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The Interplay between Preference and External Information in Value-based Decisions

A thesis presented for the degree of Doctor of Philosophy

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Abstract

The present thesis investigates the characteristics of preference-based, reward-based, and perceptual decisions and examines their interplay across a variety of decisional contexts. First, we systematically review how value-based decisions are studied in experiments using either magnetoencephalography (MEG) or electroencephalography (EEG) and we provide the overarching theoretical framework of the dissertation by dividing value-based decisions in externally-guided (i.e., reward-based) and internally-guided (i.e., preference-based) ones. The paradigms used in the extant literature are further classified to provide a common nomenclature and a guide for future research. We then shift our focus to examine whether there is an interaction between preferential choices and the surface size of a food item, showing that the perceptual and value-based domain are dissociated from each other at the behavioural level. Following this, the potential interactions between externally-guided and internally-guided decisions are tested across three online experiments, which robustly show that participants are biased by irrelevant information (specifically, preference-related information) when tasked to choose between options associated with different probability rewards, indicating an interaction between the two decisional domains. These findings are then extended with an MEG experiment. Finally, we present fMRI findings on multi-attribute preferential decisions where sets of options include both multiple items at once as well as incongruent information. The results point towards an engagement of the multi-demands network and provide support to the conceptualisation of decision-making as a flexible and integrative process. In conclusion, this diverse set of experimental and reviewed findings provide a contribution towards a deeper understanding of decisional mechanisms at the behavioural and neural level.

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1 Introduction

1.1 Background

Decision-making processes are a ubiquitous aspect of human life, and they span multiple levels and systems within which people operate, starting with the individual sphere all the way to decisions taken at an international or global level (Edwards, 1954). Given this omnipresence of decision-making as well as the adaptive nature of human beings, we can already formulate a few key assumptions on the nature of this process: it is a complex one; it is highly variable as its exact nature will depend on the context within which the decision is made; and its outcomes will have a complex and variable range of implications for the agents involved in it and their continued survival in the environment.

As a result of this intersectional nature, it is of no surprise that decision-making has been the object of philosophical, social, ethical, economic, technological, and scientific inquiry (Glimcher & Fehr, 2014). Its study has sprouted disciplines that often sit at the crossroads between different fields of human investigation, such neuroeconomics, game theory, and decision science, which draw methods and models from economics, marketing, social sciences, computer science, and machine learning, to name but a few. The line of investigation that is, however, the most pertinent for the present thesis is one that brings the decision-making process back to its roots: the study of the individual and its specific neurobiology. Ultimately, any process that results in an individual committing to a specific course of action must necessarily have a neurobiological substrate that provides the mechanistic basis allowing the process to occur in the first place. To that end, examining decision-making through a neuroscientific lens can provide in-depth insights into said underlying mechanisms, both in terms of the specific brain areas that contribute to this process as well as its temporal unfolding while the individual is actively making an intentional choice (Gold & Shadlen, 2007).

As previously mentioned, decision-making is a highly variable and context-based process, which means that different internal and external demands will shape it accordingly. This can be traced to the main macro-division discussed in cognitive science, i.e., that between perceptual (Summerfield & de Lange, 2014) and value-based decision-making (Gold & Shadlen, 2007; Rangel et al., 2008). The former involves making decisions based on the perceptual features of one or multiple stimuli (e.g., stopping at a red light or going forward at a green one), while the latter implies choosing between options that differ on a variety of criteria – all of which carry some sort of value (e.g., choosing between an apple or an orange). Both of these domains have received considerable attention over the decades and now we have a wealth of behavioural and neuroscientific evidence that sheds light on their spatial and temporal characteristics.

However, there are questions that remain unanswered or that have been the subject of far less scrutiny. Some of these will be the object of the present dissertation and are outlined in Section 1.2 below.

1.2 Aims

This thesis aims to extend the research on value-based decision making by exploring its behavioural and spatiotemporal dynamics in a variety of novel contexts, where the interplay between different decisional domains, types of values, and attributes is emphasised. The goal is to deepen our current understanding of the behavioural and neurocognitive correlates of decision-making processes in more complex contexts. In this section, we provide a brief summary of the contents of each chapter included in the present work.

Chapter 2 is an overview of the theories on decision-making, starting with a very general framework that divides it into separate macro-stages, such as input detection, information processing, output production, and feedback monitoring. This is followed by a discussion on the computational models that have been used to explain decision-making and by an evaluation of the two main domains of decision-making, i.e., perceptual and value-based. The latter receives special attention in the second part of the chapter, as most of the experimental work focuses on value-based decisions. Here

we also present the main framework that is used throughout the thesis, i.e., the differentiation between externally-guided and internally-guided decision-making (Nakao et al., 2012), which provides the operationalisations we use in the experimental chapters.

Chapter 3 presents a systematic review of the MEG and EEG literature on the spatiotemporal dynamics of value-based decision-making and the paradigms used in this field, which were classified according to the externally-guided/internally-guided dichotomy mentioned above. Following the PRISMA guidelines (Moher et al., 2015) and inspired by a similar work conducted on the MEG literature on language processes (Mundig et al., 2015), we extracted 100 papers from the PubMed and PMC databases and collated data on the significant intervals and electrodes associated with experimental contrasts sensitive to differences in value (e.g., low-value versus high-value items in a preference task). We then provide a classification of the paradigms used in these papers in order to guide future research on the topic.

Chapter 4 investigates whether perceptual and value-based decisions interact with one another. This was achieved through a novel online paradigm where, following a rating task on a continuous scale, the size of a series of food pictures was manipulated on a trial-by-trial basis to examine whether preference judgments were affected by size information. No significant effects were found. We conducted a follow-up online experiment with a different sample where participants had to provide size judgments instead of preference ones, but value-related information was still salient because of our manipulation of value conflict, a measure that provides the distance in preference between food items (a higher level of conflict is reflected in a smaller distance). Again, no significant effects were found.

Chapter 5 focuses specifically on externally-guided and internally-guided value-based decisions, i.e., reward-based versus preference-based judgments. As these two types of decision are frequently studied in isolation, the question arose regarding whether any interaction existed between the two and what the nature of said interaction might be. To that end, we created a novel paradigm where, in the stimulus presentation

phase, both reward-related and preference-related information were present. Following this, participants were made aware of which decision they needed to make based on a cue (either a dollar sign for the reward-based decisions or a heart for the preference-based ones) and had to respond accordingly. We also manipulated the reward probability at the block level as well as the congruency between reward-based and preference-based information (e.g., in some blocks, the higher rated items would be paired with the low-probability reward information). In the first online experiment, the most striking finding was that internally-guided information would "spillover" into the externally-guided trials, as evidenced by lower accuracy rates and longer reaction times in the "incongruent" trials. To test the robustness of this finding, two more online experiments (with separate samples of 80 participants each) were conducted. In the second one, we presented the decision cue before the stimuli, while in the third one, we introduced a delay of 1.5 seconds before participants could respond. In all three experiments, the main finding was replicated, essentially showing that preference-based information can trump the prospect of a reward.

Chapter 6 is a magnetoencephalography study that uses the paradigm discussed in the first experiment of Chapter 5. It replicates and expands the findings of the previous chapter, by incorporating multivariate pattern analysis (MVPA) to decode the temporal and spatial neural correlates of trial type and congruency information. The results provide further behavioural support to the spill-over effect discussed in Chapter 5 and include more detailed information on its temporal unfolding.

Chapter 7 presents a functional magnetic resonance imaging study that investigates the behavioural and spatial correlates of value-based decisions with multiple attributes that varied on a trial-by-trial basis, specifically the number of items present on each side of the screen (two or four) and the presence of congruent or incongruent information. The study aimed to replicate prior behavioural findings and to explore which areas of the brain were involved in this type of more complex decision-making. The behavioural findings were reproduced, showing that a higher number of items and the presence of incongruent information (e.g., swapping a positively rated item with a negatively rated one) resulted in lower accuracy rates and longer reaction

times. The neuroimaging analyses showed an activation of the fronto-parietal attentional or “multi-demands” network, lending further strength to similar findings in the literature.

