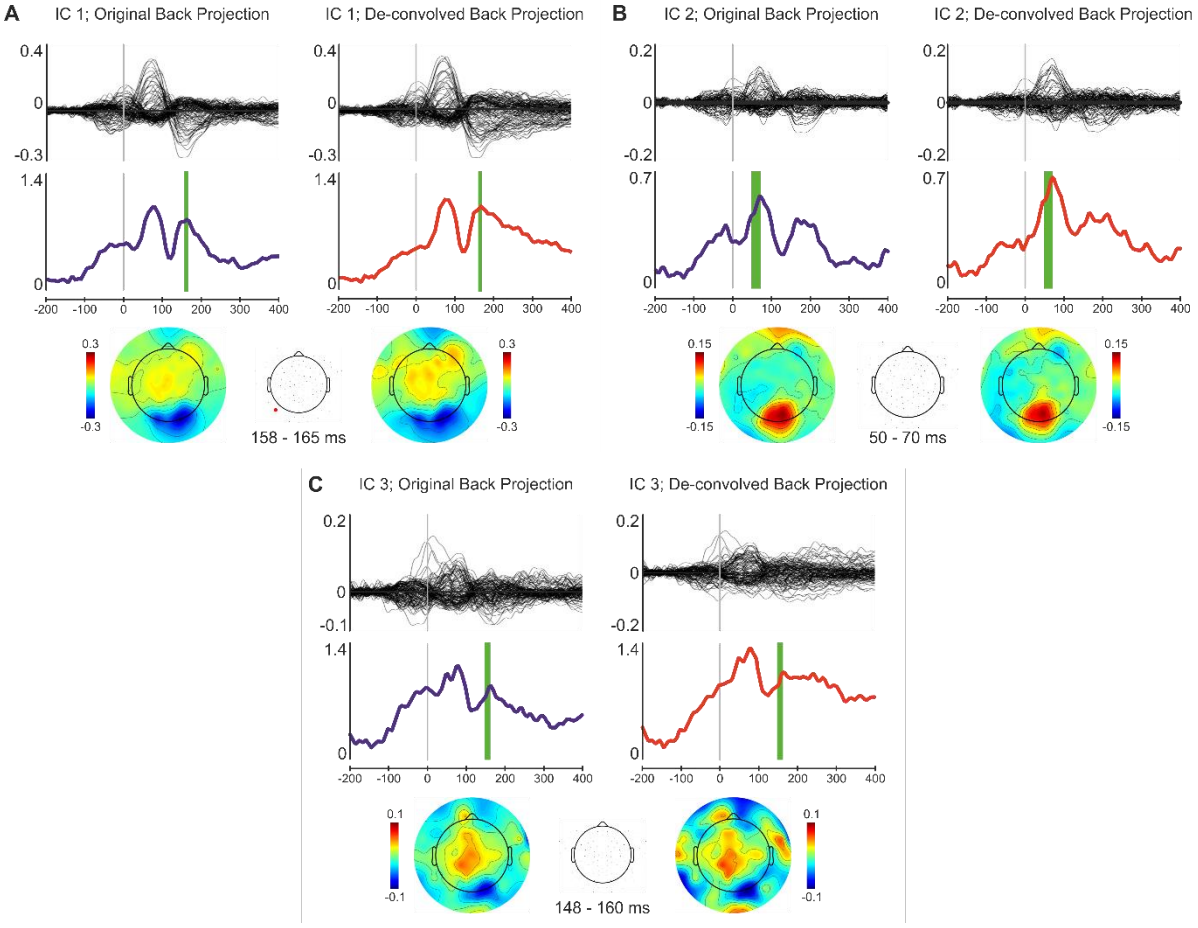

Figure 5.8. De-convolved EFRP data. De-convolved data is illustrated for IC1 (A), IC2 (B) and IC3 (C). For each cluster, a butterfly plot is shown that demonstrates activity for each electrode both before and after deconvolution using the unfold toolbox. The corresponding global field power is shown, as well as the scalp maps at the latencies of observed effects for value category. Significant differences at each electrode site between the original back projection and the de-convolved data are also shown in the centre head schematic, though only one electrode showed any differences between 158 and 165 ms.

Chapter 6

Brain components of economic decision making: an event-related potentials study

Tyson-Carr, J. [1], Soto, V. [1], Kokmotou, K. [1], Roberts, H. [1], Fallon, N. [1], Byrne, A. [1], Giesbrecht, T. [2], Stancak, A. [1]

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This experiment investigated the brain components in response to stimulus onset, extracted from independent component analysis, that represent economic valuation.

The manuscript is currently in preparation for submission.

The roles of the co-authors are summarised below:
I designed the study in collaboration with Andrej Stancak and collected the data. Vicente Soto, Katerina Kokmotou, Hannah Roberts and Adam Byrne assisted with the collection of data and contributed useful comments whilst preparing the manuscript for publication. Andrej Stancak, Nicholas Fallon and Timo Giesbrecht contributed to the experimental design as well as the large-scale planning of this project. Andrej Stancak and Timo Giesbrecht secured funding for project.

6.1. Brain components of economic decision making: an event-related potentials study

6.1.1. Abstract

The automaticity of brain valuation suggests that subjective value is likely already encoded in the first instance following stimulus presentation. Elaborating on our previous study (Tyson-Carr et al., in press), the present study aimed to determine value relevant brain processes in an electroencephalographic event-related potentials design, investigating economic decisions at the point of stimulus presentation.

Participants completed a Becker-DeGroot-Marschak auction comprising both free and forced bidding trials whilst electroencephalographic recordings were taken. Stimuli were split into low and high value products based on willingness-to-pay ratings. Brain responses time-locked to stimulus onset were extracted and analysed using ICA. The resulting independent components were clustered across subjects to identify common neural processes between subjects.

Increased cluster amplitude was observed in three clusters for high value products in the latency of the P3 and LPP event-related potential components. Moreover, one of these clusters demonstrated increased amplitude for high value products in the free bidding context only. A single cluster also demonstrated increased activation for low value products in the latency of the N2 event-related potential component.

Results suggest the employment of value encoding cortical activations immediately following stimulus onset. Distinct brain responses to low and high value products emphasised the rapid and coarse encoding of value within the brain, and the presence of value-relevant signals within early brain responses served to reiterate the automaticity of brain valuation. However, a single component cluster demonstrated value-specificity in a free bidding context only, suggesting a neural response to specific to conscious valuation.

6.1.2. Introduction

Neuroeconomic literature proposes the existence of a neural system that is responsible for choice behaviour, deciding the most subjectively useful alternative when having to decide between multiple alternatives (Glimcher & Fehr, 2014). The incorporation of tools used in economic research allows for the investigation of economic decision making in neuroscientific paradigms (Bossaerts & Murawski, 2015). For example, auction tasks such as the Becker-DeGroot-Marschak (BDM) auction mechanism (Becker et al., 1964) are a method utilised to reveal willingness-to-pay (WTP) for goods and prospects (Wilkinson & Klaes, 2012), allowing researchers to examine the neural underpinnings of subjective utility (Grabenhorst & Rolls, 2009; Grueschow et al., 2015; Kable & Glimcher, 2007; Levy & Glimcher, 2012; Peters & Büchel, 2010).

A primary aim within the neuroeconomics literature is to determine a neural system that encodes subjective value across several categories, i.e. a domain-general valuation system (Bartra et al., 2013). In their meta-analysis, Bartra et al. revealed the ventromedial prefrontal cortex and the ventral striatum to be responsible for the computation of subjective value across multiple reward categories. With the addition of the posterior cingulate cortex (PCC), this neural system was reiterated in a second meta-analysis (Clithero & Rangel, 2014).

In addition to the spatial dynamics of the brain valuation system, the temporal characteristics of subjective valuation is also critical to understand the nature of brain valuation processes on a fine temporal scale. The nature of haemodynamic responses results in poor temporal resolution of imaging techniques such as fMRI which measure blood oxygen level dependent responses (Shmuel & Maier, 2015). In contrast, the direct nature of electrophysiological methods that measure the electrical brain potentials that are propagated across the scalp, originating from the summation of neuronal potentials, permitted the investigation of cognitive processes on a fine temporal scale (Luck, 2005). Event-related potential (ERP) studies have demonstrated the rapid encoding of value in the brain, as early as 150 ms (Goto et al., 2019; Goto et al., 2017; Harris et al., 2011; Larsen & O'Doherty, 2014; Tzovara et al., 2015). In a previous study, we demonstrated a negativity-bias in the brain toward low value products, whereby increased source activation was observed within the

right anterior insula when subjects observed a low value item (Tyson-Carr et al., 2018). The specific encoding of low value products was reiterated by Roberts et al. (2018) who reported an increased P200 eye-movement related component for low value products.

The role of the context in which valuation takes places has also been frequently investigated. Value related signals have been observed in tasks whereby the value was not required to be calculated, for example, in perceptual decision tasks (Grueschow et al., 2015; Polania et al., 2014; Tyson-Carr et al., 2018). To investigate economic decisions during auction tasks, Plassmann et al. (2007, 2010) utilised a free/forced bid paradigm whereby individuals were either free to bid what they desired for a product, or where forced to bid a predefined amount. This revealed the role of the orbitofrontal cortex in the encoding of WTP, and importantly, provides us with a useful avenue for investigating economic decision making within an auction task.

The utilisation of a free/forced bidding paradigm by Plassmann et al. (2007, 2010) revealed the brain correlates of explicit value computation. However, the automaticity of subjective valuation has previously been described. One study revealed the activation of brain relevant regions of the brain during preference and perceptual rating tasks alike (Lebreton et al., 2009). Similarly, the PCC has been speculated to be responsible for automatic value encoding resulting from value-driven attentional capture (Grueschow et al., 2015).

We have previously observed a set of brain components tuned specifically to low, medium and high value products during free viewing (Tyson-Carr et al., in press). The present study aimed to further analyse this data to investigate the brain response at the point of stimulus onset during a free/forced bidding paradigm modified based on Plassmann et al. (2007, 2010). Firstly, we aimed to determine whether comparable neural responses were observed at the point of stimulus onset in comparison to across an extended viewing period. Secondly, extending on our previous methodology, we utilise source dipole analysis techniques to describe possible neural generators of value relevant brain responses. Lastly, the utilisation of an ERP design allows for the investigation of the importance of different ERP components relevant to valuation processes.

6.1.3. Methods

6.1.3.1. Participants

Participant information is identical to that described in Chapter 5. The experimental procedures were approved by the Research Ethics Committee of the University of Liverpool. All participants gave written informed consent in accordance with the declaration of Helsinki. Participants were reimbursed for their time and travel expenses. Since eye-tracking data is not utilised in the current study, the exclusion of participants due to technical difficulties with eye-tracking data is ignored here. Therefore, the present study submitted 20 participants for analysis in comparison to the 18 participants analysed in our previous study.

6.1.3.2. Procedure

Experimental procedures were identical to those outlined in Chapter 5. Stimuli were comprised of 180 everyday household items and presented within a series of auctions to obtain WTP for each item.

6.1.3.3. EEG recordings

EEG was recorded continuously using the 128-channel Geodesics EGI system (Electrical Geodesics, Inc., Eugene, Oregon, USA) with the sponge-based HydroCel Sensor Net. The sensor net was aligned with respect to three anatomical landmarks (two pre-auricular points and the nasion). Electrode-to-skin impedances were kept below 50kΩ and at equal levels across all electrodes as recommended for the system (Picton et al. 2000; Ferree et al. 2001; Luu et al. 2003). The sampling rate was 1000 Hz and electrode Cz was used as the initial reference. The recording bandpass filter was 0.1-200 Hz.

6.1.3.4. Auction task

The protocol for the auction task was adapted from previous studies (Plassmann et al., 2007, 2010) and employed the BDM mechanism (Becker et al., 1964; Wilkinson & Klaes, 2012). Each stimulus was presented once in either a free

bid or forced bid protocol. After a 1 s fixation cross, a stimulus was presented on screen for 4 s, followed by the opportunity to bid on the item. In free bid trials, participants were able to bid their own WTP. In forced bid trials, participants were required to bid the amount shown on screen. After bid selection, feedback was presented indicating whether the auction was won or not. Further details of the auction procedure are described in Chapter 5.

6.1.3.5. Split of WTP values

The stimulus set was divided into two groups of high and low subjective value products for both the free bid and forced bid stimuli, in comparison to the three value categories utilised in Chapter 5. The reduced number of value categories is due to the smaller number of data epochs when synchronising data to stimulus onset compared to fixation onset. To avoid overlapping values between these conditions, stimuli were removed randomly so that there were four groups of equal size (low value free bids; low value forced bids; high value free bids; high value forced bids), with each value category containing unique WTP values that did not overlap with any other value category. An average of 155 ± 16.1 trials were submitted for analysis for each subject, giving 38.8 ± 4.02 trials per condition.

6.1.3.6. ERP analysis

For full details of pre-processing and artefact correction, see Chapter 5. ERPs were computed in response to stimulus onset for each level within conditions (low value free bids; low value forced bids; high value free bids; high value forced bids) by averaging respective epochs in the intervals ranging from 300 ms before image onset to 1000 ms after image onset. Data was baseline corrected using an interval of -300 to 0 ms relative to stimulus onset. Following artefact correction, an average of 31.6 ± 4.57 trials per condition were analysed.

6.1.3.7. Component clustering

ICA was carried out on the EEG data before fitting dipoles to the independent components using EEGLab (Delorme & Makeig, 2004). In order to identify similar

independent components across subjects, independent components were clustered using the EEGLab STUDY protocol. Firstly, independent components were excluded if they were not located within the brain, or if they had more than 30% residual variance. Secondly, independent components were clustered into 10 clusters using k-means clustering based on scalp map, ERP, spectra and dipole measures. Next, the most significant clusters were identified by computing 99% confidence intervals for the cluster ERP waveforms. If confidence intervals overlapped with zero, or the cluster contained independent components from less than half of the subjects, the cluster was excluded.

6.1.4. Results

6.1.4.1. Behavioural data

Mean WTP was calculated for each condition (see Figure 6.1). In the free bid condition, low value stimuli had an average WTP of £1 ± 0.76 and high value stimuli an average of £4.11 ± 1.37. In the forced bid condition, low value stimuli had an average WTP of £0.99 ± 0.94 and high value an average of £3.67 ± 1.7. As expected, high value stimuli elicited significantly increased WTP in comparison to low value stimuli, F(1,19) = 241, P < .001, η_p^2 = 0.93. Free bid trials also elicited greater mean WTP than forced bid trials, F(1,19) = 4.62, P = .042, η_p^2 = 0.2. Additionally, a significant interaction between value category and trial type was revealed, F(1,19) = 12.8, P = .001, η_p^2 = 0.4. Post-hoc tests revealed a significant increase in WTP of high value stimuli in free bids in comparison to forced bids, t(19) = 2.85, P = .009, *d* = 0.28.