Chapter 8 summarises the findings presented in the thesis and contextualises them within the extant literature, providing both an evaluation of their contributions and limitations and ending with a discussion on the possible directions for future studies.

Finally, the results of Chapters 3 and 5 have been presented as posters or as data-blitz talks at the following conferences: the BraYn conference in Rome in September 2022, the BNA conference in Brighton in April 2023 and at the BACN conference in Cardiff in September 2023.

2 Literature Review

2.1 Rapid Decision-Making and its Neural Implementation

Decision-making is a ubiquitous process in daily life, and it relies on the concerted action of multiple sensory, mnemonic, and cognitive processes (Balleine, 2007). It involves choosing between different options, either in the perceptual or value-based domain, by accumulating and weighing the evidence needed to result in a behavioural response (Busemeyer et al., 2019). Due to its pervasive nature, decision-making has been the subject of investigation across a multitude of disciplines, ranging from psychology, neuroscience, economics, and computer science to name only a few. This has resulted in a wide variety of models, frameworks, and theories, which on the one hand, provide researchers with ample opportunities to cross disciplinary boundaries, but on the other, it complicates any unification efforts towards a comprehensive view of this phenomenon and its related mechanisms. This literature review will examine those facets of decision-making that are pertinent to the whole dissertation, namely how it has been conceptualised and studied in healthy human participants, clinical samples, animal studies, and with the aid of computational models. We will then look into the behavioural and neural components and the different methods that have been used to shed light on the underlying mechanisms of decision-making. Finally, we will zoom in on the relationship between decision-making and contextual variables, such as cognitive conflict. We will explore how this has been examined with different paradigms in the experimental chapters included in the present thesis.

2.1.1 Conceptualisations of Decision-making Processes

In addition to being a multifaceted and dynamic process, decision-making can also be characterised as voluntary, conscious, and deliberate. This distinguishes it from habitual or reflexive actions, which are instead unvoluntary, unconscious, and automatic (Erdeniz & Done, 2019; Rangel et al., 2008). Decision-making also happens in stages that can be grossly divided in: input detection (where the inputs can come from the external and/or internal environment, i.e., the organism itself); information

processing (which takes on different characteristics depending on the specific type of decision being made), output production (which can be an overt or a covert response, such as the inhibition of a response), and finally output monitoring/feedback (which can then feed into the information processing stage to sway the next decision). This flow is schematized in Figure 1 below. It does not ascribe to a specific theory as much as it tries to provide a general framework of the different components of the decision-making process, although it is closer to the framework espoused by Rangel et al. (2008). Contrasting views on specific substages and their temporal unfolding (e.g., sequential versus parallel stages) will be further explored in the following subsections.

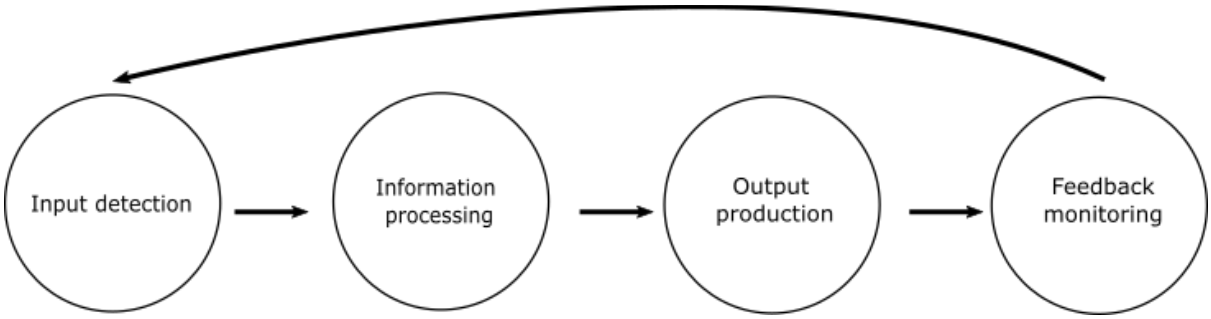


Figure 1 A general framework of decision-making stages, starting with input detection and information processing, followed by output production and ending with feedback monitoring, whose input is then used to start the cycle again.

2.1.1.1 Input Detection and Information Processing

Depending on the methods used, we will have a very different view of the scope at which decision-making mechanisms occur. This, in turn, will inform our frameworks and our hypotheses of how these mechanisms work. For instance, if we focus on single- or multi-cell recordings in primates or rodents, our understanding of decision-making will be based on the frequency of spikes traversing specific cells in constrained regions of the brain (Duncan, 2010; Haber & Knutson, 2010; Hanks & Summerfield, 2017). This means that we will be able to assess what goes on at the cellular level when a stimulus is shown, appraised, and chosen, but we will lack an appreciation of what happens at a more macroscopic level in the brain. On the contrary, if we use methods such as neuroimaging techniques, lesion studies, or pharmacological interventions, our views will be more concerned with macroprocesses that involve widespread neural circuits and networks, and this will be reflected in the theories being put forward (Padoa-

Schioppa & Cai, 2011). While this might be an obvious statement, we believe it is important to highlight the methodological and theoretical constraints present in the extant literature in order to appreciate the potential connections and implications between different works to start building a more comprehensive view of human decision-making.

In fact, despite the resulting variety of potential explanations as well as the separation between approaches, we can bridge that gap by underlying the commonalities across research streams (i.e., perceptual versus value-based decision research) and by using the flow depicted in Figure 1 as a guide. We can see the starting stages labelled as "input detection" and "information processing" are simple window dressing for the first two key questions our brains have to answer during the decision process, i.e., "what is the stimulus?" and "what do I do with it?" (Summerfield & Tsetsos, 2012). Regardless of the paradigm and the equipment we use, we can always peel back the superficial layers and go back to these two questions.

However, a comprehensive picture of these initial stages would be incomplete if we did not address the existing tensions across the aforementioned research streams. One of these tensions concerns whether the detection and processing of different inputs (or choice alternatives) occurs in absolute or relative terms, i.e., whether contextual forces play a role (relativist approach) or not (absolutist approach) (Bogacz, 2007; Kahneman & Tversky, 1979). The absolutist approach is articulated, for instance, by (Bogacz, 2007; Vickers, 1970), whose race model assumes that input streams are accumulated in parallel but independent fashion, and by the Expected Utility Theory (EUT) (Von Neumann & Morgenstern, 1944), which posits that utilities (i.e., the values associated with each option available) are not influenced by the context and that each utility is independent from another. The relativist approach, instead, argues that contextual effects have an impact on the decision process, and that human behaviour is better explained via a non-linear probabilistic approach, as seen in the Prospect Theory (Kahneman & Tversky, 1979), where values are computed starting from a reference point but are still independent from one another. In other formulations of the relativist approach, however, values are assumed to be calculated and integrated by

taking into account the values of other available alternatives, i.e., there is a value-dependency factor embedded in the model. Indeed, the latter approach has been more substantiated by empirical evidence (Lim et al., 2011; Philiastides et al., 2010) compared to the absolutist one. Finally, the contrast between absolute and relative views of decision-making inputs can also be traced to another debate, that of normative versus descriptive theories and, implicitly, that of a rational agent versus an "irrational" one. These aspects will be explored in more detail in later sections.

A second source of tension stems from the fact that neither the absolute nor the relative approaches consider the possibility that *not all* the information available to the organism in question is actually detected and processed when making a decision. Indeed, alternative frameworks suggest that exogenous and endogenous factors, such as attentional allocation, temporal effects, information uncertainty, and individual preference state, act as 'filters' that bias the sampling of incoming inputs (Summerfield & Tsetsos, 2012) (see Figure 2). These approaches move away from a strict optimisation-based view (e.g., reward maximization or statistical optimisation of the speed-accuracy trade-off) to consider how information relevant to the decision is sampled when systemic constraints are in place, i.e., the limited processing capacity of the brain. One proposal in line with this view suggests that the attributes of different options are sampled sequentially, and that the decision-maker switches the attentional allocation from one attribute to the next until a decision threshold is reached (Donohue et al., 2016; Gluth et al., 2018; Tversky, 2004). This simpler and more linear assumption is further expanded by the work of Afacan-Seref et al. (2018), which indicates that value and sensory biases both exert overlapping, simultaneous, and contrasting influences on the accumulation (or information processing) stage. A question, however, remains: how is the sampled multi-attribute information then integrated to allow for effective decision-making to take place?