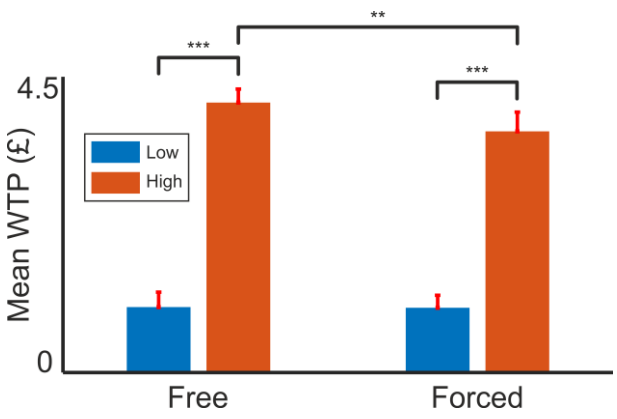

Figure 6.1. Mean WTP for low and high value items in both free and forced bid conditions. Significant differences between conditions are also shown. P < .05 = *; P < .01 = **; P < .001 = ***.

6.1.4.2. Event-related potentials

After clustering independent components into 10 clusters, one cluster was excluded since it contained components from only 9 of the 20 subjects. The remaining nine clusters all had confidence intervals that did not overlap with zero at the peak of the cluster ERP. Cluster 3 showed activation over a left frontal region, likely originating from the parahippocampal gyrus (approximate Talairach coordinates: x = -28 mm, y = -44 mm, z = 4 mm). Cluster 4 had a prevalence over the vertex and the occipital lobe, with a dipole centroid in the cingulate gyrus (Brodmann area 24; approximate Talairach coordinates: x = 5 mm, y = 5 mm, z = 32 mm). Cluster 5 was also located within the cingulate gyrus (Brodmann area 31; approximate Talairach coordinates: x = 16 mm, y = -42 mm, z = 33 mm), but with a prevalence extending more over the right hemisphere. Cluster 6 produced activation over a posterior region and bilaterally over a frontal area originating in the posterior cingulate cortex (Brodmann area 30; approximate Talairach coordinates: x = 17 mm, y = -59 mm, z = 4 mm). Cluster 8 produced a similar topography, originating in the perirhinal cortex (Brodmann area 35; approximate Talairach coordinates: x = 0.4 mm, y = -53 mm, z = -29 mm). Cluster 9 produced activation over the vertex and central parietal region, and the dipole centroid was located in the cuneus (Brodmann area 18; approximate Talairach coordinates: x = -8 mm, y = -70 mm, z = 17 mm). Similar to cluster 3, cluster 10 was also located within the parahippocampal gyrus (approximate Talairach coordinates: x = 29 mm, y = -22 mm, z = -16 mm), but with activation being spread over the right scalp region. Cluster 11 was dominant over the vertex and the left occipital region, originating in the thalamus (approximate Talairach coordinates: x = 0 mm, y = -25 mm, z = 11 mm). Finally, cluster 12 was the third cluster to be located within the cingulate gyrus (Brodmann area 31; approximate Talairach coordinates: x = -13 mm, y = -29 mm, z = 45 mm), but with a different dipole orientation producing activity over the left occipital region. Figure 6.2 summarises the scalp map for each cluster and the corresponding ERP.

In order to test for the influence of value category and trial type on cluster activation, the ERP for each cluster was submitted to a permutation-based repeated-measures ANOVA utilising 5000 permutations, limited to the latency intervals ranging from 80 to 600 ms to capture only the relevant ERP components. Subjects

can contribute more than one independent component to a cluster, and subjects do not necessarily contribute an equal number of components within any cluster. Hence, independent components belonging to the same subject within a cluster were summated to allow appropriate hypothesis testing. To restrict analysis to the most significant effects, latencies containing significant effects must have an absolute component activation that exceeds 3 standard deviations of the mean baseline amplitude. Significant effects also had to be observed for a minimum of 10 ms.

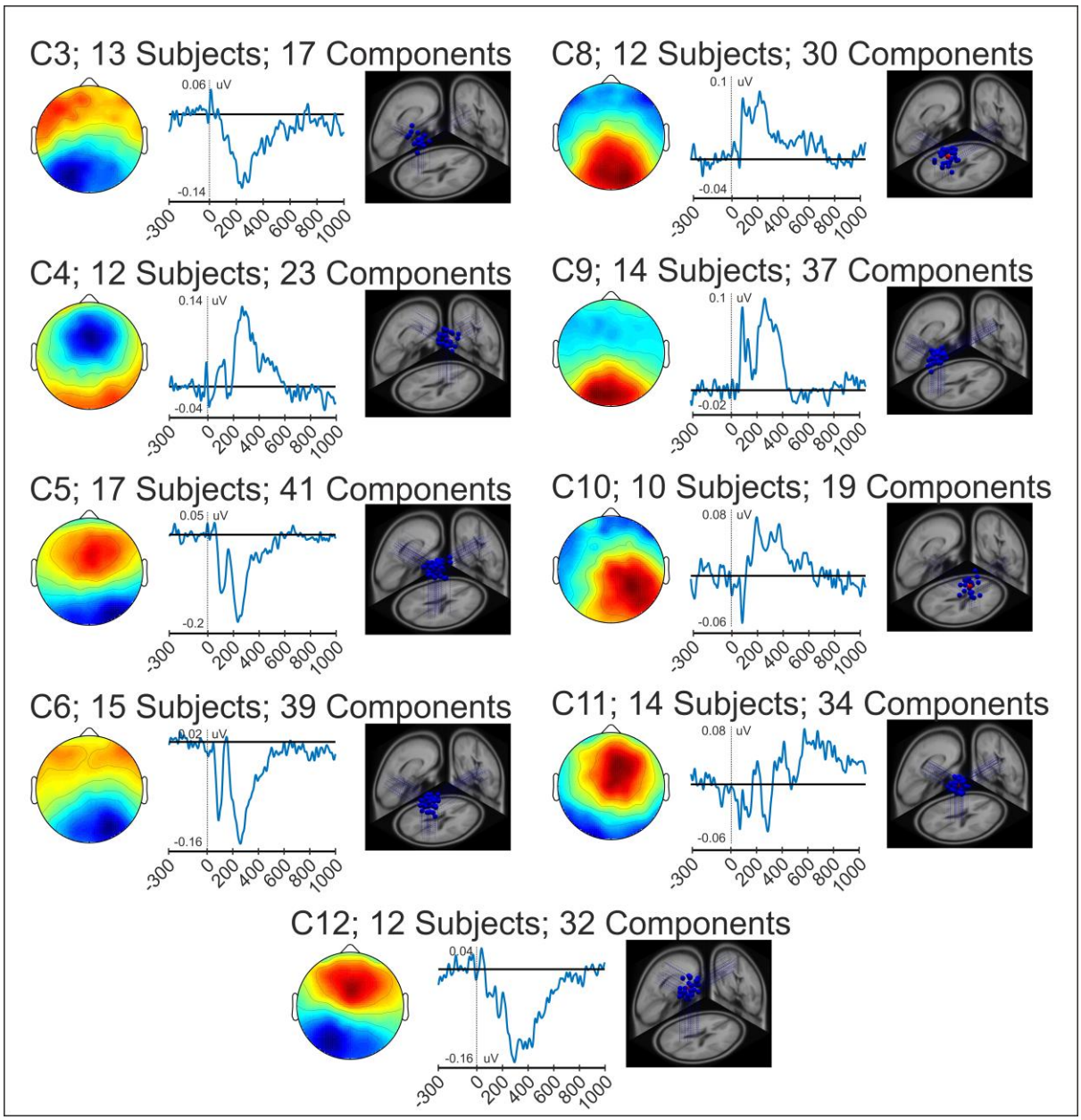

Figure 6.2. Scalp map, ERP waveform and component dipoles for each cluster that passed the confidence interval test. The number of subjects contributing components to the cluster, as well as the total number of components present in the cluster, are reported.

Figure 6.3A illustrates three main effects of trial type. Firstly, significantly increased cluster activation was observed for forced bids (-0.09 ± 0.13) in comparison to free bids (0.01 ± 0.09) between 563 and 570 ms in cluster 3, F(1,12) = 4.87, P = .047, a cluster with prevalence over a left frontal region. Secondly, cluster 4, which had a spatial maximum over the vertex and an occipital region, demonstrated significantly increased activation between 262 and 272 ms for free bids (0.27 ± 0.24) in comparison to forced bids (0.19 ± 0.22), F(1,11) = 8.58, P = .01. Lastly, the vertex and occipital activation of cluster 5 demonstrated increased activation between 486 and 502 ms for free bids (-0.15 ± 0.21) compared to forced bids (-0.02 ± 0.18), F(1,16) = 7.07, P = .016.

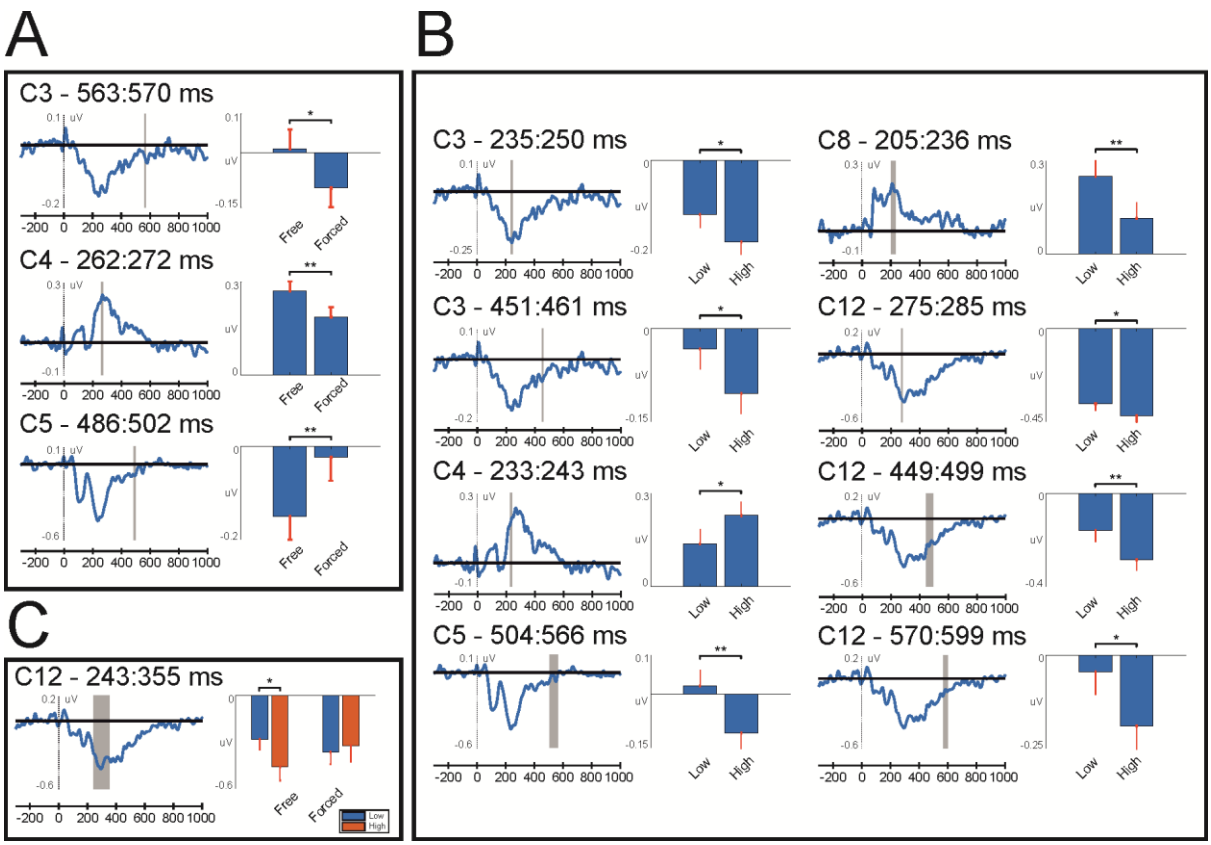

Figure 6.3. Latencies demonstrating main effects of trial type (A) and value category (B). An interaction between trial type and value is also shown (C). For each effect, the grand average ERP waveform is shown, along with a bar graph illustrating results from post-hoc testing.

A total of eight main effects of value category are summarised in Figure 6.3B. Two significant latencies were observed for cluster 3, which was characterised by activation over a left frontal area of the scalp. Firstly, significantly increased activation was elicited for high value items (-0.19 ± 0.27) between 235 and 250 ms

compared to low value items (-0.13 ± 0.21), F(1,12) = 5.84, P = .031. Secondly, increased activation was observed between 451 and 461 ms for high value items (-0.1 ± 0.12) compared to low value (-0.03 ± 0.1), F(1,12) = 6.16, P = .024. For cluster 4, a cluster which produced activation over the posterior and vertex region of the scalp, increased activation between 233 and 243 ms was observed for high value items (0.23 ± 0.23) compared to low value (0.14 ± 0.14), F(1,11) = 5.1, P = .037. Cluster 5, a cluster which had a spatial maximum over a vertex and posterior region, demonstrated increased power between 504 and 566 ms for high value items (-0.1 ± 0.14) in comparison to low value (0.02 ± 0.15), F(1,16) = 11, P = .003. A single main effect was revealed within the posterior activation of cluster 8 between 205 and 236 ms, with larger activation for low value items (0.25 ± 0.26) than for high value (0.12 ± 0.14), F(1,11) = 9.31, P = .01. Three main effects were observed for cluster 12 which was prevalent across the vertex. Firstly, between 275 and 285 ms there was increased activity for high value products (-0.43 ± 0.33) compared to low value (-0.37 ± 0.31), F(1,11) = 4.98, P = .04. Secondly, increased activation was found for high value items (-0.28 ± 0.22) compared to low value (-0.16 ± 0.16), F(1,11) = 9.67, P < .007. Lastly, larger amplitude was observed for high value items (-0.18 ± 0.17) in comparison to low value (-0.04 ± 0.09), F(1,11) = 7.22, P = 0.023.

Figure 6.3C shows a single interaction between trial type and value category observed in cluster 12 between 243 and 355 ms, F(1,11) = 12.2, P = .006. Post-hoc testing revealed that in the free bid trials, significantly increased activation was observed for high value items (-0.46 ± 0.46) in comparison to low value items (-0.28 ± 0.36), t(11) = 3.79, P = .001. No other significant differences were revealed.

6.1.5. Discussion

The present study aimed to reveal whether comparable brain activations were observed at the point of stimulus onset in comparison to those previously detected during free viewing. Similar to our previous study (Tyson-Carr et al., in press), we observed unique brain activations for low and high value products. High value products were encoded in similar scalp patterns across both studies with electrical potentials observed across a posterior region of the left scalp area, as well as over the vertex. Low value products elicited activation that extended over a right scalp

region in both studies. Second to these scalp patterns, we also highlighted the importance of the cingulate gyrus in the valuation of high value products, extending on our previous study. Additionally, high value items produced significantly increased activation in two approximate latency intervals between 230 and 290 ms, and also between 450 and 600 ms, whereas low value items produced significantly increased activation between 200 and 240 ms. Lastly, the observed differentiation of value as early as 230 ms provided further evidence for the automaticity of brain valuation.

Previous studies have frequently illustrated the encoding of value in specific ERP components. For example, the P3 component is a positive wave occurring approximately 300 ms following stimulus onset (Nieuwenhuis et al., 2005) and has been shown to be an index of motivational significance (Duncan-Johnson & Donchin, 1977). Although many studies have demonstrated either the bias of the P3 towards negative outcomes (Ito & Cacioppo, 2000; Ito et al., 1998) or an insensitivity of the P3 to valence (Keil et al., 2002; Yeung & Sanfey, 2004), alternative findings have been reported. For example, Yeung and Sanfey (2004) also reported the encoding of reward magnitude within the P3. Additionally, a previous study revealed an enhanced P3 in response to positive feedback in comparison to negative feedback (Hajcak et al., 2005; Johnson & Donchin, 1985). The present study observed increased cluster activation in various latencies between 230 and 290 ms for high value products, implicating an early P3 component in the valuation of high value products. High value products also elicited increased cluster activation in a delayed latency window, occurring between 450 and 600 ms. This latency corresponds to the late positive potential (LPP) which is a slow-wave deflection occurring after 300 ms (Chen et al., 2010), with a similar scalp distribution to the P3 (Cacioppo et al., 1994). The LPP is another ERP component frequently implicated in economic decision-making research (Hakim & Levy, 2019), albeit indirectly due to its role in emotional processing. A study by Hajcak and Olvet (2008) revealed enhanced LPP power for emotional stimuli, irrespective of valence, demonstrating the role of the LPP in emotional processing. The LPP has also related to consumer herding whereby increased LPP power indexed a consumers' purchase intent when provided only with other consumers' perceptions of a product (Chen et al., 2010). The current study extends on these findings, providing evidence for the role of the LPP in the encoding of high value products. Finally, differences relating to the P3 and LPP were seen

primarily for clusters localised to the cingulate gyrus, encompassing both the posterior and anterior cingulate cortices. This corresponds to a meta-analysis highlighting the crucial role of the posterior cingulate cortex in a domain-general valuation system (Clithero & Rangel, 2014).

An interaction was revealed in one cluster between trial type and value category. In their two studies, Plassmann et al. (2007, 2010) reasoned that correlations between subjective value and the haemodynamic response within free bids alone would constitute a neural signal of subjective valuation specifically. Similar to their findings, we report here an increased activation for high value products in the free bid trials alone. This provides strong evidence for a brain component representing subjective valuation specifically in the latency of a late N2 or early onset P3 component between approximately 240 and 360 ms.

A single cluster encoded the value of low value products between approximately 200 and 240 ms. This latency corresponds to the N2 ERP component, a deflection occurring after 200 ms (Folstein & Van Petten, 2008) and this component has various functions associated with it in subjective valuation research. For example, increased N2 has been observed for high reward or preferred targets (Kiss et al., 2009; Telpaz et al., 2015) and automatic preference encoding (Goto et al., 2017). However, our recent paper revealed increased N2 over a right frontal region for low value products at a similar latency (Tyson-Carr et al., 2018), with a very similar scalp distribution but different source localisation results. The current study localised the nearest Brodmann area as being the perirhinal cortex, a region associated with memory and object recognition (Murray & Bussey, 1999; Murray & Richmond, 2001). The perirhinal cortex also has connections with the orbitofrontal cortex and regions of the insula (Kondo, Saleem, & Price, 2005), regions that are frequently reported to be involved in subjective valuation (Kuhnen & Knutson, 2005; McGinty et al., 2016). However, these findings are heavily speculative given the limited spatial resolution of EEG techniques, especially in these cortices that are located a large distance from the scalp.

Significantly increased cluster activation was revealed within one cluster for forced bids in comparison to free bids at approximately 570 ms following stimulus onset. It could be reasoned that the one task demand that forced bids require is the

utilisation of memory processes to remember the value in which they are required to bid. It has been shown that memory related processes are related to P3 and late positive components occurring after 300 ms (Klimesch, Schimke, & Schwaiger, 1994), which is similar to the effect observed in the current study. Additionally, the nearest Brodmann area associated with this cluster centroid is the retrosplenial cortex, a region implicated in memory processes (Vann, Aggleton, & Maguire, 2009). Again, however, this is heavily speculative given the limited spatial resolution of EEG.

To conclude, the current study provided evidence for the rapid, but coarse, encoding of subjective value in brain responses in the time interval immediately following stimulus onset. Findings reported in Chapter 5 suggested the neural representation of value that was built and maintained over an extended period of free viewing. However, the current results suggest that these representations are already present immediately following stimulus presentation without need for further, conscious deliberation. Moreover, the current findings reiterate the lateralisation of neural responses to low and high value items in the right and left hemispheres respectively, providing further support for the lateralisation of brain responses to subjective value observed in Chapter 5. The immediate representation of subjective value emphasises the automaticity of brain valuation.

Chapter 7

The neural correlates of bundle valuations: An eye-fixation related potentials study

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This experiment investigated the spatial and temporal dynamics of brain processes during the subjective valuation of products and product bundles.

The manuscript is currently in preparation for submission.

The roles of the co-authors are summarised below:
I designed the study in collaboration with Andrej Stancak and collected the data. Hannah Roberts, Vicente Soto, Alice Newton-Fenner, Danielle Hewitt and Katerina Kokmotou assisted with the collection of data and contributed useful comments whilst preparing the manuscript for publication. Andrej Stancak, Nicholas Fallon and Timo Giesbrecht contributed to the experimental design as well as the large-scale planning of this project. Andrej Stancak and Timo Giesbrecht secured funding for project.

7.1. Evaluation of product bundles: an eye-fixation related potentials study

7.1.1. Abstract

The subjective value of product bundles often falls short of the sum of the constituent product valuations, an effect referred to as sub-additivity. Using electroencephalographic eye-fixation related potentials, the present study aimed to investigate the neural representation of bundle valuation and the resulting sub-additivity observed when pairing disparately priced products of varying complementarity.

Participants completed a Becker-DeGroot-Marschak auction task, producing willingness-to-pay for a set of individual products and complementary/non-complementary product bundles. All stimuli were split into low and high value based on subjective willingness-to-pay. Neural activity in response to fixation onset was extracted and submitted to an ICA to identify unique cortical activation patterns representing economic valuation. Independent components were clustered across subjects to identify common brain components across subjects.

Participant WTP was increased for complementary bundles in comparison to non-complementary bundles. Further to this, sub-additivity increased as the price disparity between bundle constituents increased. A single cluster of brain components demonstrated increased activation for low value products and non-complementary bundles, originating from the right insula. Increased activation within a second cluster of brain components was observed for high-value products and product bundles, originating in the precuneus. Furthermore, activity in the high value encoding cluster was significantly modulated by mean bundle additivity.

Results provide further evidence of sub-additive effects for product bundles characterised by reduced product complementarity and increased price disparity. Results also indicate the presence of a neural representation of this additivity, possibly within the precuneus, which also responded primarily to high value products. Similar to previous studies, low value products elicited activity over the right scalp region, potentially originating from the right insula, a region commonly implicated in negative motivation.

7.1.2. Introduction

Product bundling is a potent method employed by companies to maximise profits. Although product bundling takes many forms (Simon & Fassnacht, 1993), it generally entails the grouping of at least two products into a singly priced package (Fang et al., 2017). Although benefiting retailers (Naylor & Frank, 2001), it does not preclude benefits for the consumer and bundling often provides monetary savings for the consumer (Yan & Bandyopadhyay, 2011).

Price framing, the shifting of preferences from the presentation of identical information in different ways, is also highly relevant for bundle pricing (Khan & Dhar, 2010). Zero-pricing is the practice of offering add-on products for free and can significantly enhance perceived values, possibly due to the inflation of benefits and deflation of costs associated with the service (Hüttel et al., 2018; Shampanier et al., 2007), and induce reciprocity social-norms to encourage acceptance of non-monetary costs such as advertising (Hüttel et al., 2018). A further line of research has also investigated the possible benefit of, instead of offering a component within a bundle as being free, but offering it a very small token price if purchased within the bundle (Palmeira, 2011). It has been shown that this small fee can increase purchase intention and the perceived attractiveness of the purchase in comparison to offering an upgrade at a zero-price (Mao, 2016).

Multiple factors can influence bundle valuations by an individual. Super-additivity, which is the subjective value of a bundle extending beyond the sum of its components, is frequently observed. For example, when several components only offer benefit as a composite, especially if an individual is not familiar enough with the product to buy the components individually (Simonson, Carmon, & O'Curry, 1994). Individuals may also prefer consolidated costs (Naylor & Frank, 2001), possibly due to the integration of losses (Thaler, 1985). Component complementarity is also crucial (Economides, 1996), since it increases functionality between the products (Estelami, 1999), reduces the need for product advertising (Yan, Myers, Wang, & Ghose, 2014) and increases purchase intent (Harlam et al., 1995). It has been summarised by Guiltinan (1987) that super-additivity may be due to saving time and effort from obtaining products in a single package, the enhanced experience from

obtaining a secondary product, or the enhancement to overall image of the seller for the variety provided.

Conversely, there is evidence for scenarios whereby the additions of extra features can reduce overall purchase intentions (Hsee, 1998; List, 2002). Sub-additivity is observed when bundle valuations fall short of the sum of their components. This has been demonstrated when individuals infer the price of a bundle based on the known value of low-value component when the value of the high-value component is uncertain (Popkowski Leszczyc et al., 2008). Similarly, extra features can reduce purchase intent if value of the main component is uncertain, possible due to an additional component leading individuals to make inferences of reduced quality, the dilution of high value aspects from an unneeded feature, the averaging of value across all components, or attention drawn from the high value to the low value component (Simonson et al., 1994).

Measuring purchase intentions and subjective valuations is critical to understand preferences (Schultz, 2017), and these valuations need to be measured reliably. One such method is through auction tasks such as the Becker-DeGroot-Marschak (BDM) auction paradigm (Becker et al., 1964) which reveals willingness-to-pay (WTP) for goods and prospects. This method is utilised in decision making research frequently (Chib et al., 2009; Grueschow et al., 2015; Hare et al., 2008; Harris et al., 2011; Peters & Büchel, 2010; Plassmann et al., 2007, 2010; Roberts et al., 2018; Tyson-Carr et al., 2018; Weber et al., 2007).

Neuroscience research has aimed to uncover the neural underpinnings governing valuation behaviour in a variety of contexts. Typically, these experiments utilise the exceptional spatial resolution of functional magnetic resonance imaging (fMRI) to detect the brain structures responsible for valuation. Meta-analytic methods suggest the importance of the ventromedial prefrontal cortex, the orbitofrontal cortex and the ventral striatum in carrying out subjective valuations (Bartra et al., 2013; Chib et al., 2009; Clithero & Rangel, 2014; Lebreton et al., 2009; Levy & Glimcher, 2012), and it is likely to be an automatic process (Grueschow et al., 2015; Plassmann et al., 2007, 2010; Polania et al., 2014; Tyson-Carr et al., 2018).

Whilst the spatial aspects of valuation are critical, these methods do not permit investigation of the temporal aspects of valuation behaviours given their

relatively poor temporal resolution (Shmuel & Maier, 2015). Valence encoding has been associated with EEG components such as the N1, N2, P2 and P3 (Lithari et al., 2010), and also the LPP (Huang & Luo, 2006; Schupp et al., 2004b). Importantly, signals relating directly to value have been observed in latencies as early as 150 ms (Harris et al., 2011; Larsen & O'Doherty, 2014; Tzovara et al., 2015) and the N2 component is frequently implicated. Various forms of the N2 have been shown to be related to encoding product preference (Telpaz et al., 2015), the encoding of low value products (Tyson-Carr et al., 2018), play a role in counter-conformity decisions (Gajewski et al., 2016), and the encoding of high reward targets (Kiss et al., 2009). Another critical EEG component in economic decision making is the late positive potential (LPP). Pozharliev, Verbeke, Van Strien, and Bagozzi (2015) observed an increased LPP for luxury products in comparison to basic branded products. Furthermore, Goto et al. (2017) implicated both the N2 and LPP in their research, positing that the N2 may be responsible for automatic preference calculation, whereas the LPP may reflect preferences as a result of deliberate cognitive processing.

The strong influence of framing on purchase intentions has resulted in investigation into the neural underpinnings of such framing effects in relation to purchase decisions. An fMRI study by Votinov et al. (2016) revealed the importance of the choice network, comprised of the inferior parietal lobe, the posterior cingulate cortex (PCC) and the medial prefrontal cortex, in preference changes as a result of zero-pricing. Additionally, activation within the medial prefrontal cortex correlated with happiness ratings of getting the free products. In relation to bundle presentation, Ma, Mo, Zhang, Wang, and Fu (2018) revealed that presenting bundles of two products wherein one of the components was indicated as being free resulted in higher purchase rates. Using an ERP design, the authors also revealed how the power of the LPP in response to bundle presentation was increased for zero-pricing relative to normal pricing.

The present study had three primary aims. Firstly, the study aimed to reveal the processes underpinning brain valuation, specifically for product bundles. The explicit representation of subjective value within neural responses measured by means of EEG has been shown in our previous studies (Tyson-Carr et al., 2018; Tyson-Carr et al., in press). To extend on these previous findings, the neural

representation of bundle valuation was examined here. Secondly, brain responses to additivity were investigated to reveal patterns of activation explained by observed additivity from product bundling. Lastly, the impact of product complementarity on bundle valuation is to be examined, as well its impact on resulting brain responses. These aims were achieved by examining the neural responses to the valuation of products and product bundles in the context of a BDM auction, whereby product bundles were comprised of two disparately priced products with varying levels of complementarity.

7.1.3. Methods

7.1.3.1. Participants

A total of 25 healthy participants took part in the experiment (9 female) having a mean age of 23.1 ± 3.41 years (mean ± SD). Due to technical issues with EEG recordings, data from 5 participants were excluded, as well as a further 5 participants being excluded due to excessively noisy EEG data, resulting in a total of 15 participants being submitted for analysis. The experimental procedures were approved by the Research Ethics Committee of the University of Liverpool. All participants gave written informed consent in accordance with the declaration of Helsinki. Participants were reimbursed for their time and travel expenses.