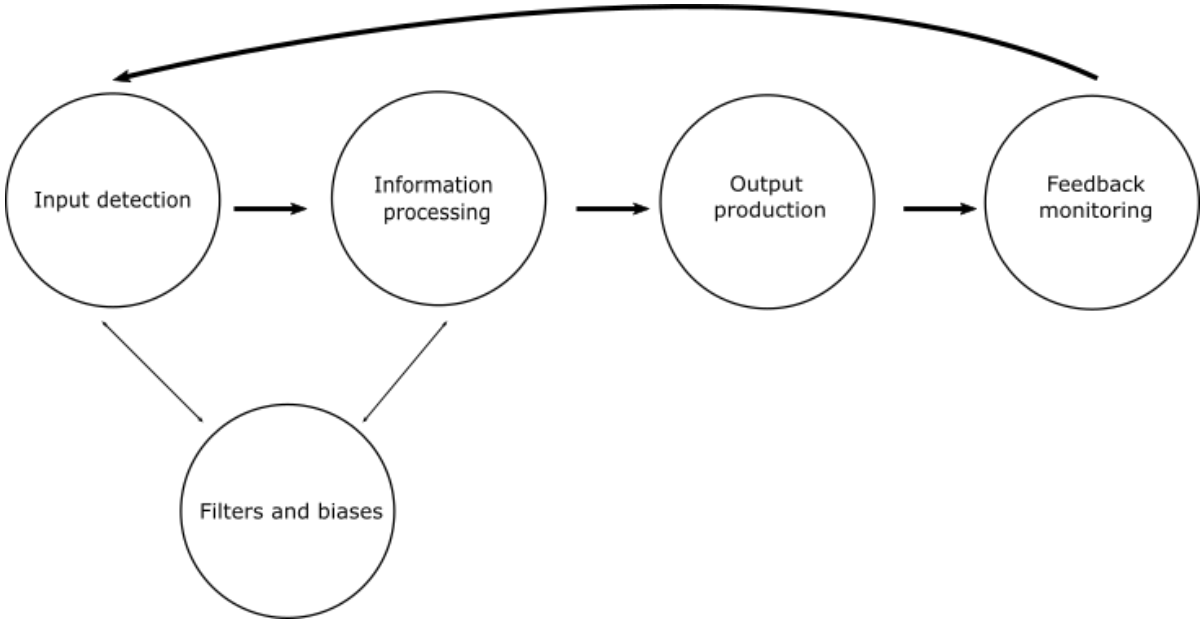


Figure 2 Revised version of decision-making stages to account for the influence of filters and biases on the early stages.

Seemingly conflicting hypotheses have been put forward in an attempt to resolve the issue of information integration during decision-making. On the one hand, we have the concept of a so-called "common currency" (Basten et al., 2010; Kim et al., 2011; Kobayashi & Hsu, 2019; Peters & Büchel, 2009), where different values are integrated and compared on a common scale in a "menu-invariant" fashion; on the other hand, there is evidence suggesting that different attributes are processed in domain-specific areas of the brain in a parallel and competitive manner (Nakahashi & Cisek, 2023). Neuroimaging data has been crucially important to investigate the assumptions connected to each of these hypotheses. Most findings point towards a combination of the two, namely that parts of the valuation and information processing occur in distinct regions depending, for instance, on the type of reward-based trial (e.g., probabilistic versus delayed) (Peters & Büchel, 2009), while still maintaining that the common-scale integration between attributes or values happens in the ventromedial prefrontal and orbitofrontal cortices as well as the ventral striatum. The integration phase, therefore, needs to be examined and modelled as relying on both types of circuitry, the domain-general network and the domain-specific one, to ensure that we are able to capture the interplay and the connections between the two. Overall, we can see that the input detection and information processing stages are underpinned by computational and

implementational complexities, such as regarding the influence of contextual effects and of sampling biases or filters.

We now turn to a closer examination of the neurobiological underpinnings involved in these two stages. Concerning input detection, different studies have, unsurprisingly, observed relevant activity in sensory-specific areas depending on the modalities (e.g., visual vs. auditory) of stimulus presented to the subject (Castelhano et al., 2014; Harris et al., 2011; Philiastides et al., 2010; Philiastides & Sajda, 2007). Several other studies (Bartra et al., 2013; Basten et al., 2010; Clithero & Rangel, 2014; Gluth et al., 2013; Hanks et al., 2015; Hunt et al., 2012) point to a predominant role of various frontal and parietal areas in information processing and integration, which is consistent with their purported involvement in attentional mechanisms, executive functioning, and working memory, as explored in experiments employing a variety of methods, such as comparing healthy controls and patients with focal lesions (Peers et al., 2005), functional magnetic resonance imaging (Basten et al., 2010; Fedorenko et al., 2013; Parlatini et al., 2017), and animal studies (Hanks et al., 2015). The specific frontal and parietal areas involved in these stages include the ventromedial and orbitofrontal areas, the dorsal portions (both lateral and medial) of the frontal cortex, the superior parietal cortex, and the different subregions of the intraparietal sulcus. Indeed, temporal reconstructions of decision-related signals with electro- and magnetoencephalography show that stimulus-locked signals tend to occur between 300 and 500 milliseconds after the stimulus onset (Harris et al., 2011; Harris & Hutcherson, 2022) and are stronger in frontocentral and frontoparietal sensors, thus providing additional support to the evidence coming from localisation-based studies.

2.1.1.2 Output Production, Monitoring, and Feedback

Every decision results in a voluntary output, whether an overt one, such as a motor or verbal response, or a covert one, i.e., the deliberate inhibition of that same response (see Figure 3). The former is the more common endpoint of a decision, and it can translate into a button press during an experimental task, reaching for a specific item at the supermarket, or saying ‘I do’ at one’s own wedding. The latter form, instead, reflects circumstances in which an overt response is suppressed. Examples can

include no-go responses in a go/no-go paradigm or not crossing the street at a red light or not buying a hypercaloric treat when doing grocery shopping. Regardless of the nature of the output, the agent has to commit to a specific behavioural course (Summerfield & Tsetsos, 2012) at the cost of any other alternative behavioural plan. This, however, does not mean that the output of a decision is final, rigid, and unchangeable. On the contrary, decision-making is an adaptive and flexible process that exploits incoming streams of information (that is, from the final stage outlined in Figure 1 the agent goes all the way back to the first one in a recurrent fashion) to modulate the next behavioural response. For this recurrent loop to happen in the first place, one must posit the existence of a monitoring mechanism that compares the actual result of the decision with the predicted outcome (Philiastides et al., 2010). Discrepancies between the two outcomes (the real one versus the predicted one) can then lead to a change in following outputs in order to minimise said discrepancies (Figure 4). The presence or lack of this discrepancy, which can be described more generally as feedback, is a powerful indicator for needed behavioural adjustments as well as for learning processes (Cohen et al., 2007; Cooper et al., 2014; Gheza et al., 2018; Schultz et al., 2017).