7.1.3.2. Procedure

All experimental procedures were carried out in a dimly lit, sound attenuated room. Participants sat in front of a 29-inch LCD monitor. The experimental procedure was carried out in a single experimental session involving two computerised tasks. Firstly, participants completed a standard BDM auction task including 140 stimuli, 70 of which were priced between £0 and £4 (low value), and 70 priced between £8 and £12 (high value) in a shopping catalogue. These stimuli were also grouped to produce a product bundle condition consisting of one low value and one high value product, producing 70 unique product bundles. In addition, each bundle belonged to one of two conditions. In 35 of the bundles, the products within the bundle were complementary, whilst 35 bundles contain non-complementary products. This resulted in 140 trials involving the individual presentation of stimuli and 70 trials

involving product bundles for a total of 210 trials. Secondly, participants completed a computer task wherein they rated product bundles on the similarity of the products within the bundle. This was done using a visual analogue scale ranging from “No Similarity” to “Very Similar” and followed the main task. This data was used to confirm bundle complementarity. Presentation of stimuli was controlled using Cogent 2000 (UCL, London, UK) in MATLAB 7.8 (MathWorks, Inc., USA).

7.1.3.3. EEG recordings

EEG was recorded continuously using the 128-channel Geodesics EGI system (Electrical Geodesics, Inc., Eugene, Oregon, USA) with the sponge-based HydroCel Sensor Net. The sensor net was aligned with respect to three anatomical landmarks (two pre-auricular points and the nasion). Electrode-to-skin impedances were kept below 50kΩ and at equal levels across all electrodes as recommended for the system (Ferree et al., 2001; Luu et al., 2003; Picton et al., 2000). The sampling rate was 1000 Hz and electrode Cz was used as the initial reference. Data was filtered online using a 0.1-200 Hz bandpass filter.

7.1.3.4. Eye-tracking recordings

Gaze positions were taken using the Pupil head-mountable eye-tracker (Kassner et al., 2014). Pupils were tracked using monocular tracking with a 200 Hz camera, whilst the world view camera was recorded at 60 Hz. Gaze tracking was calibrated using a 9-point marker calibration procedure on the stimulus presentation monitor. Gaze tracking accuracy was confirmed using a simple marker tracking protocol to confirm accuracy was within 1° of visual angle. Pupil Capture software was used for data collection. Pupil Player software was used for data visualisation and raw data exporting.

During the auction task, a series of digital surface markers were placed in each corner of the screen in order to define the surface of the monitor display. These markers were displayed continuously throughout the trials. Offline surface detection was carried out post data-collection but prior to fixation detection to allow fixations to be localised relative to the surface.

7.1.3.5. Auction task

The protocol for the auction task (see Figure 7.1) employed the standard BDM auction mechanism (Becker et al., 1964; Wilkinson & Klaes, 2012). Each of the 140 stimuli were presented either individually, or as part of a complementary or non-complementary product bundle giving a total of 210 auctions.

Each trial consisted of a fixation cross followed by stimulus presentation. If a single product was presented, it was presented centrally on the screen. If a product bundle was presented, the products were placed side-by-side and placed centrally on the screen. After 4 s of image presentation, the image disappeared, and participants were free to bid on the product(s). During the bidding stage, a series of boxes were displayed, each indicating a single monetary amount that could be put forward as a bid. These prices varied uniformly between £0 and £16 in increments of £1, giving a total of 17 options. The trial was concluded when the participant did not move the mouse cursor for 3 s, upon which feedback was presented indicating whether the auction was won or not. Auction outcome was dependent on a randomly generated integer ranging between 0 and 16 wherein an auction was won when $b \geq r$, where *b* represents the bid and *r* represents the randomly generated number for that auction. Following the experiment, a single auction was selected at random and the outcome was implemented. Here, the participant's endowment of £16 was reduced by an amount equal to *r* for the implemented auction. The item(s) purchased could be picked up within a few days of completion of the experiment.

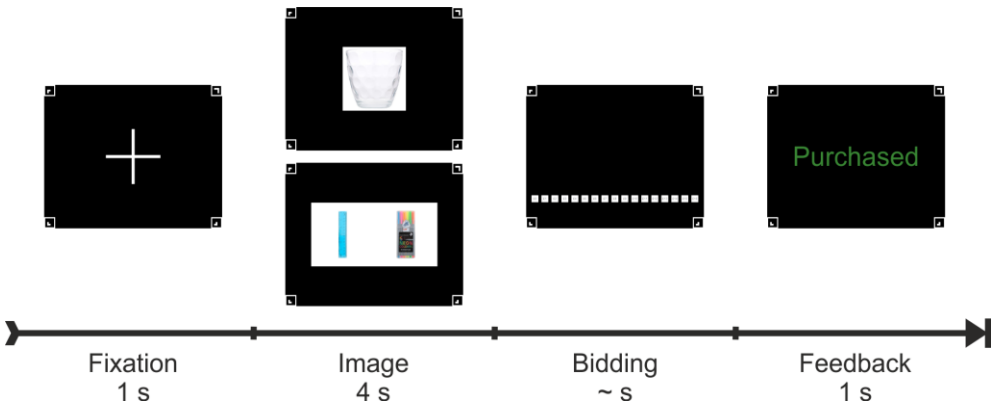

Figure 7.1. Experimental protocol. A fixation presented for 1 s is followed by an image of either a product or product bundle for 4 s. Following image offset, subjects are free to bid their own WTP for the product(s). Following bid offset, feedback is presented for 1 s indicating the outcome of the auction.

7.1.3.6. Split of WTP values

Following completion of the auction task, the subjective WTP ratings for all stimuli were split into low and high value with no overlap in value between value categories. Overlap in value between categories was accounted for by removing stimuli with identical WTP randomly from either side of the split, which had the added benefit of equalising the number of stimuli in each category. This was done for products presented individually and as bundles separately, producing two conditions corresponding to low and high value for individually presented products as well as bundles (Low Value Products; High Value Products; Low Value Bundles; High Value Bundles). Following this procedure, there was a mean of 64.4 ± 4.16 trials remaining in both the low and high value category for individually presented bundles, and 32.7 ± 2.03 trials for both the low and high value category in the bundle condition.

To ensure that each bundle comprised a single low and high value item, the difference in WTP between products within each bundle was calculated. If the absolute difference exceeded £1, then the bundle was excluded from further analysis.

7.1.3.7. EEG pre-processing

EEG data were pre-processed using BESA v. 6.0 program (MEGIS GmbH, Munich, Germany). Oculographic artefacts and electrocardiographic artefacts were removed using principle component analysis based on averaged eye-blinks and artefact topographies (Berg & Scherg, 1994). Data were also visually inspected for the presence of artefacts. Data were filtered from 0.5-45 Hz and exported to EEGLab (Delorme & Makeig, 2004) for further processing.

7.1.3.8. Eye-fixation detection

Raw eye-tracking data during image presentation was exported using the Pupil Player software for fixation detection. The event detection algorithm selected was the identification by two-means clustering (I2MC) algorithm (Hessels et al., 2017), chosen for its ability to detect fixation events in a wide range of noise levels. Events were detected using the X and Y coordinates of gaze positions (in pixels) on

the computer monitor and a viewing distance of 80 cm. This produced a set of fixation events synchronised to fixation onset.

A mean of 2340 ± 165 fixations were extracted for each subject across all trials, with a mean of 11.1 ± 0.79 fixations per trial. Since stimuli were removed due to the splitting of WTP categories, and also due to bundles containing products of equal value, this reduced the mean number of fixations per subject to 1976 ± 231 and 10.6 ± 0.79 fixations per trial. Eye-movement characteristics were calculated and fixations with a fixation duration of < 150 ms, saccade amplitude of > 10°, or saccade duration of > 100 ms were excluded. A fixation duration of 150 ms is frequently used in eye-tracking literature as the minimum threshold for a relevant fixation (Nyström & Holmqvist, 2010). Saccade amplitudes of > 10° would indicate that a fixation was made following a saccade extending beyond the computer monitor, and a saccade duration of > 100 ms is beyond what is expected of typical fixations (Rayner, 1998), or could indicate fixation offset or onset could not be accurately located. These criteria resulted in a mean of 1426 ± 159 fixations per subject and 8.07 ± 0.74 fixations per trial. Finally, fixations were removed if they overlapped with an artefact in the EEG data, producing a mean of 1182 ± 169 fixations per subject and 7.06 ± 0.8 fixations per trial. Ultimately, this produced 376 ± 71.6 fixations per subject for the low value condition and 443 ± 68.1 for high value. Low and high value bundles were also split into complementary and non-complementary products, resulting in 80.9 ± 25.5 fixations per subject in the low value complementary bundles, 98.5 ± 22.7 in the high value complementary condition, 94.1 ± 20.4 in the low value non-complementary bundle and 89.5 ± 16.7 in the high value non-complementary bundles.

7.1.3.9. Eye-fixation related potentials

A TTL pulse input into the EEG data was used to indicate stimulus onset for each trial. This, along with stimulus onset as shown in the world-view camera of the eye-tracker, allowed for the synchronisation of the EEG and eye-tracker.

EFRPs were computed in response to fixation onset and separately for each condition (low value products, high value products, low value complementary bundles, high value complementary bundles, low value non-complementary bundles,

high value non-complementary bundles) by averaging epochs ranging in the latency from -200 to 600 ms respective to fixation onset and using an individual baseline correction in the time window -200 to -100 ms. The baseline period was used due to its avoidance of the saccadic spike potential (SP) originating from the initiation of a saccade that occurs immediately before fixations (Nikolaev et al., 2016).

7.1.3.10. Component clustering

EFRPs were analysed using the STUDY protocol implemented in the EEGLab toolbox (Delorme & Makeig, 2004) which allows for the clustering of independent components (ICs) across subjects. Firstly, an ICA was carried out for the data from each subject to produce a set of ICs for each subject and dipole fitting was carried out. To restrict analysis to the most relevant components, dipoles with more than 40% residual variance were excluded. Scalp, ERP, spectra and dipole component measures were computed for the remaining ICs, before being clustered using k-means clustering into 15 component clusters. To identify the most significant clusters, confidence intervals were computed on the ERP for each cluster and were analysed further if 99% confidence intervals exceeded zero at the peak of the cluster power. If the confidence interval overlapped with zero, the cluster was excluded. Additionally, clusters were excluded if less than half of the subjects contributed at least a single IC to the cluster.

7.1.4. Results

7.1.4.1. Behavioural data

Mean bundle WTP was calculated to determine any significant differences between complementary and non-complementary bundles. In order to highlight the effects of pairing disparately priced products on bundle valuations, based on individual subject WTP, product bundles comprised of equally priced products were required to be removed. However, in order to investigate the impact of complementarity directly, bundle WTP was calculated prior to any exclusion of stimuli as to avoid biasing the data. Any t-tests or analysis of variance (ANOVA) carried out are permutation-based utilising 5000 permutations. Complementary bundles were found to have a mean WTP of £6.65 ± 2.14 whilst non-complementary

bundles had a mean of £6.29 ± 2.3, which a paired-samples t-test revealed to be significantly different, $t(14) = 3.76$, $P = .001$. To ensure this difference can be attributed to the modulation of complementariness, and rather just due to inherently more expensive products forming the bundles, a further analysis was carried out. Here, the supermarket value of the products and bundles were calculated and subtracted from the corresponding WTP. This analysis revealed that complementary bundles produced a WTP £5.23 ± 2.14 below the supermarket value of the stimuli, whereas non-complementary bundles were £6.11 ± 2.3 below the objective value, indicating a mean difference of £0.88. These two values were significantly different, $t(14) = 9.17$, $P < .001$, indicating that WTP was influenced by the manipulation of complementariness and the presence of complementary products increases WTP.

Similarity ratings indicated that the pairing of products within bundles was appropriate, with complementary bundles producing a mean similarity rating of 0.76 ± 0.1 and non-complementary bundles a mean of 0.07 ± 0.08.

Next, bundles were removed that were comprised of two products of equal value, i.e. bundles were required to have a disparity of at least £1 between the products within it, allowing us to investigate bundles that were made up of a single high and low value product. The bundle additivity was then calculated by subtracting the sum of the WTP of the products within the bundle from the bundle WTP. A mean bid additivity of -£0.89 ± 0.79 was observed for complementary bundles and -£1.04 ± 0.8 for non-complementary bundles, which were not significantly different from each other, $t(14) = 0.94$, $P = .355$.

To further investigate additivity, it was hypothesised that the additive effect would be dependent on the disparity between the WTP of the products within the bundles. To investigate this, a regression model was built for each subject with the bundle product WTP disparity as a predictor and bundle additivity as the response. A mean R^2 of 0.1 ± 0.08 was revealed, which was significantly different from zero, $t(14) = 4.74$, $P < .001$, and a mean β of -0.28 ± 0.21. In order to test whether this disparity dependent sub-additive effect was different between complementary and non-complementary bundles, the same models were computed separately for complementary bundles, $R^2 = 0.09 \pm 0.08$; $\beta = -0.29 \pm 0.25$, and non-complementary bundles, $R^2 = 0.13 \pm 0.18$; $\beta = -0.26 \pm 0.25$. No significant differences were found

between these two groups, although the R^2 values were both significantly different from zero ($P < .05$). Thus, although price disparity significantly modulated the sub-additive effect, the price disparity between products did not differentially influence sub-additivity between complementary and non-complementary bundles.

Mean WTP was calculated for each condition following the split of stimuli into the appropriate conditions (see Figure 7.2). Here, stimuli were further pruned to equalise the number of stimuli comprising the individual product conditions and product bundle conditions separately. A mean of £1.44 ± 0.65 was found for low value products, £6.06 ± 1.87 for high value products, £3.82 ± 1.91 for low value complements, £9.51 ± 2.5 for high value complements, £4.02 ± 1.87 for low value non-complements and £8.83 ± 2.71 for high value non-complements. WTP values were compared between conditions, but within trial types. As expected, high value products produced significantly higher WTP ratings than low value products, $t(14) = 12.7$, $P < .001$. A 2×2 ANOVA for repeated measures revealed that complementary bundles produced similar WTP values to non-complementary bundles, $F(1,14) = 5.08$, $P = .051$, and high value bundles had significantly higher WTP than low value bundles, $F(1,14) = 339$, $P < .001$. An interaction was also found between complementariness and value, $F(1,14) = 8.33$, $P = .007$. Post-hoc testing revealed that whilst low value complementary bundles had similar WTP to low value non-complementary bundles, $t(14) = 1.82$, $P = .088$, high value complementary bundles produced significantly higher WTP than high value non-complementary bundles, $t(14) = 2.86$, $P = .013$. This effect can likely be attributed to the fact that, as previously mentioned, complementary bundles produced inherently larger WTP than non-complementary bundles.