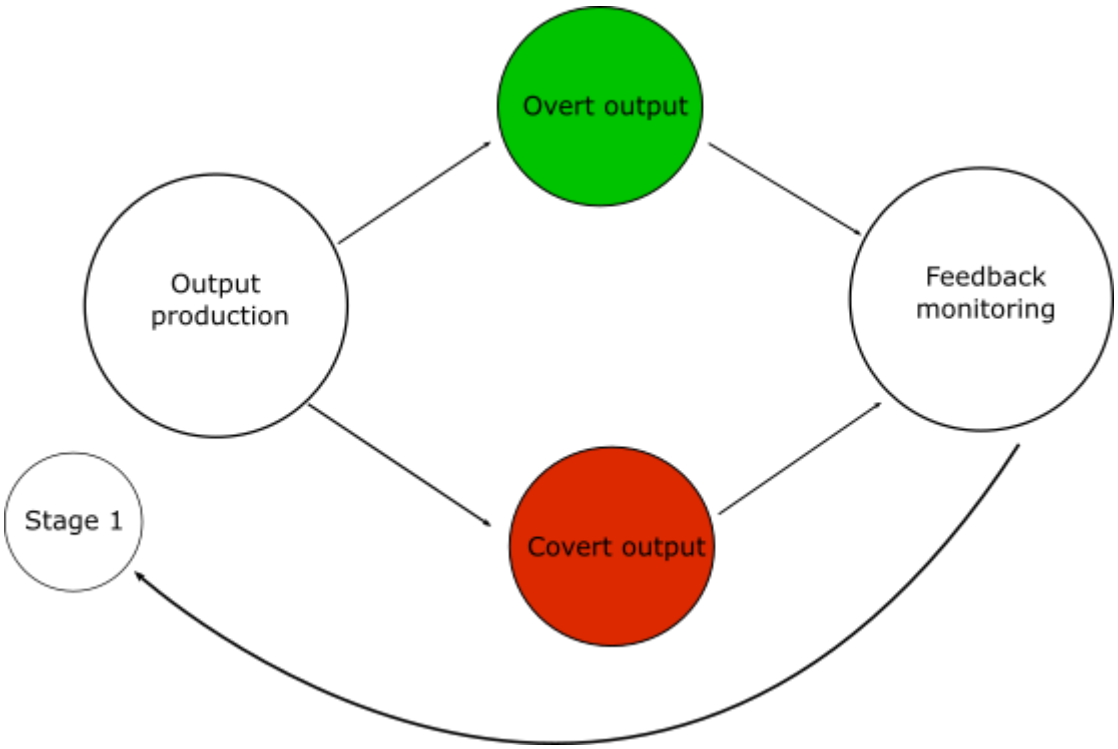


Figure 3 Disaggregation of the output production stage. Here the output production stage is divided into overt and covert outputs. Both types then contribute to the feedback monitoring stage, which returns the updated information to stage 1 (input detection).

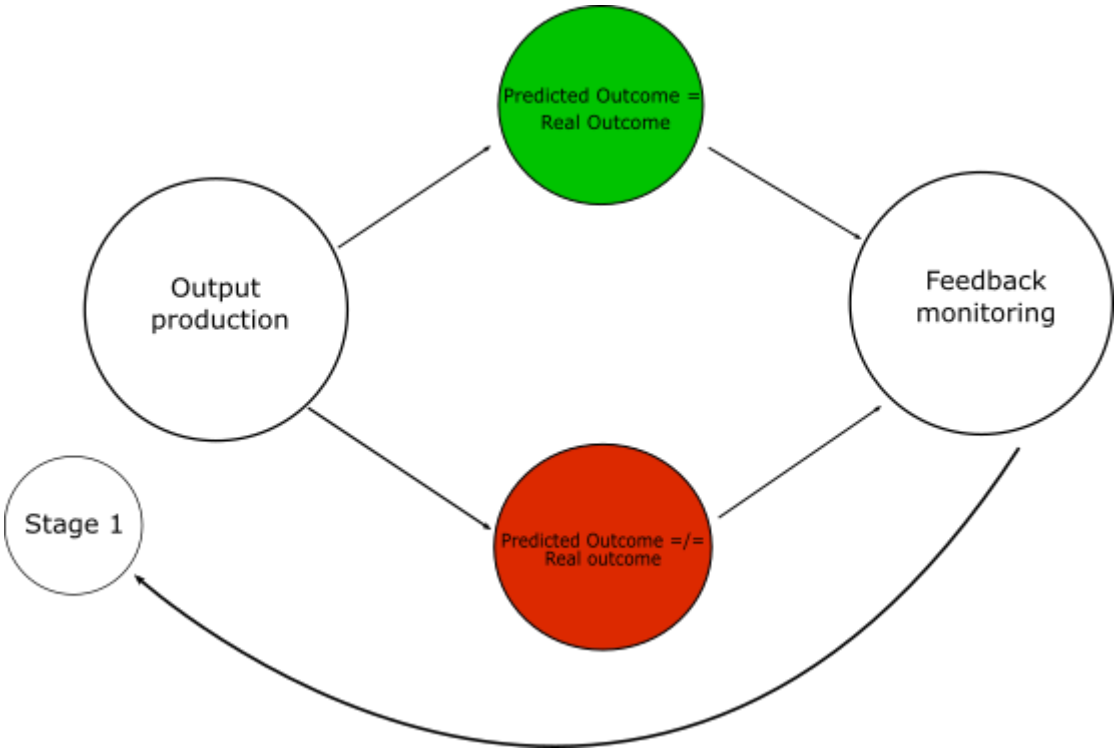


Figure 4 A different disaggregation of the output stage, where the output is divided into whether the outcome of the output action (covert or overt) corresponds to the predicted outcome, i.e., the so-called Reward Expectation Error (RPE). This information is then fed into the feedback monitoring stage and used to start the decision making process again.

Another factor that can drive differences between produced or suppressed outputs is response competition or conflict, as irrelevant information or the presence of environmental uncertainties can interfere with optimal decision-making. Thus, there is a need for a mechanism that oversees the inhibition of responses that are misaligned with internal or external goals (Chouiter et al., 2014). Such a mechanism has been identified most often in the anterior cingulate cortex (ACC) (J. W. Brown & Alexander, 2017), in the dorsolateral and dorsomedial prefrontal cortex (Oehrn et al., 2014) and in frontal theta oscillations (Feuerriegel et al., 2021). Feuerriegel et al.'s (2021) work, in particular, raises an important question about existing conflict monitoring accounts regarding the implementation of the adapted responses following the experience of conflict. Their findings suggest that the exposure to incongruent stimuli is followed by two distinct adaptation strategies: first, signals representing the relevant stimuli show an increased magnitude in the visual cortex in the subsequent trial, meaning that the correct stimulus receives more attention compared to the distractor; secondly, the rate of evidence accumulation in a post-conflict trial is slower for the irrelevant stimulus, indicating a down-weighting of the evidence associated with it, possibly associated with a reluctance to respond following the exposure to conflicting information (Patai et al., 2022). Another gap in our understanding of cognitive conflict is addressed by Kałamała et al. (2020), whose findings uncover the temporal unfolding of co-occurrent conflict monitoring, highlighting parallel conflicts are processed simultaneously but independently. Oehrn et al. (2014) provide further elucidation on how different brain areas, namely the dlPFC and dmPFC, communicate with each other during conflict situations, i.e., with the dmPFC causally entraining the dlPFC during conflict detection while conflict resolution and adaptation are underpinned by oscillatory coupling going in the opposite direction, from the dlPFC to the dmPFC. Subcortical areas also seem to play a role, in particular the subthalamic nucleus (STN) (Patai et al., 2022), which displays prolonged beta oscillations and an increase in its oscillatory coupling with frontal areas when subjects are presented with conflict trials in a sequential decision-making task.

Overall, evidence shows that each stage of decision-making contains multitudes, which are dependent on the decisional context and the goals set by the

agent or by environmental demands. This in turn leads to a proliferation of accounts and theories that need to be reconciled whilst considering that they all germinate from slightly different assumptions about the brain and human behaviour.

2.1.2 Key Models and Methodologies

2.1.2.1 Evidence Accumulation Models

Sequential Sampling Models (SSMs), such as the Drift-Diffusion Model (DDM), have been central to the computational and theoretical advancements in psychology and neuroscience, specifically in the field of decision-making (Ratcliff et al., 2016). Their first key contributions happened in the domain of perceptual decisions (Shadlen & Newsome, 2001), where simpler models could reasonably account for the underlying processes of evidence accumulation, but over time, these models have become more dynamic and complex, able to capture multi-attribute decisions (Busemeyer et al., 2019). The cornerstone of these models consists of one key assumption: the decisional process is noisy, and the agent accumulates evidence in favour of one option over another over time. When a threshold of significantly strong evidence for one of the options is reached, this prompts a motor response, meaning that SSMs can account for the probability of making a certain choice as well as the associated response times (i.e., the speed-accuracy trade-off, SAT) (Diederich & Busemeyer, 2006). This makes the SSMs an improvement on the classical formulation of signal detection theory (SDT), which saw the evidence accumulation process as static and did not account for the SAT, not to mention that there is both behavioural (i.e., eye tracking and pupil dilation) (Boucher et al., 2007; Cavanagh et al., 2014; Ratcliff & Childers, 2015) and neurophysiological evidence (e.g., frontoparietal and centroparietal activations) in humans and animals (Bode et al., 2012; Brunton et al., 2013; Frank et al., 2015; Huk & Shadlen, 2005; Ratcliff et al., 2009; Schall, 2003; Shadlen & Newsome, 2001), thus supporting the temporal unfolding espoused by these computational models.

There are several classes of SSMs, each with their specific characteristics and strengths. One of these comprises Drift-Diffusion Models (DDMs), which assumes that the decision maker sequentially samples the evidence, and a response is made once

the evidence in favour of one option reaches the decision threshold (Figure 5). The two key components of DDMs are: the decision threshold, i.e., how much evidence is needed before prompting a response (Harris & Hutcherson, 2022) and the quality of the accumulated evidence, i.e., the "drift rate". Changes in decision thresholds or boundaries are what drives the speed-accuracy trade-off (Ratcliff & Rouder, 1998), while biased responses towards one option are explained by differences in the starting point of accumulation (Diederich & Busemeyer, 2006; Leite & Ratcliff, 2011; Mulder et al., 2012), in the drift rate (Hanks et al., 2011), or a combination of both (Dunovan et al., 2014). The simplicity and empirical robustness of this class of SSMs has resulted in a wide range of applications in psychology, economics, and decision neuroscience (Ratcliff et al., 2016), starting from perceptual and categorisation tasks to then be expanded to account for more complex decisions, such as gambling tasks or consumer choices, where the DDM took the name of attention Drift-Diffusion Model (aDDM). The underlying principles are the same, with one important variation: attentional allocation to an option drives changes in the drift rate during evidence accumulation. Empirical evidence has shown support for this modified version of the DDM in accounting for eye-tracking data, neural oscillations, and behavioural responses (choice distributions and reaction times) (Gottlieb et al., 2014; Hare et al., 2011; Krajbich et al., 2012; Lim et al., 2011; Polanía et al., 2014, 2015). However, the aDDM does not account for the context effects of attraction, similarity, and compromise formalised by Tversky & Kahneman (1981), which diminishes its predictive and explanatory power (Busemeyer et al., 2019). In a similar vein, the DDM also suffers from a few shortcomings. For instance, Sun & Landy (2016) affirm that a two-stage model fits their visual discrimination data better than the DDM, since the DDM's predictions of (1) multiplicative effects of stimulus value and strength on reaction times and of (2) temporal independence between RTs, stimulus strength and stimulus onset asynchrony (SOA) do not hold up even in simple perceptual tasks. Additionally, the DDM's focus on optimality, i.e., the maximisation of gains, puts it at odds with the sub-optimal behaviour displayed under uncertain conditions, for example where the expected gain and the difficulty of choosing the best option out of a set of alternatives result in longer reaction times and lower accuracy (Oud et al., 2016). Finally, while the DDM's neurophysiological correlates have often

been linked to the increased firing rate of a pool of neurons (e.g., in the LIP area in the macaque brain) (Shadlen & Newsome, 2001), thus implying that the firing rate reflects the decision outcome, contrasting evidence suggest that neural activity from areas like the LIP could reflect an ensemble of both decision- and task-related factors, such as saccadic responses and noisy motion stimuli (Park et al., 2014).

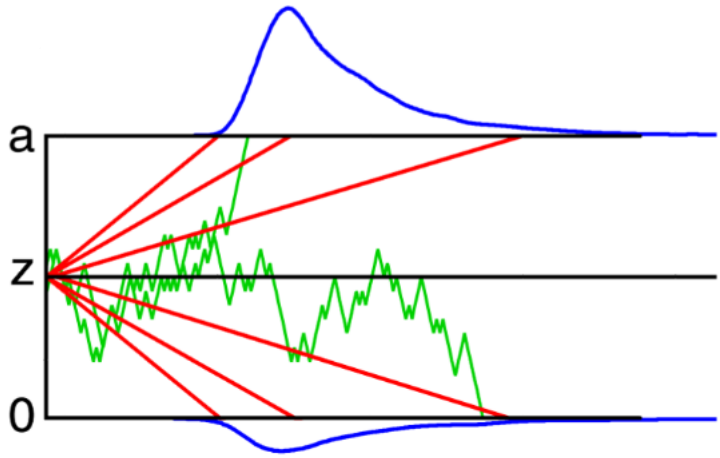


Figure 5 Example of Drift-Diffusion Model (Ratcliff et al., 2016). The vertical axis represents accumulated evidence, while the horizontal axis represents time. The blue curves represent the RT distributions for correct (top) and incorrect (bottom) responses, while the red lines represent the fastest, medium, and slowest responses. The symbol z on the vertical axis indicates the bias, i.e., how far from the starting point the evidence accumulation starts.

Other SSMs still rely on the sequential sampling of information until a criterion is reached, but they use distinguishingly different mechanisms than DDMs, such as switching one's attention in a stochastic fashion between attributes instead of between alternatives, which is the case in the aDDM, lateral inhibition, and loss aversion (see Section 2.1.2.2.2 for the theoretical background of this concept) (Busemeyer et al., 2019). Decision Field Theory (DFT) relies on both switching attentional resources between attributes and on distance-dependent lateral inhibition (Roe et al., 2001); Leaky Competing Accumulator models (LCA) also use both of the aforementioned mechanisms, with the addition of loss aversion as an explanation for context effects, but in this class of models, lateral inhibition is uniformly applied and distance-independent (Usher & McClelland, 2001). Finally, another class of SSMs emphasises the importance of attribute values, albeit in slightly different ways within each specific model. This category includes the Selective Integration Model, whereby the agent's

attention is biased by ordinal comparisons between attribute values (Tsetsos et al., 2012); the Associative Accumulator, where attentional allocation is determined instead by the *magnitude* of the attribute values (Bhatia, 2013); the Linear Ballistic Accumulator Model (LBA), where weighted attribute values compete independently from each other until one value reaches the decision criterion first (Brown & Heathcote, 2008); and the Decision by Sampling Model, where decisions depend on pairwise ordinal comparisons between attribute values (Noguchi & Stewart, 2018).

Moving away from and partly building upon the previous models, which have predominantly been used in simple two-choice paradigms, multi-attribute and multi-alternative models have become more widespread in recent years. These include the Multi-alternative Decision Field Theory (MDFT) (Roe et al., 2001), the Multi-attribute Linear Ballistic Model (MLBA) (Trueblood et al., 2014), and hierarchical accumulator models (Hunt et al., 2014). The MDFT proposes a connectionist view of decision field theory (DFT), and it has been able to account for all three context effects, as well as their interactions (Mohr et al., 2017; Roe et al., 2001). The MLBA also makes a similar claim, while also asserting that it can remove loss aversion and that context effects can be reformulated as selection tendencies that then transform into over responses (Trueblood et al., 2014). The model used by Hunt et al. (2014) is based on a "competition by mutual inhibition" mechanism that occurs at multiple stages of the decision-making process (Hunt et al., 2012). More specifically, their fMRI and MEG findings show that the intraparietal sulcus is linked to attribute competition and that this area also displays different connectivity profiles with regions involved in within-attribute comparisons, while parts of the mPFC seem to reflect an integration of these value signals, which further reinforces the extant literature (see Section 2.2.3).