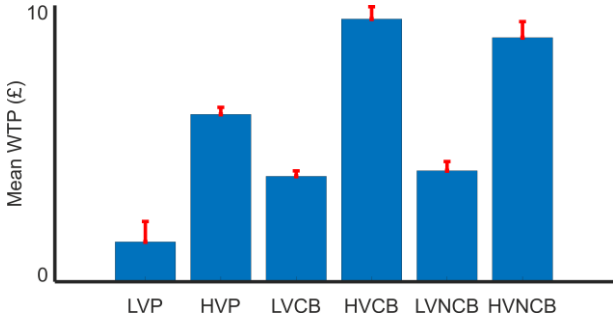

Figure 7.2. Mean stimulus WTP for each condition (LVP = Low Value Product; HVP = High Value Product; LVCB = Low Value Complementary Bundle; HVCB = High Value

Complementary Bundle; LVNCB = Low Value Non-Complementary Bundle; HVNCB = High Value Non-Complementary Bundle).

7.1.4.2. Interim summary

Complementary bundles elicited significantly increased WTP in comparison to non-complementary bundles and this effect was not explained by variations in the supermarket prices of the constituent products. When investigating only the bundles that were comprised of disparately priced products, a sub-additive effect was observed across both complementary and non-complementary bundles, though no significant differences in sub-additivity between bundle types were observed. However, regression analysis revealed that price disparity between constituent products predicted the resulting sub-additive valuations.

7.1.4.3. Eye-movement parameters

In order to illustrate fixation locations across the stimulus presentation screen, fixation locations and their corresponding latency were extracted and averaged for each subject. The fixation locations and durations were converted into a 40×40 bivariate histogram to represent the distribution of fixations, and their corresponding duration, for each condition. Figure 7.3A illustrates the mean duration of fixations across the stimulus presentation screen during individual product trials. Next, a paired-samples t-test was carried out on each histogram bin to determine any differences in fixation duration between low and high value products. As expected, fixations are distributed across the region containing the stimulus, and no significant differences between conditions were observed, other than a small cluster of differences above the stimulus area. Hence, fixation durations were equally distributed between low and high value products.

The same 40×40 bivariate histogram was computed for each condition within the product bundle trials. Figure 7.3B shows the distribution of fixation durations across the stimulus presentation monitor for each condition. Fixations were distributed between two regions of the screen, corresponding to the location of the two products comprising the bundle, however, there was a slight bias towards the product on the right side for all conditions. A 2×2 ANOVA was carried out for each

histogram bin with value (low value, high value) and complementarity (complementary, non-complementary) as independent variables. No significant main effects or interactions were observed, except for an interaction in a single bin on the bottom left region of the screen. Hence, fixation durations across the screen were equal between conditions within the product bundle trials.

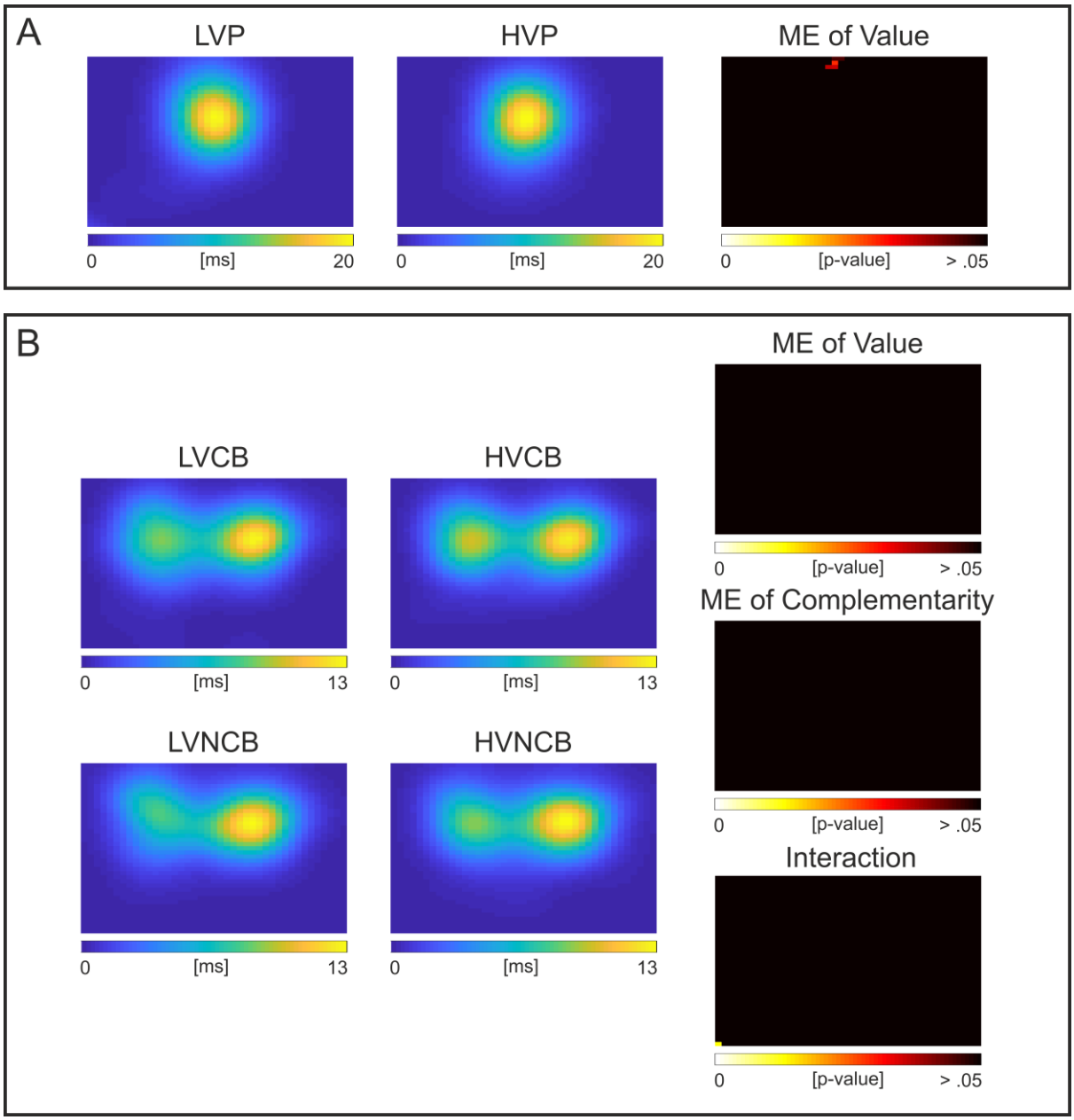

Figure 7.3. Distribution of fixation durations across the stimulus presentation monitor displayed in a 40×40 bivariate histogram. Fixation duration is measured in milliseconds per histogram bin. Differences between conditions within individual product trials (A) or within product bundle trials (B) are also shown (LVP = Low Value Product; HVP = High Value Product; LVCB = Low Value Complementary Bundle; HVCB = High Value Complementary Bundle; LVNCB = Low Value Non-Complementary Bundle; HVNCB = High Value Non-Complementary Bundle).

Eye-movement parameters were calculated to highlight any condition-wise differences that may influence further analyses (see Table 7.1). Two separate analyses were computed to compare eye-movements characteristics within each trial type separately. From here on out, all t-tests and ANOVAs are permutation-based utilising 5000 permutations. Firstly, a paired samples t-test was ran to compare low and high value products, revealing no significant differences between conditions in terms of fixation duration ($P > .05$). Significant differences were observed regarding saccade amplitude, $t(14) = 2.86$, $P = .013$, wherein fixations for low value products had smaller saccade amplitudes (3.15 ± 0.32) than those for high value products (3.26 ± 0.39). Secondly, a 2×2 ANOVA testing for differences within product bundles was carried out, with the two factors being bundle value (low value products, high value products) and bundle type (complementary bundles, non-complementary bundles). No main effects or interactions were found regarding fixation duration ($P > .05$). A significant interaction between value and bundle type was revealed for saccade amplitude, $F(1,14) = 10.1$, $P = .007$. Post-hoc t-tests revealed that high value complements resulted in fixations that had increased saccade amplitude (3.56 ±0.41) in comparison to both low value complements (3.33 ±0.42), $t(14) = 4.34$, $P < .001$, and high value non-complements (3.22 ± 0.39), $t(14) = 4.19$, $P < .001$.

Table 7.1
Mean ± SD fixation duration and saccade amplitude for individually presented products and product bundles. The circular mean and SD is also displayed for saccade direction (LVP = Low Value Product; HVP = High Value Product; LVCB = Low Value Complementary Bundle; HVCB = High Value Complementary Bundle; LVNCB = Low Value Non-Complementary Bundle; HVNCB = High Value Non-Complementary Bundle).

	LVP	HVP	LVCB	HVCB	LVNCB	HVNCB
Fixation Duration (ms)	356 ± 29.6	349 ± 27.3	322 ± 36.1	305 ± 17.9	313 ± 23.6	315 ± 40.9
Saccade Amplitude (°)	3.15 ± 0.32	3.26 ± 0.39	3.33 ± 0.42	3.56 ± 0.41	3.41 ± 0.37	3.22 ± 0.39
Saccade Direction (°)	262 ± 63	351 ± 71.9	315 ± 43.9	77.3 ± 83.7	22.6 ± 46.1	80.1 ± 51.5

Saccade direction is classified as a circular data type. Thus, the appropriate descriptive and inferential analyses must be employed to investigate saccade

direction given its circularity. Here, we employed the bpnreg package (Cremers & Klugkist, 2018) implemented in R (R Core Team, 2018). A mixed effects model was produced to identify any condition-wise differences within the individual product trials. The model included only a single factor of value category with two levels (low value, high value). The 95% highest posterior density (HPD) intervals were extracted for each condition, an interval allowing probability statements about the parameters. The HPD intervals between low and high value products overlapped, indicating no differences in saccade direction between low and high value product conditions (see Figure 7.4). A second mixed-effects model was produced to determine any condition-wise differences within the product bundles conditions, comprised of two factors (trial type, value), each with two levels (individual product, product bundle; low value, high value). All HPD intervals overlapped with each other, indicating no significant differences within the product bundle conditions. Lastly, comparison of all HPD intervals between trial types indicated no differences in saccade direction between any conditions. Therefore, saccade direction was similar across all conditions.

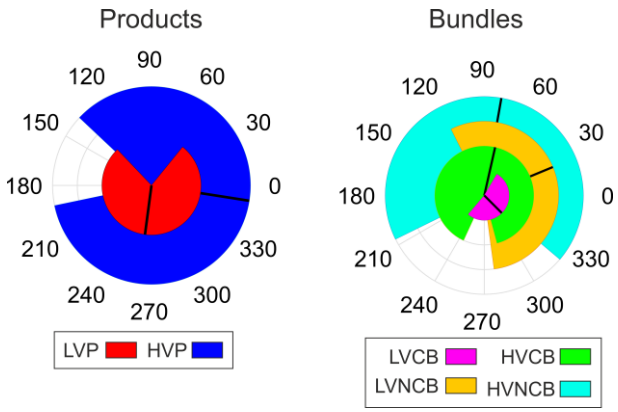

Figure 7.4. 95% HPD intervals for saccade direction. Mean circular direction is indicated by the black line (LVP = Low Value Product; HVP = High Value Product; LVCB = Low Value Complementary Bundle; HVCB = High Value Complementary Bundle; LVNCB = Low Value Non-Complementary Bundle; HVNCB = High Value Non-Complementary Bundle).

To test the plausibility of comparing product with bundle presentation trials, three more ANOVAs were carried out to compare eye-movement characteristics across all conditions. Here, each analysis consisted of a one-way ANOVA with 6 conditions (low value products, high value products, low value complementary bundles, high value complementary bundles, low value non-complementary bundles,

high value non-complementary bundles) testing for differences between conditions regarding fixation duration and saccade amplitude. A main effect was revealed for fixation duration, $F(5,70) = 14.5$, $P < .001$, as well as saccade amplitude, $F(5,70) = 5.79$, $P < .001$. P-values from post-hoc testing are summarised in Table 7.2 and 7.3 for fixation duration and saccade amplitude respectively. Regarding saccade amplitude, differences are observed sporadically, and the largest absolute mean difference detected was 0.41°. In terms of fixation duration, differences were observed entirely between trial types with the greatest absolute mean difference being 50.8 ms. Due to the presence of slight differences in eye-movement characteristics between some conditions, any observed effects discussed from here on out will be subject to the appropriate covariate analyses to rule out the modulatory effect of saccade amplitude and fixation duration.

Table 7.2
P-values indicating any significant differences between conditions for saccade amplitude (LVP = Low Value Product; HVP = High Value Product; LVCB = Low Value Complementary Bundle; HVCB = High Value Complementary Bundle; LVNCB = Low Value Non-Complementary Bundle; HVNCB = High Value Non-Complementary Bundle; * = P < .05; ** = P < .01; *** = P < .001).

	HVP	**LVCB**	**HVCB**	**LVNCB**	**HVNCB**
LVP	.01 *	.027 *	< .001 ***	.006 **	.427
HVP	-	.408	.005 **	.053	.722
LVCB	-	-	< .001 ***	.461	.142
HVCB	-	-	-	.195	< .001 ***
LVNCB	-	-	-	-	.133

Table 7.3
P-values indicating any significant differences between conditions for fixation duration (LVP = Low Value Product; HVP = High Value Product; LVCB = Low Value Complementary Bundle; HVCB = High Value Complementary Bundle; LVNCB = Low Value Non-Complementary Bundle; HVNCB = High Value Non-Complementary Bundle; * = P < .05; ** = P < .01; *** = P < .001).

	HVP	**LVCB**	**HVCB**	**LVNCB**	**HVNCB**
LVP	.125	.005 **	< .001 ***	< .001 ***	< .001 ***
HVP	-	.01 **	< .001 ***	< .001 ***	< .001 ***
LVCB	-	-	.151	.291	.492
HVCB	-	-	-	.21	.304
LVNCB	-	-	-	-	.835

7.1.4.4. Interim summary

No significant differences were observed between conditions regarding the distribution of fixation durations across the stimulus presentation screen. To determine the potential impact of eye-movement characteristics on the observed differences in measured EEG, condition-wise differences in fixation duration, saccade amplitude and saccade direction were calculated. No differences in fixation duration or saccade direction where observed between low and high value products, and also between any low/high value or complementary/non-complementary bundles. High value products elicited significantly larger saccade sizes than low value products. Additionally, high value complementary bundles produced significantly larger saccade sizes in comparison to low value complementary bundles and high-value non-complementary bundles. However, the observed differences in saccade amplitudes were minimal.

Eye-movement characteristics were also compared between trial types (individual products, product bundles) and their corresponding conditions. Significant differences in saccade amplitude were observed sporadically, however, the largest mean difference was 0.41º. Fixation duration was systematically different between

trial types, whereby fixation duration for all product bundle conditions were significantly larger than the fixation duration for all individual product conditions. No significant differences in saccade direction were observed.

7.1.4.5. Eye-fixation related potentials

Clustered ICs obtained from EFRPs were compared between conditions to determine brain responses reflecting the observed behavioural differences in WTP and sub-additivity. Of the 15 clusters extracted, 10 clusters were excluded due to being represented across less than half the participants or having had confidence intervals that overlapped with zero at the peak of the cluster power. The scalp maps and waveforms for the remaining clusters are shown in Figure 7.5. Cluster 6 was represented over a right frontal region and source the cluster centroid was located within the insula of the right cerebrum (Brodmann area 13; approximate Talairach coordinates: x = 39 mm, y = -9 mm, z = -5 mm). Cluster 10 showed prevalence over the vertex and source analysis revealed that the cingulate gyrus was responsible for this pattern (Brodmann area 24; approximate Talairach coordinates: x = 5 mm, y = -15 mm, z = 36 mm). Cluster 13 displayed a similar pattern to cluster 10, but the source of this cluster was the posterior cingulate (Brodmann area 29; approximate Talairach coordinates: x = 9 mm, y = -36 mm, z = 13 mm). Cluster 14 produced a pattern with a prevalence over a posterior region, originating in the precuneus (Brodmann area 31; approximate Talairach coordinates: x = 4 mm, y = -67 mm, z = 18 mm). Cluster 15 showed strongest activation over a left parietal region, originating within the precuneus (Brodmann area 7; approximate Talairach coordinates: x = -6 mm, y = -50 mm, z = 39 mm).

To reveal brain components representing the valuation of individual products, paired sample t-tests were computed to compare cluster amplitude between low and high value products, for each cluster that was submitted for analysis. For cluster 6, activation between 125 and 200 ms was significantly larger for low value products (0.02 ± 0.02), than for high value products (-0.003 ± 0.02), $t(8) = 2.94$, $P = .01$. Cluster 14 showed increased activation between 289 and 294 ms for high value products (-0.22 ± 0.17) than for low value products (-0.15 ± 0.18), $t(9) = 2.54$, $P = .033$. Cluster 15 demonstrated two significant latencies. Firstly, activation was

greater for high value products (-0.14 ± 0.32) than for low value products (-0.1 ± 0.32) between 107 and 131 ms, t(12) = 4.06, P < .001. A repeated measures analysis of covariance (ANCOVA) revealed that saccade amplitude had a significant influence on this effect, F(1,11) = 6.38, P = .028, however, the main effect remained after controlling for this relationship, F(1,11) = 29, P < .001. Secondly, activation was greater for high value products (0.06 ± 0.13) than for low value products (-0.005 ± 0.11) between 276 and 298 ms, t(12) = -3.01, P = .004.

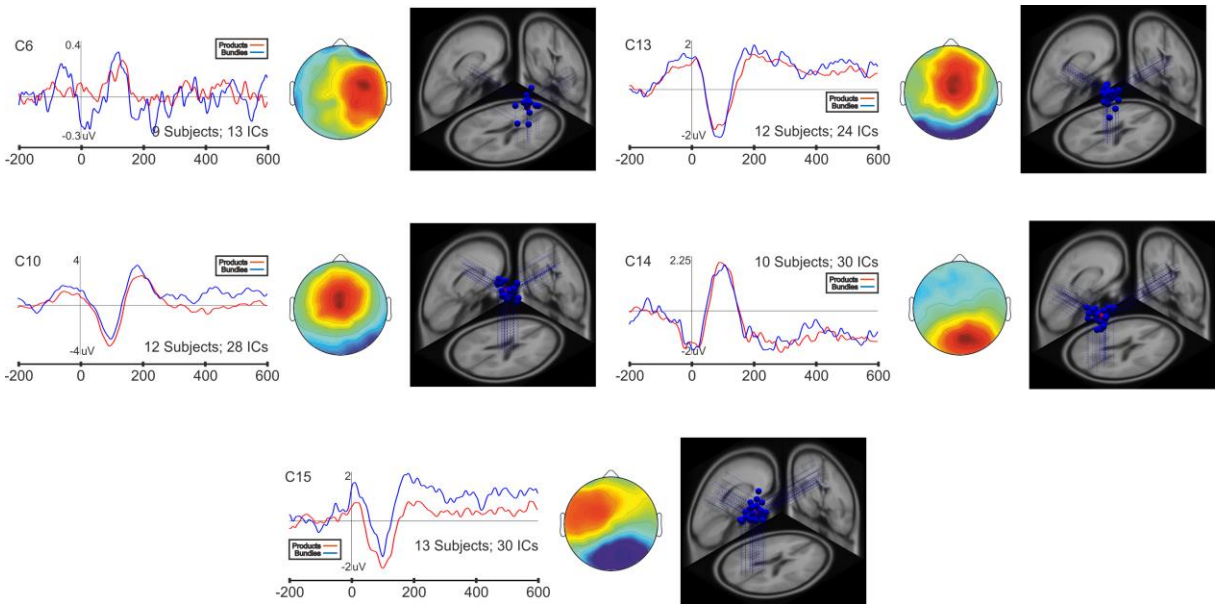

Figure 7.5. Clusters and their corresponding ERP waveforms, scalp maps and component dipoles. The ERP waveform is shown for both products and product bundles separately. The number of components included in the cluster and the number of subjects contributing to the cluster is also indicated.

Repeated measures ANOVAs were carried out for each cluster to investigate any interactions between value category (low, high value) and complementariness (complementary, non-complementary). For cluster 6, activation was significantly greater for non-complementary bundles (0.04 ± 0.05) than for complementary bundles (0.003 ± 0.02) between 124 and 149 ms, F(1,8) = 4, P = .048. Similarly, cluster 14 showed increased activation for non-complementary bundles (-0.25 ± 0.28) than for complementary bundles (-0.1 ± 0.2) between 240 and 247 ms, F(1,9) = 6.303, P = .032. Finally, cluster 15 demonstrated increased activation for high value

bundles (0.16 ± 0.27) than for low value bundles (0.09 ± 0.21) between 193 and 198 ms, F(1,12) = 4.395, P = .048.

A series of repeated measures ANOVAs were also carried out to investigate differences across all stimuli (low value products, high value products, complementary bundles, non-complementary bundles) for each cluster. Figure 7.4 summarises all main effects and interactions revealed. A significant main effect was revealed for cluster 6 between 120 and 133 ms, F(3,24) = 3.899, P = .017. Post-hoc t-tests revealed that activation elicited by low value products (0.04 ± 0.05) was significantly higher than that by high value products (0.01 ± 0.04), t(8) = 2.451, P = .033. Additionally, non-complementary bundles elicited significantly greater activation (0.05 ± 0.06) than both high value products (0.01 ± 0.04), t(8) = -3.745, P = .012, and complementary bundles (0.007 ± 0.04), t(8) = -2.073, P = .022. A significant effect was also revealed for cluster 10 between 399 and 447 ms, F(3,33) = 3.644, P = .004. Post-hoc tests revealed significantly increased cluster amplitude for complementary bundles (0.16 ± 0.34) compared to both low value products (-0.03 ± 0.078), t(11) = 1.91, P = .044, and high value products (-0.042 ± 0.056), t(11) = 2.04, P = .037. Lastly, a significant was revealed for cluster 15 between 160 and 187 ms, F(3,36) = 3.455, P = .004. Post-hoc tests revealed that complementary bundles (0.14 ± 0.3) produced significantly increased cluster amplitudes than both low value (0.023 ± 0.13), t(12) = -1.835, P = .025, and high value products (0.055 ± 0.16), t(12) = -2.15, P = .024. Similarly, non-complementary bundles (0.14 ± 0.29) produced increased cluster amplitude in comparison to both low value, t(12) = -2.016, P = .023, and high value products, t(12) = -2.081, P = .037. However, using an ANCOVA for repeated measures, this effect was found to be accounted for by differences in fixation duration between conditions, F(1,35) = 5.14, P = .03, which reduced the main effect to non-significant, F(3,35) = 2.29, P = .096.

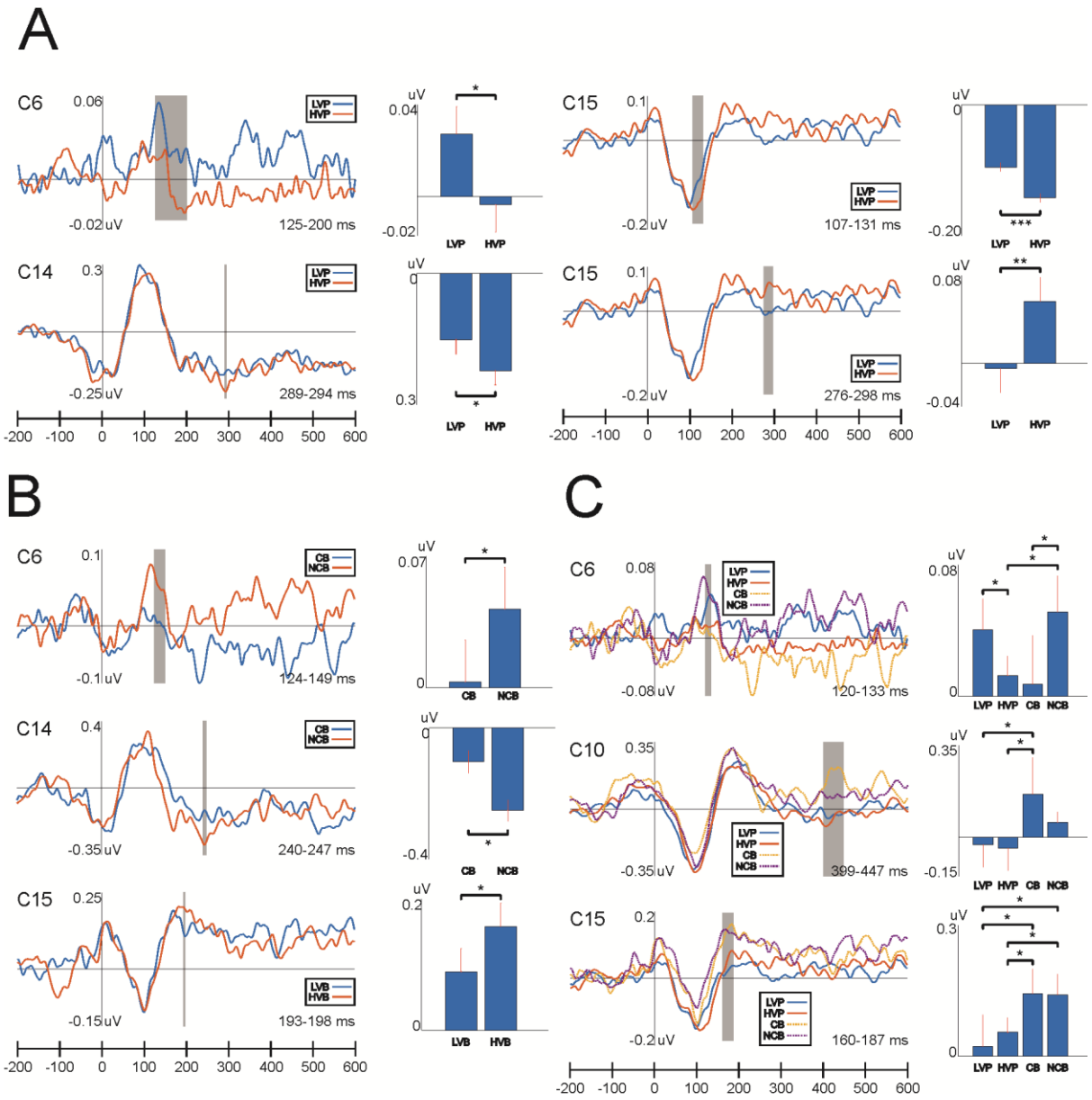

Figure 7.6. Latencies demonstrating main effects of value category (A) and trial type (B) are shown. Interactions between value category and trial are also illustrated (C). For each effect, the ERP waveform between conditions is shown, as well as the corresponding bar graph indicating results from post-hoc testing.

7.1.4.6. Regression analysis of clustered components

In order to investigate neural processes relating to additivity, cluster amplitudes were submitted to a regression analysis. For each subject, the mean additivity from bundle presentation was calculated and input as a predictor with cluster amplitude as the dependent variable. This was done for each time point in the epoch between 150 and 400 ms in order to capture relationships in the latencies of

value relevant EEG components, e.g. N2, P2 and P3. P-values corrected for the false discovery rate were obtained using the protocol described by Storey (2002). The only latencies revealed to significantly predict additivity were between 243 and 296 ms in cluster 15. Cluster power between these latencies was extracted, averaged and submitted as the dependent variable in a further regression analysis with mean bundle additivity as the predictor. It was revealed that additivity significantly predicted cluster activation between 243 and 296 ms in cluster 15 (see Figure 7.5), beta = 0.21, t(12) = 3.377, P = .006, and also explained a significant proportion of variance in cluster activation, R^2 = 0.51, F(1,12) = 11.4041, P = .006.

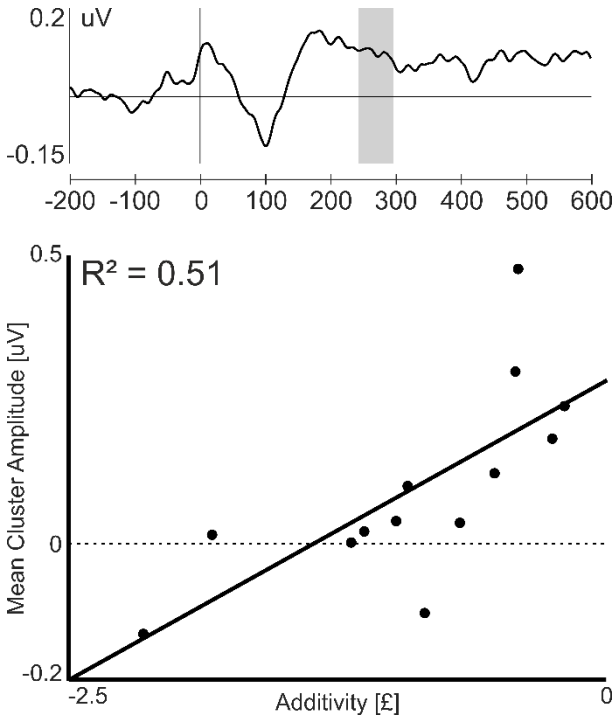

Figure 7.7. Relationship between mean bundle additivity and mean cluster amplitude between 243 and 296 ms for cluster 15. The latency of interest is highlighted in the corresponding IC waveform.