While several efforts have been made to connect computational models and neuroscientific evidence, the relationship between the two remains a challenging one to define. The wealth of available models and the evidence in support of their claims further complicates the picture, as multiple models seem to provide robust answers to psychological phenomena, thus potentially undermining their usefulness and explanatory power. If multiple models that rest on different assumptions and different

mechanisms can explain the same phenomena, e.g., context effects, which model actually reflects the biological reality? This, in turn, highlights one of the crucial issues at the heart of decision-making research: the lack of an overarching and biologically plausible framework that provides clear and operationalizable definitions of fundamental constructs such as "value", "attribute", "gain", or "reward" (see also Section 2.2.2). Indeed, one of the aims of this dissertation is to use an existing framework (Nakao et al., 2012) in an attempt to provide neurobiologically viable answers to the conceptualisation and operational translation of value-based decisional processes.

2.1.2.2 Normative and Descriptive Decision Theories

2.1.2.2.1 Expected Utility Theory

The Expected Utility Theory (EUT) describes how decision-making processes occur in uncertain contexts. It has been highly influential in the second half of the 20th century (Fishburn, 1981; Schoemaker, 1982; Tversky, 1975; Von Neumann & Morgenstern, 1944), with a wide range of declinations and applications in mathematics, economics, behavioural decision theory, to name a few. It has been used as a prescriptive theory in finance and as a descriptive one in psychology (Schoemaker, 1982) but its key tenet remains the same: in a risky or uncertain decisional context, a rational agent aims to maximise utility, i.e., the value of an option given the expectation of a specific outcome (e.g., gaining a monetary reward), its probability and the resources already available (e.g., how much money the individual already possesses). First formulated by Bernoulli (1738) under the name of marginal utility, then expanded by Von Neumann & Morgenstern (1944), who proposed an axiomatic version of the theory, and by Savage (1951), who introduced the concept of subjective utility, another key tenet of EUT affirms that marginal utility has three different relationships with gains (Mishra, 2014) delineating three different individual attitudes to reward variance. If we consider a *risk averse* attitude, then expected utility has a decreasing relationship with additional gains, i.e., the law of diminishing returns, whereby the expected utility of an object or action decreases with each additional unit gained, leading to a utility plateau. A *risk neutral* approach is instead characterised by a linear relationship between utility

and the considered currency. Finally, an individual with a *risk seeking* or *risk preferring* attitude will make decisions based on a utility curve where each additional unity of reward is valued *more* than the last (Figure 6). These curves are also constructed based on the five axioms proposed by Von Neumann & Morgenstern (1944), i.e., completeness, transitivity, continuity, monotonicity, and independence. This axiomatic view assumes and further reinforces the notion that decision behaviour is rational and follows strict rules, but evidence accumulated over the past few decades has shown that human behaviour complies with the axiomatic version of EUT only in "small world" environments (Savage, 1951), where all the decisional parameters are known to the agent. This is one of the key reasons that prompted economists and psychologists to look for alternative answers, such as Prospect Theory (Kahneman & Tversky, 1979).

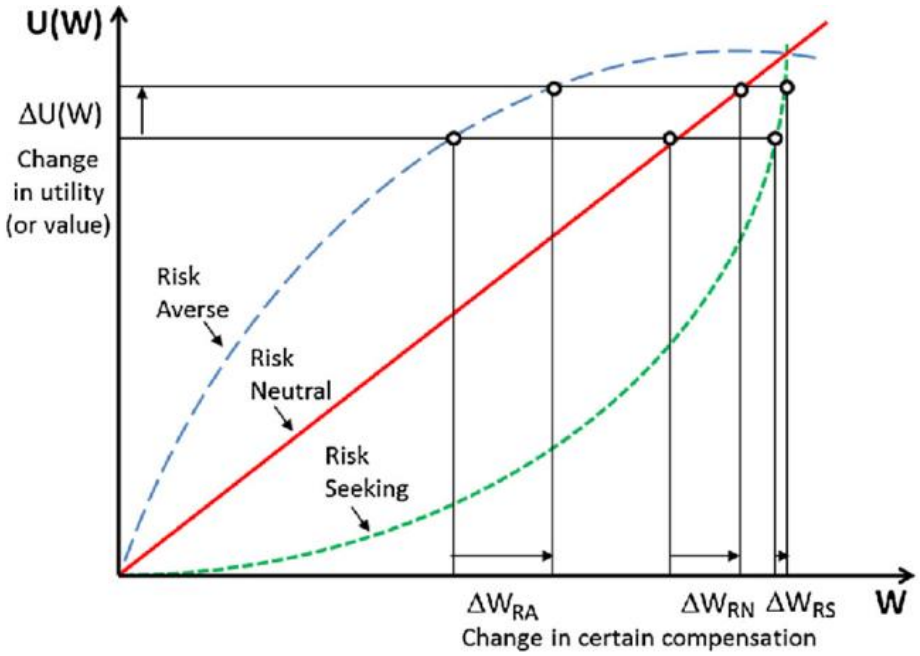


Figure 6 Depiction of the different attitudes to risk in Expected Utility Theory (risk seeking, risk neutral, risk averse). The vertical axis (U(W)) indicates the changes in utility or value, while the horizontal axis indicates the changes in certain compensation. Picture copied from Harris & Wu (2014).

Indeed, while theoretical frameworks, mathematical models and axioms provide important constraints and potential explanations for human phenomena, it is only by addressing the behavioural and the neurobiological substrate that we can get to the root of said phenomena (Glimcher et al., 2005). In the case of decision-making, the field of

neuroeconomics might offer new biologically informed insights into this process and can bring together the prescriptive and descriptive approaches within the economic field. However, combining the study of economic theories that have, for decades, been used as explanatory models of human behaviour, resting on the assumption that human agents are governed by a principle of rationality, with the study of the human brain, with its methodological constraints, has proven challenging (d'Acremont & Bossaerts, 2008; Glimcher et al., 2005). While progress has been made over the past two decades (Dennison et al., 2022), the extant neuroeconomic literature shows that ascertaining which parameters of EUT or its variations reflect actual brain computations is still a matter of debate, as some findings align with expected utility (Gilaie-Dotan et al., 2014), while others seem to support mean-variance frameworks, where subjective values are computed based on the trade-off between expected reward and risk (or reward variance) (Grabenhorst et al., 2019). Nevertheless, theoretical and methodological advances in both neuroscience and economics are paving the way to new ways of understanding choice mechanisms, moving away from a conceptualisation of decisional behaviours as simply adhering or deviating from economic theories such as EUT. In the following Section, we will discuss the key assumptions of Prospect Theory (Kahneman & Tversky, 1979), how it has been delineated as the evolution of EUT, as well as the evidence in support of and against it.

2.1.2.2.2 Prospect Theory

The other highly influential theory of decision-making that sprang directly from EUT to address those situations that it could not satisfactorily explain is Prospect Theory (Kahneman & Tversky, 1979). Key cornerstones of the theory include, first and foremost, the framing effect, whereby framing a decisional scenario with a positive or a negative phrasing affects the agent's choice. Specifically, Tversky & Kahneman (1981) provided empirical evidence in support of this effect both in situations concerning real or hypothetical monetary gains and in scenarios involving the loss of human lives. Their findings indicate that there is a reversal of attitudes depending on whether the decision is framed as a loss or as a gain even if both choices were logically identical, which goes against the rational view of neoclassical economists and provides a more nuanced

understanding of choice mechanisms. Indeed, the authors show that decision-makers display a risk-averse attitude when the scenario is framed as a gain and, instead, display a more risk-prone approach when confronted with a loss scenario – a finding that has been robustly reported in the literature (Levin et al., 1998). This means that utility is again a non-linear function that delineates how – based on a reference point determined by the agent's state, expectations, and biases – individuals underestimate their gains, according to the law of diminishing returns, and overestimate their losses (Figure 7).