7.1.5. Discussion

Results indicate the role of price disparity in driving sub-additivity within product bundles, which is enhanced as the price disparity increases. The sub-additive effect did not differ between complementary and non-complementary bundles, however, complementarity enhanced bundle WTP. A spatiotemporal pattern of activation observed over the right hemisphere was amplified during the

viewing of low value products and non-complementary bundles. In contrast, a pattern of activation over the left hemisphere was amplified when viewing high value products and product bundles. Furthermore, the amplitude of the high value encoding cluster was modulated by mean bundle additivity. Findings suggest the presence of a neural representation signifying the perceived advantage, or disadvantage, of purchasing a product bundle.

Product bundling is a method frequently used by companies to enhance the perceived value of a set of products (Naylor & Frank, 2001). However, there are multiple factors that can alter the perceived value when product bundling is used. The present study found that the pairing of two unequally priced products can result in a sub-additive effect whereby the bundle valuation falls short of the sum of the product valuations when presented individually. With the additional manipulation of product complementarity, it was revealed that although the sub-additive effect did not differ between complementary and non-complementary bundles, price disparity between products within a bundle significantly predicted the resulting sub-additive effect. This provides evidence that product bundles comprised of unequally priced products can actually decrease the ultimate valuation, with the sub-additive effect scaling with price disparity within the bundle. Potential mechanisms for the negative impact of additional features on product valuations have been speculated on previously. Simonson et al. (1994) highlighted how extra features may result in the dilution of the most attractive features, how unneeded features may be used to justify the rejection of the product, and the averaging of value across all constituent products. Although Simonson et al. (1994) did not find evidence for the averaging effect in their research, the averaging effect has found evidence in more recent studies. Weaver, Garcia, and Schwarz (2012) revealed that the addition of mildly favourable information to highly favourable information reduced overall evaluations via an averaging process, and this can extend to persuasive arguments (Weaver, Hock, & Garcia, 2014). Similarly, Gaeth, Levin, Chakraborti, and Levin (1990) indeed show that the tie in product, regardless of value, has an almost equal weighting compared to the primary product when evaluating a product bundle. Another plausible explanation for the observed sub-additive effect is the role of uncertainty. Popkowski Leszczyc et al. (2008) demonstrated that when uncertain about the value

of a high value product within a bundle, we may use the value of the low value product within the bundle to infer its value.

The pairing of complementary products within product bundles has been previously shown to increase purchase intent (Harlam et al., 1995), and Yan and Bandyopadhyay (2011) describe a profit-maximisation model indicating how complementarity plays an important role in bundling strategies. These effects are likely to come about due to the purchasing of products that have enhanced functionality when being paired (Estelami, 1999). Although the current study did not demonstrate different levels of additivity between complementary and non-complementary bundles, complementary bundles did produce significantly increased WTP than non-complementary bundles. Essentially, complementarity increased WTP without producing a super-additive effect. One possible explanation for this may be due to the unequally priced products present within the product bundles. The super-additivity often observed when pairing complementary products may be attenuated when the secondary product is of low value. Previous studies found that complementarity can attenuate the negative effect of price discounting when selling product bundles (Sheng et al., 2014), and complementarity can reduce the need for advertising (Yan et al., 2014). Hence, it is possible that the various influences on bundle valuations may have interactive effects, in that unequally priced products within a bundle can moderate the super-additive effect that complementarity can produce. However, the current study can only postulate on this without further research.

A component cluster showing activation in the right frontal electrodes and originating in the right insula appeared to be responsible for the encoding of low value products, similar to what we found in previous work (Tyson-Carr et al., 2018). In our previous study, an equivalent current dipole placed in the right anterior insula displayed increased activity during the valuation of low value products, possibly pertaining to the aversion that low value products may induce in economic situations. Activation in the insula has previously been implicated with disgust, whether that be a response to disgust or recognising disgust in others (Toronchuk & Ellis, 2007). More specifically, the right insula has been observed to response to disgusting odours (Heining et al., 2003) as well as disgusting non-food items (Calder et al., 2007). A vast amount of other studies investigating decision making have alluded to

the role of the insula in decisions producing some aspect of negative affect. Sanfey et al. (2003) implicated the insula during the presentation of unfair offers during the ultimatum game and highlighted the importance of emotions in decision making. This gains further support in a study by Kuhnen and Knutson (2005) who found that insula activity was indicative of loss prediction. Critically, activity within the insula has been reported to be negatively correlated with expected value in a decision-making task (Rolls et al., 2008). A similar role of the insula has also been reported in rats whereby activation was increased during risk-taking behaviours (Mizoguchi et al., 2015) and following negative outcomes (Jo & Jung, 2016). The role of the insula in risky decisions and various forms of negative emotions validate the findings of the current study. The link between decision making and emotion make it possible that low value stimuli, especially in a realistic economic decision, may be aversive as they provide little benefit. Importantly, Shenhav et al. (2018) argue that low value items can be interpreted as aversive, rather than simply unrewarding.

A cluster showing activation across left frontal electrodes originating in the precuneus was activated primarily during the valuation of high value products. A recent study highlighted the role of the precuneus in preferences during economic decision making (Voigt, Murawski, Speer, & Bode, 2019), reporting that activity within the precuneus was predictive of upcoming preference changes. However, the localisation of this component in the present study bordered very closely with the PCC and this must be considered in the context of the spatial resolution of EEG methods. Although the precuneus and PCC are functionally different, they do indeed share functions, especially in terms of their involvement in the default mode network (Fransson & Marrelec, 2008; Leech et al., 2012; Leech, Kamourieh, Beckmann, & Sharp, 2011; Margulies et al., 2009). Previous studies have showed how the PCC is involved in the evaluation of reward magnitude (Knutson, Adams, Fong, & Hommer, 2001; Knutson et al., 2003) and also of expected value during lotteries (Knutson et al., 2005). A meta-analysis by Bartra et al. (2013) comprising fMRI data on value-based decision making reveals the importance of the PCC, especially for positive effects during the decision stage. This was further iterated in a second meta-analysis (Clithero & Rangel, 2014), and may explain the implication of the PCC in the current study during the valuation of high value products.

To date, there has been no research investigating neural processes during valuation of product bundles. The bundling of products introduces a challenge to a prospective buyer in that there are multiple products that need to be valuated to reach a decision. The limited capacity for the human brain to process information makes these purchase decisions especially hard (Cheng et al., 2014). However, previous work investigating the zero-price effect has went some way to help understand neural mechanisms during the valuation of products presented in parallel. A study by Ma et al. (2018) found an increased LPP amplitude when tie-in products within a product bundle were presented as being “free”, in comparison to when being offered at its normal price. This is similar to the brain component encoding additivity reported in the current study. Here we reported a brain component that produced a wave over the vertex, spanning over the left portion of the scalp, in the latency of the P3 component. Although slightly later, Ma et al. (2018) report an LPP measured over the vertex that was indicative of this zero-price effect. An fMRI study by Votinov et al. (2016) demonstrated how preferences can switch from a more expensive and preferred product, to a cheaper and less preferred alternative when the alternative product is presented as being free. Importantly, the authors implicated the PCC in this zero-price effect. This could lend evidence to the observed effect in the current study regarding the encoding of additivity, likely originating in the PCC. It is possible that the PCC in the current study was responsible for encoding the perceived benefit of purchasing the products in conjunction, similar to how Votinov et al. (2016) suggest that the PCC is involved in zero-related changes of preference in bundling contexts.

To conclude, the present study demonstrated the sub-additive effect induced by the bundling of disparately priced products, as well as the enhancement of WTP from the bundling of complementary products. Furthermore, a set of spatiotemporal cortical activation patterns that reflected the valuation of products and product bundles were revealed. Similar to previous studies, the observed patterns showed specificity to either low or high value alternatives (Roberts et al., 2018; Tyson-Carr et al., 2018). Findings indicated the presence of a neural representation of the perceived benefit of purchasing a product bundle, reflected in the modulation of cortical activation by bundle additivity. The modulatory effect was observed within an activation pattern that showed specificity to high value alternatives, implicating a

single brain network in the estimation of overall utility. In contrast, an activation pattern which responded uniquely to low value products and non-complementary bundles highlighted a network responding to perceived disadvantage.

Chapter 8

8.1. General Discussion

Research in the field of neuroeconomics has been aimed toward investigating the neural substrate of decision variables described in economic models. Although these efforts have been fruitful for accurately describing the spatial aspects of the brain valuation system, the temporal dynamics of subjective valuation are much less clear. The implementation of EEG methods described in the previous chapters aimed to describe the temporal characteristics of subjective valuation, whilst also using source analysis techniques to complement the descriptions.

8.2. Summary of Findings

- In Chapter 4, low value items provoked increased source activity in the right AIC and the left OFC in comparison to high value items at approximately 200 ms, during both value-relevant and value-irrelevant choices.
- Source activity in the right PHG was amplified during value-relevant choices in Chapter 4.
- Distinct patterns of cortical activity over the left and right hemispheres, observed in Chapter 5, were intensified during the viewing of high and low value items respectively. A cortical activation over the fontal midline electrodes was strongest during the viewing of medium-priced items.
- An EFRP component unique to high value items in Chapter 5 was active early on during free-viewing and maintained throughout the viewing period.
- The differential encoding of low and high value items was present within cortical responses immediately following stimulus presentation in a BDM auction task within Chapter 6.
- Product bundles presented in Chapter 7 comprised of disparately priced products elicited a sub-additive valuation.
- Bundle WTP in Chapter 7 was enhanced when bundles contained complementary products.

- A spatiotemporal pattern of cortical activation over the left hemisphere, originating in the precuneus, was intensified during the viewing of high value products and product bundles and modulated by bundle additivity (Chapter 7). A second cortical activation component present over the right scalp region and fitted to the right insula was strongest during the viewing of low value products and non-complementary bundles.

8.3. Themes

Several common themes were observed across the experimental chapters of this thesis. Primarily, distinct ERP and EFRP components were observed for low and high value products individually. Further to this, hemispheric asymmetry was observed whereby low and high value related activity was elicited predominantly over the right and left hemispheres respectively. Regarding the temporal dynamics, the importance of the latencies post 150 ms are emphasised, encompassing the P2, N2, P3 and LPP component latencies. However, these components seem to have some specificity regarding low and high value encoding.

8.3.1. Negativity bias towards low value

Across the experimental chapters in this thesis, we have observed separate and unique responses to low value stimuli. Significantly larger responses to low value products were observed in Chapter 4 within the latency of the N2 ERP component, represented by brain potentials over the right hemisphere, and originating from the right insula. Similarly, an EFRP component in Chapter 5 extending over the right scalp region was strongest during the viewing of low value products. A component cluster within the right insula was also strongest when viewing low value products and non-complementary bundles in Chapter 7. Findings suggest the ability of the brain to be able to rapidly categorize incoming stimuli as being of low value, and possibly suggesting an aversive response towards these low value stimuli.

The role of emotion in decision-making has been investigated greatly (for a review, see Seymour & Dolan, 2008). For example, using data from anxious and

depressed individuals, Paulus and Yu (2012) demonstrated the altered value computation that can result from emotional dysfunction. It is possible that low value stimuli, in the context of an incentive compatible auction, may produce negative affect. The aversion to low value products in the present study largely replicated that reported by Shenhav et al. (2018) who reported across several studies subjects' perception of low value products being aversive rather than simply unrewarding. The authors of this study also reported that the aversion is due to the anxiety from choosing between low value and relatively benign products. One possible reason for the development of this mechanism in humans may be the evolutionary benefit that it provides. It is obviously beneficial to be able to detect high value stimuli in our environment, which will likely produce the relevant approach behaviour. Conversely for low value products, it is beneficial to be able to rapidly detect options with the lowest subjective value so as to avoid expenditure of resources for little reward. A motivational significance of both low and high value stimuli is also reflected in the study by Shenhav et al. (2018) who not only reported the elicitation of anxiety by low value choices, but also from a set of high value alternatives.

In Chapter 4 of the current thesis, we did not observe any increased source activity for high value stimuli. Therefore, we speculated that the brain displayed a negativity bias towards the low value products. Additionally, we hypothesised that given the relatively small range of values, it may be that none of the items were perceived as particularly rewarding. The small range of possible values utilised could have meant that the stimuli in the "high value" category did not have a high enough WTP to be perceived by the individual as truly high value. Consequently, it is necessary to discuss the neural encoding of absolute relative to normalised value encoding. Research has shown that responses to rewards are highly influenced by the range of options presented to an individual in a given setting, in that our reference point for making an evaluative judgement is shifted based on the alternatives we are presented with (Rangel & Clithero, 2012). The ability to shift the reference point is indicative of a neural system that undergoes a process of value normalisation, but research indicating the absolute encoding of value in the brain is also present (Kennerley, Behrens, & Wallis, 2011; Kobayashi, Pinto de Carvalho, & Schultz, 2010). If we had observed a shift in the reference point, then subjects should have perceived the greater value products as rewarding. Conversely, if the

absolute value of the stimuli was being encoded, both low and high value stimuli may be perceived as unrewarding. To answer this dichotomy, we can draw evidence from our other experimental chapters with extended ranges of value. When investigating brain potentials in response to stimuli with a much broader range of subjective values, such as in Chapter 5, 6 and 7, we observed increased neural responses to both low and high value products, in separate brain components. The observation of value encoding extending to high value products indicates that the high value stimuli in Chapter 4 were indeed unrewarding, given that the extension of values produces activity unique to high value stimuli. Regardless, the increased response to low value items in distinct brain components, often source localised to the right insula, indicates the ability to determine low value stimuli in the environment, and the role of the insula in loss aversion reiterates this. Additionally, the aversive response to low value products observed by Shenhav et al. (2018) was localised to the insula which emphasises the distinct encoding of low value in the brain.

8.3.2. Lateralisation of economic value in the brain

Across all experimental studies in the current thesis (Chapters 4-7), there were systematic patterns present regarding the lateralisation of brain components for different value categories. All results indicating increased activity for low value products were accompanied by activity across the right hemisphere. Results indicate a slight bias towards the left hemisphere regarding the valuation of high value products, though this finding is much less evident. However, brain potentials demonstrating increased power for high value products consistently produce an almost identical topography, described by activation over the vertex and a posterior region. Although the posterior component varies in its location, it is frequently observed over a left posterior region.

Hemispheric asymmetry is observed across many domains. Most prominently, the left and right hemispheres have been described as being responsible for approach and withdrawal behaviours respectively (Davidson, 1990), as well as for positive and negative affect (Davidson, 1998a). Since high quality products provide security and value (Hankuk & Aggarwal, 2003), the presentation of these stimuli may therefore induce approach behaviour (Ravaja, Somervuori, & Salminen, 2013). In

contrast, the compromise on quality that low value products often provide may have the opposite effect and, in turn, induce avoidance behaviour. Furthermore, a study by Windmann et al. (2006) revealed increased activity within the right OFC during punishments, in contrast to the representation of rewards in the left OFC. Additional examples of the lateralisation of function come from neuromarketing research. During the viewing of TV commercials, previous studies reported that positive TV commercials produced amplified alpha and theta activity over the left hemisphere, whereas alpha and theta activity was stronger over the right hemisphere for negative TV commercials (Vecchiato et al., 2014; Vecchiato et al., 2011). Similarly, Ravaja et al. (2013) observed enhanced left-frontal alpha activity in the pre-decision period of decisions that ultimately lead to a purchase. The enhanced left-frontal alpha activity also extended to predicting the perceived need for the product as well as the perception of quality of the product. Therefore, the findings of the present thesis across Chapters 4 to 7 corroborate the potential role of hemispheric asymmetry as an index of valuation processes, as well as the general role of the left and right hemispheres in the valuation of high and low value products respectively.

8.3.3. Unique brain components for value categories

Neuroeconomic research has benefitted greatly from functional imaging methods such as fMRI, allowing researchers to accurately localise neural regions involved in subjective valuation (Bartra et al., 2013; Clithero & Rangel, 2014), revealing a domain-general valuation system that linearly encodes subjective value. In contrast, the electrophysiological methods utilised in the current thesis reveal distinct processes that responded to unique value categories, for example, low and high value items. Results from Chapter 4 to 7 indicated that a coarse neural response is initially made to broadly categorise the incoming stimuli as being of low value, or as being highly rewarding.

The rapid categorisation of stimuli is evolutionarily beneficial to organisms, allowing them to rapidly identify the most useful options in the current situation. Cacioppo, Gardner, and Berntson (1999) developed a model of affective processing that describes the multiple levels of stimuli evaluation. The model suggests an initial, primitive and low-level response occurs rapidly, before a higher-level response takes

place within integrative regions. It is unlikely that the low temporal resolution of fMRI would capture the initial categorisation during subjective valuation, and hence, the rapid responses (< 500 ms) observed in the current thesis may reflect the initial, coarse response of the brain to economically salient stimuli. The primitive responses in low-level regions are also more responsive to negative stimuli (Cacioppo et al., 1999; Smith et al., 2003), possibly explaining the readiness of the brain in response to low value stimuli in the results across the previous experimental chapters, reflected in earlier responses to low value items in the N2 ERP component, or in the possible absence of high value encoding at all in Chapter 4.

Based on this information, it appears that fMRI methods may lack the ability to reveal the initial response of the brain to crudely define the general value category of the stimuli, measuring only the summation of evaluative responses over an extended period of time including late integrative processes. Consequently, subjective value measured by WTP appears to largely mimic affective valuation, with economic valuation utilising the brains ability to rapidly evaluate the affective valence of a stimuli. The utilisation of emotion related processes could explain the employment of unique brain processes during subjective valuation, most prominently the aversive response to low value products as indicated by the frequent observation of insula activation. Our observations are further supported by the findings from Shenhav et al. (2018) who reported that low value items are aversive rather than merely unrewarding, thus suggesting the direct link between low subjective value and avoidance processes, which may extend to high subjective value and approach responses.

8.3.4. Roles of N2, P3 and LPP

The limited previous electrophysiological research has already established the role of the various ERP components in subjective valuation processes (see Hakim & Levy, 2019). Results from the current thesis have demonstrated the importance of distinct latency intervals for economic valuation.

The N2 component and its corresponding latency between approximately 200 and 350 ms was highlighted to be of importance in Chapter 4 and 6, wherein low value items were primarily encoded within this latency. The N2 component has been

implicated in conflict-processing (Larson et al., 2012; Ma et al., 2015; Ma et al., 2007; Wang et al., 2016), suggesting a potential conflict induced by the low value products. The N2 is also frequently implicated in attentional processes (Folstein & Van Petten, 2008), and the increased N2 amplitude described here for low value products may simply reflect the facilitated attention towards low value stimuli, possibly due to the negative response they produce (Shenhav et al., 2018). The latency interval encompassing that of the N2 is the earliest latency we reveal to consistently represent value relevant signals. Given the negative nature of low value items, it follows that the earliest value encoding ERP component would also be specific to low value stimuli for rapid categorisation of the most relevant stimuli.

Further to the encoding of value in the N2 latency, other important and distinct latency intervals are also highlighted across the current results. High value products produced increased activation predominantly in the latency interval of the P3 component within Chapter 6, albeit an early form of it, possibly overlapping with the N2 component. The P3 component has been implicated in motivational significance in previous studies (Duncan-Johnson & Donchin, 1977; Johnston et al., 1986; Keil et al., 2002), which could explain the current finding that highly valuable stimuli may be perceived as more motivationally significant since they represent the most valuable alternative. The latency interval of the P3 overlap somewhat with the N2, making it difficult to discern value specific ERPs. However, another distinct latency period encompassing the LPP was found to represent value related signals in Chapter 6. The LPP is similar to the P3, often referred to as a maintained P3 wave (Hajcak & Olvet, 2008), and is the main candidate reported in previous studies as being an index of product preference (see Hakim & Levy, 2019). Findings from Chapter 6 therefore suggested the importance of these delayed components in representing high value encoding, occurring much later than the early low-level evaluative judgements. The latencies of value encoding for high value items across the results are temporally distant from the effects observed for the N2 and P3 effects discussed, and it is therefore easy to differentiate a period of high value encoding within the LPP interval.

8.3.5. Automaticity of valuation

Results from Chapter 4 and 6 illustrated the rapid differentiation of low and high value, approximately 200 ms following stimulus onset. The categorisation of stimuli in an early ERP component reflected the automaticity of valuation, occurring before any conscious processing. Similarly, source activity differentiating low and high value products did not differ between the value-relevant and value-irrelevant contexts in Chapter 4, nor did the value-encoding cortical responses observed in Chapter 5 differ between free and forced bids. Similar to previous research (Lebreton et al., 2009), the presence of value differentiation within cortical responses across multiple contexts, regardless of the need for the computation of subjective value, highlighted the automaticity of brain valuation.

Previous studies have highlighted the potential automatic nature of brain valuation. In an fMRI study investigating choice behaviour, Levy et al. (2011) observed how BOLD activity during the passive viewing of consumer goods predicted the subsequent purchase decision made following the scan. The BOLD signal within the striatum and the PFC showed the strongest prediction, highlighting these regions in the representation of value in the absence of choice. Similarly, Grueschow et al. (2015) revealed the role of the PCC in representing subjective value, regardless of whether the value was choice relevant. An EEG study by Polania et al. (2014) highlighted a commonality between both value-based and perceptual-based decisions in parietal gamma oscillations, suggesting a potential neural generator projecting to parietal regions of the scalp may represent a common decision variable across tasks. The automaticity of brain valuation suggested in previous studies highlights the general processes underpinning valuation, whereby subjective value is computed regardless of its current relevance and drawn upon only if necessary. Similar to Grueschow et al. (2015), findings from Chapter 6 which highlighted the importance of the cingulate gyrus, and findings from Chapter 7 which implicated the closely neighbouring precuneus, served to corroborate the possible role of the PCC in choice-independent value representation.

8.3.6. Sub-additive effect in bundles

Results from Chapter 7 indicated that the addition of an extra product to form a bundle may actually harm the subsequent valuation that individuals make. Although product bundling is frequently used by organisations to increase sales (Fang et al., 2017), the “more-is-less” and the “less-is-better” effect are highly prevalent in economic literature (Hsee, 1998; List, 2002; Popkowski Leszczyc et al., 2008), indicating that the addition of extra features can actually decrease valuations. This was evidenced in Chapter 7 which reported that as the disparity in price between two products in a bundle increases, the sub-additive effect increases, i.e. the added value from bundling two products decreases as disparity in individual WTP increases.

Multiple mechanisms have been put forward for the sub-additive effect (Simonson et al., 1994), such as averaging the values of the counterparts of a bundle. Sub-additivity may also be due to the inference of values of uncertain items based on the values we are certain of (Popkowski Leszczyc et al., 2008). Based on the overarching findings from the current thesis, we could speculate that it may be the aversion that low value products induce that drives the sub-additive effect. Since bundles were comprised of a single low and high value item, and findings from the experimental chapters have demonstrated consistently the aversive nature of low value items, it is possible that sub-additive effect is driven predominantly by the negative motivation induced by the low value product. Furthermore, it was also observed in Chapter 7 that increasing sub-additivity scaled with increasing disparity. Given that options may be evaluated in the context of a given scenario to normalise value (Rangel & Clithero, 2012), the increasing disparity would reduce the relative value of the low value counterpart. Thus, the increasing disparity could increase the perceived negativity of the low value option through value normalisation.

8.4. Limitations

The primary limitation of the research conducted, and EEG research generally, is the ability to locate the neural generators of the brain processes discussed. During the experimental tasks of the current thesis, the brain potentials

measured were conducted across organic matter with varying levels of conductivity, producing spatially mixed signals measured across multiple neighbouring electrodes. However, complex head models and methods such as ICA have given EEG researchers the ability to solve the inverse problem much more efficiently, often allowing a spatial resolution of approximately 1 cm (Onton, Westerfield, Townsend, & Makeig, 2006). Limitations in spatial resolution should therefore be considered when interpreting the findings relating to spatial approximation within Chapters 4, 6 and 7. Further to the limitation on spatial resolution, the method for source localisation in Chapter 6 and 7 was implemented in EEGLab (Delorme & Makeig, 2004), a protocol implementing a single dipole solution to explain the distribution of brain potentials. This is in contrast to procedures implementing multiple dipole solutions to explain observed patterns, such as the sequential fitting of dipoles to produce a dipole model (Scherg & Berg, 1996), which may more accurately represent the actual neural generators producing the observed cortical activation patterns.

The simultaneous use of EEG and eye-tracking in research brings with it many issues. As outlined by Nikolaev et al. (2016), eye-movements can have a sporadic effect on resulting brain potentials. Eye-movements can contaminate the baseline periods of epochs synchronised with fixation onset, as well as the post-saccadic interval encompassing the brain components that correspond to higher-order processes. Not only do the eye-movements contaminate the brain potentials, but systematic differences between conditions in the characteristics of the eye-movement can induce differences not attributable to experimental manipulations. Nevertheless, the experimental chapters utilised several methods to account for the potential influence on the findings reported. Linear deconvolution methods such as Unfold (Ehinger & Dimigen, 2019) make it easier to account for linear and non-linear influences on measured responses and the variable temporal overlap between events. The utilisation of appropriate covariate analyses also allowed for the assessment of potential influences on our findings. However, it is likely that some remnant of activity attributable to eye-movements will remain despite efforts to reduce it.

The present thesis focussed mainly on categorically defining value categories by splitting stimuli into equally sized conditions. However, it may have been more fruitful to investigate brain potentials encoding value linearly by treating value as a

continuous variable. Previous fMRI research largely involves the investigation of continuous encoding of value in the brain (e.g., Plassmann et al., 2007; 2010). A limitation in EEG research is the restricted signal-to-noise ratio (Luck, 2005), making it difficult to investigate data on a single-trial level. The reduced signal-to-noise ratio in EEG research makes it much more viable to investigate decision making processes in a categorical manner.

An issue in the current set of studies which is prevalent across the literature is the use of principally undergraduate and postgraduate students, and the extent to which the findings can be extrapolated to other populations is an important consideration (Henrich, Heine, & Norenzayan, 2010). Furthermore, the perception of monetary outcomes may change drastically between populations. In line with prospect theory (Kahneman & Tversky, 1979), individual variability in wealth may greatly influence the subsequent reference points for gains and losses. Therefore, the utilisation of a student population with low income may result in very different responses in economic situations than that we would observe in a more representative population.

8.5. Suggestions for Future Research

The present thesis goes some way to understanding the temporal characteristics of subjective valuation, primarily within the context of a BDM auction task. The use of categorical predictors of value allowed for the identification of the general signals related to subjective valuation. In theory, value could be treated as a continuous predictor, and future research should determine whether similar effects arise when extending to continuous predictors of value. It is possible that the splitting of value into separate conditions does not capture the entirety of the relationship between subjective valuation and the underlying cortical processes. An overarching theme of the present thesis is the coarse encoding of value in brain potentials. For example, we reported brain components responding to low/medium value products. However, further investigation treating WTP as a continuous predictor with regression methods may reveal the full extent of the relationship within value encoding brain components.

Although EEG methods benefit from excellent temporal resolution, the simplicity of EEG makes it remarkably useful in the field of mobile brain/body imaging (MoBI). In the past decade, there has been a vast amount of research utilising EEG to investigate brain processes in naturalistic settings (Gramann, Gwin, Bigdely-Shamlo, Ferris, & Makeig, 2010; Makeig, Gramann, Jung, Sejnowski, & Poizner, 2009). Implementing simultaneous EEG and eye-tracking recordings in mobile settings is a simple but effective method for investigating naturalistic brain processes, with eye-fixations offering an important synchronisation point for synchronising brain data. A previous study has already investigated value-related brain components in mobile settings (Roberts et al., 2018), and future research would benefit from utilising the methods described in the current thesis for the investigation of subjective value computation in naturalistic settings.

8.6. Concluding Remarks

The spatial characteristics of brain processes related to subjective valuation have been described in great detail. The current thesis described the temporal dynamics of subjective valuation during economic decision making within the context of the BDM auction. Previous studies have observed value related signals across the scalp as early as 150 ms (Harris et al., 2011; Larsen & O'Doherty, 2014; Tzovara et al., 2015), something that has been replicated in the current thesis. Additionally, the importance of the N2 ERP component in the encoding of low value products is emphasised. Conversely, the P3 and the LPP ERP components were implicated in the encoding of high value products. These findings contribute to literature concerning subjective valuation processes, informing the role of distinct ERP components in evaluative processes. Although fMRI research has described a domain-general valuation system responsible for the linear encoding of value across multiple reward types, the current thesis described a coarse encoding of value across the brain in response to low and high value products, something which may only be observable using methods achieving a high temporal resolution such as EEG. Similar to the fMRI literature, the present thesis also utilised source analysis methods to reveal the importance of the cingulate gyrus and insula in the valuation of products. The consistent observation of insula activation in response to low value products and product bundles highlights the aversion that low value products elicit.

Additionally, the utilisation of neural systems responsible for emotion is emphasised with this aversion.

In closing, the current thesis has provided a detailed description of the temporal dynamics of economic decisions in the brain. The utilisation of simultaneous EEG and eye-tracking has been revealed to be a useful tool in the investigation of brain processes relating to decision making over a prolonged period of time, in contrast to simple stimulus response paradigms, something we hope can be exploited in future research within neuroeconomics.

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