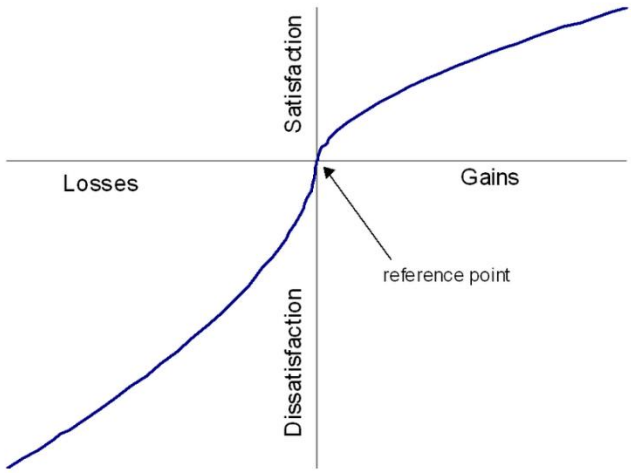


Figure 7 Depiction of the utility function according to Prospect Theory. The y axis represents the satisfaction spectrum, while the x axis represents losses and gains. At the origin of the graph is the reference point. Picture copied from Larrick et al. (2009).

Two more violations of EUT that Prospect Theory can explain based on empirical observations concern the certainty effect, i.e., a tendency to overestimate certain outcomes while underestimating probabilistic outcomes, regardless of the valence of the outcome (i.e., whether it is a gain or a loss) and of expected value; and the isolation effect, whereby decision-makers ignore commonalities across alternatives in an effort to simplify the decisional process (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981). Overall, these amendments and expansions of EUT enhance the explanatory power of Prospect Theory while using the same construct, i.e., utility. However, at the same time, these expansions and overlaps conceal crucial theoretical issues, as more

recent work (De Martino, 2006; Mishra, 2014) points out three weaknesses of Prospect Theory. First, utility has been classified as a poorly defined construct with limited predictive power in EUT especially, but also within the boundaries of Prospect Theory. Secondly, a lack of a biologically informed approach further undermines the normative and descriptive capabilities of both theories (as discussed in Section 2.1.2.2.1). Thirdly, the rationality argument that sustains these approaches misses the central role that heuristics and emotions play in the decisional process, as organisms need to act efficiently on incomplete, uncertain, or overly complex information (De Martino, 2006). Neuroscientific evidence, in fact, suggests that these different sources of information, i.e., framing effects, heuristics (Gigerenzer & Gaissmaier, 2011), emotions, are integrated in the brain to allow for optimal and flexible decisions mediated by a network that comprises the orbitofrontal cortex, the amygdala, and the anterior cingulate cortex (Baxter & Murray, 2002; Damasio et al., 1994; De Martino, 2006). This provides support to the notion of "bounded rationality", which affirms that the constraints of human cognitive and emotional processing affect how individuals, groups, and societies make decisions. Therefore, individual and collective agents do indeed attempt to choose amongst alternatives in a rational manner, but systemic in-built boundaries can prompt the deviations from perfect rationality seen empirically (Jones, 1999).

2.1.2.2.3 Alternative Theories: Risk-Sensitivity Theory and Expected Subjective Value Theory

Two alternatives to Expected Utility Theory and Prospect Theory are found in Risk-Sensitivity Theory (RST), which descends from the tradition of behavioural ecology (Mishra, 2014; Mishra & Fiddick, 2012) and, as such is focused on providing a normative explanation of risky foraging decisions, and in the Expected Subjective Value Theory (ESVT) (Tymula & Glimcher, 2016), which offers a neurobiologically plausible revisitation of Prospect Theory. Risk-Sensitivity Theory predicts that risk-related attitudes, i.e., risk aversion or risk seeking, are employed by an organism depending on its needs, which are defined as the distance between its current state and the desired one (Mishra & Fiddick, 2012). One aspect that differentiates RST from other frameworks is the focus not on maximising a utility, e.g., a desirable outcome in terms of fitness and survival, but

rather on avoiding outcomes that hamper the organism's needs, meaning that the agent operates in terms of satisfactory decisions, instead of optimal ones. A second difference is the emphasis on reproductive success and continued survival, which take the place of utility as the decisional currency. However, RST suffers from the same shortcomings as Prospect Theory and EUT, namely the fact that both currency definitions (utility vs reproductive success/fitness) are vaguely and differently defined in the literature (Mishra, 2014). Nevertheless, RST has received empirical support in both humans and non-human animals (Mishra & Fiddick, 2012) and it can be argued that it provides a normative account of the framing effects described by the Prospect Theory: more specifically, overweighing losses compared to gains acquires a new significance when viewed through the lens of the reproductive success or environmental fitness of an organism. A marginal loss would potentially have much more catastrophic consequences (i.e., death or inability to reproduce) compared to a marginal gain (McDermott et al., 2008). In turn, being loss-focused would prompt an individual to adopt a more risk-prone attitude in order to meet a strong need, again providing an evolutionary basis for the utility curve proposed by Prospect Theory (Mishra, 2014).

Expected Subjective Value Theory also builds upon and expands Prospect Theory, by arguing that utility, or subjective value, functions are bounded by the informational processing constraints of the central nervous system, have a finite precision, and are dynamic (Steverson et al., 2017; Tymula & Glimcher, 2016). Biological boundaries take up a central role in this theory to explain why in Prospect Theory decision-makers evaluate their options against a reference point, instead of in absolute terms (see also Section 2.1.1.1). These biological boundaries lie specifically in the number of reward-coding neurons and the maximum firing rates of each of these neurons, indicating that there is a ceiling to the amount of information carried in each value-related neural representation (Bartra et al., 2013). Additionally, ESVT is also a mathematical model that posits two assumptions: first, that each individual agent has an idiosyncratic reference point (i.e., a set of expectations about the state of the world that, at the neurobiological level, has been made to correspond with the reward prediction error (Ichikawa et al., 2010)); secondly, that there is an external free parameter known as "predisposition" (Tymula & Glimcher, 2016), which has been

proposed to capture the nonlinear neural response to incoming stimuli, although more theoretical and empirical work is necessary to provide a stronger operationalisation. Concerning the changes in risk-related attitudes posited in Prospect Theory, ESVT indicates that these attitudes are emergent properties of the individual's reference point and vary as a function of predisposition.

To summarise, the evolution of these normative and descriptive theories of decision-making delineates a path of both increasing complexity and increased grounding in biological rules. Each theory espouses a specific view of human behaviour, rationality, and motivations and it is the result of specific cross-disciplinary contaminations and of specific historical contexts. Therefore, as decision-making researchers, it is imperative to remember that these theoretical frameworks are guiding tools that are informed by a multitude of factors and that, in turn, they colour our understanding of the different facets of decisional processes. Not one theory is all-encompassing, but efforts should be made to find common ground within the field in terms of key constructs and their operationalisations. This aspect will be further explored within the field of value-based decision making in Section 2.2.2.

2.1.2.3 Neuroimaging Methods

2.1.2.3.1 Functional Magnetic Resonance Imaging (fMRI)

The use of functional MRI (fMRI) has revolutionized the field of cognitive neuroscience and, to this day, remains a popular non-invasive brain imaging method that has been used to investigate the role of different brain regions in a wide variety of tasks and paradigms (Logothetis, 2008). While MRI is used to acquire structural images of organs, including the brain, functional MRI measures the Blood Oxygenation Level Dependent (BOLD) signal, an indirect correlate of neural activity that measures how the brain's haemodynamic changes in response to metabolic activation (Peppiatt et al., 2006). Despite the indirectness of the BOLD signal, MRI images are characterised by a high spatial resolution on a millimetric scale, making it the method of choice when the main objective is to localise the brain regions correlated to a specific process. However, its temporal resolution is low, i.e., in the order of seconds, due to the slow unfolding of the BOLD response. To remedy this, it has become increasingly common to conduct

fMRI studies where complementary methods with higher temporal resolution, such as electroencephalogram (EEG), are also implemented (Huster et al., 2012; Jorge et al., 2014; Menon & Crottaz-Herbette, 2005; Ritter & Villringer, 2006). Finally, as is the case with most neuroimaging methods, fMRI provides us with correlational findings about the role of said brain regions, thus highlighting the need for caution when interpreting fMRI results (Logothetis, 2008).

Chapter 0 used fMRI to measure BOLD response while participants carry out a preference-based decision-making task where they are forced to choose between sets of options with multiple items and, at times, incongruent information.

2.1.2.3.2 Magnetoencephalography (MEG)

Magnetoencephalography is a non-invasive direct neuroimaging technique first invented in 1972 by David Cohen (Cohen, 1972) that allows researchers to measure the small magnetic fields (which are in the order of femto-tesla, fT, to pico-tesla, pT) perpendicular to the electric currents produced by the post-synaptic dendritic activity of pyramidal neurons located in the sulci (Singh, 2014). To measure these magnetic fields while simultaneously cancelling out the much stronger environmental magnetic fields has required a crucial engineering feat, i.e., the development of the Superconducting Quantum Interference Device (SQUID). MEG scanners use these SQUID sensors, arranged in different configurations of magnetometers and gradiometers, to best capture the strength (magnetometers) and the gradient (gradiometers) of the magnetic fields perpendicular to the helmet in which the SQUIDs are placed. Current MEG machines provide whole-head coverage with 200~300 channels but are characterised by a shared shortcoming: to ensure that the SQUIDs do not lose their superconductive properties, the sensor array needs to be cooled with liquid helium at a temperature below -269 °C, making the machines costly to acquire and maintain over time.

Compared to fMRI, MEG provides a direct signal of brain activity with sub-millisecond temporal resolution. Additionally, MEG offers an advantage over EEG as the magnetic fields are not distorted as they pass through the various layers of the head

(meninges, skulls, scalp, hair) (Perry, 2022), which is instead an issue that affects the electrical currents measured by EEG with implications for the localisation of the current sources. However, MEG is insensitive to radial sources, while EEG is not, meaning that the two techniques offer complementary data on the temporal unfolding of brain activity. Indeed, MEG and EEG can also be acquired simultaneously to provide a more complete picture.

One other issue that affects MEG concerns the source localisation of the sensor-level activity. In fact, because the brain activity picked up by the SQUID sensors could come from a multitude of cortical and subcortical sources, MEG source-level analysis requires solving the so-called "inverse problem", which, in turn, is complicated by a lack of a univocal solution. Multiple algorithms have been proposed over the years, each with their strengths and weaknesses (Nawel et al., 2019), such as Linearly Constrained Minimum Variance (LCMV) beamformers (Hillebrand & Barnes, 2005), Minimum Norm Estimation (MNE) (Dale & Sereno, 1993), dynamical Statistical Parametric Maps (dSPM) (Pascual-Marqui et al., 2002), and standardized Low Resolution Brain Electromagnetic Tomography (sLORETA) (David et al., 2002). Chapter 6 presents an MEG study on internally-guided vs. externally-guided decisions.

2.2 Value-based Decision-Making

2.2.1 Decision-making in different domains: Perceptual and Value-based

As anticipated in Section 2.1.1.1, rapid perceptual and value-based decisions correspond to the two main subdivisions of the decision-making process, and they display both differences and similarities. Concerning the similarities, both processes involve similar stages, as outlined in Figure 1: first, the detection followed by the integration of information about the external environment and the internal state of the individual, where the integration involves the accumulation and evaluation of the evidence, including additional factors such as costs and uncertainties, and finally, the transformation of this "decision signal" into a final choice or response (Fellows, 2004; Gold & Shadlen, 2007; Heekeren et al., 2008; Sugrue et al., 2005). This resemblance has also led Gold and Shadlen (2007) to advance the hypothesis that perceptual and value-

based decisions exploit the same mechanism, that is both use a “decision rule” to compare the evolving decision to a fixed criterion before selecting the appropriate course of action. Whether this also translates into a (partially) shared neural substrate for perceptual and value-based decisions remains to be thoroughly assessed, even though attempts have been made to bridge this gap (Summerfield & Tsetsos, 2012).

Additionally, evidence suggests that both kinds of decisions are stochastic, i.e., they fluctuate over time due to the presence of “noise” either in the external or internal environment (Gold & Shadlen, 2007; Loomes et al., 2002; McFadden, 2005). *External* “noise” can be translated into stimulus-related factors such as saliency, ambiguity, and uncertainty, all of which also determine the degree of difficulty of the decision. In the case of a perceptual decision-making (PDM) paradigm, like a dot motion discrimination task, these factors refer to physical aspects of the stimuli, such as the luminance of the dots compared to the background, the number of dots moving in a coherent or random manner, and their speed. For VDM tasks, such as gambling tasks, this can include the probability of an action to result into a gain or loss, which is manipulated beforehand by the experimenter, or the type of reward that can be obtained (e.g., primary or secondary reinforcers). On the other hand, *internal* “noise” is associated with the physiological, motivational, and attentional state of an individual and their beliefs and expectations about the state of the world (Fellows, 2004). One additional similarity between perceptual tasks and, specifically, “external value-based” decision-making tasks is that both imply the presence of an objectively correct response, regardless of the uncertainty that might be associated with the decision itself (Nakao et al., 2012).

Nevertheless, PDM and VDM differ in substantial ways. To begin with, the parameters of perceptual tasks are much easier to design, control, and measure in an objective and accurate manner, thanks to a long and established tradition in the field of psychophysics (Klein, 2001; Newsome et al., 1989; Strasburger, 2001). Instead, certain value-based decisions, more specifically preference-based judgments, rely on the intrinsic value that an individual attaches to different goods or actions, an aspect that is difficult to reliably quantify. Additionally, PDM and VDM activate different neural substrates. For perceptual decisions, one key region is the dorsolateral prefrontal cortex (dlPFC), which is involved in the accumulation and comparison of sensory evidence and

in the final categorisation response (Heekeren et al., 2004, 2008). For value-based decisions, on the other hand, the key regions are located in the medial regions of the prefrontal cortex (e.g., ventromedial and orbitofrontal areas), whose function is to compute the value associated with a certain item or course of action (Kennerley & Walton, 2011; Levy & Glimcher, 2012). Further details on the neurobiological aspect of VDM will be discussed in Section 2.2.3.

In summary, perceptual and value-based decision-making have been the object of study of long-standing research traditions that are still evolving and developing into new models, frameworks, and task designs. Despite their obvious differences, both processes also share surprising similarities, and new research will help shed a light on the degree of overlap between these two types of decision-making. The next section will focus specifically on the theories of value-based decision-making and its own subdivisions.

2.2.2 Key Theories, Concepts, and Debates

In the field of value-based decision-making, there is a wealth of theories and models that try to address which processes are involved in VDM, its subsystems, their interactions, and neural implementations. This abundance of evidence has, in turn, sparked debates in the research community, especially concerning the nature and the number of the so-called "valuation systems". However, based on the current state of the literature, there is still a way to go before we can arrive to a definitive framework of value-based decisions.

Before diving into the details of the different theories, let us reiterate the definition of value-based decision-making: it is a decisional process during which different options are associated with a value, which is either intrinsic (i.e., internal or subjective) or extrinsic (i.e., external); these options are then weighed and chosen based on the goals set either by the external context or by the individual. The key concept of this general definition is that of "value", whose exact meaning has been the subject of much debate (Nakao et al., 2012). In fact, the term "value" can be decomposed into different aspects (e.g., "wanting", "liking", "reward"), which are also ambiguous and difficult to operationalise and might involve different computations and

neurobiological substrates. Additionally, by its own nature, the "value" of something is not a fixed and stable property, but a flexible and relative one, that is affected by external and internal factors, some of which are listed in the "Perceptual vs Value-Based Decision-Making" section (Fellows, 2004; Slovic, 1995). Moreover, the concept of "value" has been assigned different names depending on the theoretical context, such as "utility" in the economic field or "reinforcer" in the field of animal learning (Fellows, 2004). All of this prevents the creation of a common lexicon (Rangel et al., 2008) and a common framework through which researchers from different disciplines can approach this specific type of decision-making.

Despite these conceptual limitations, attempts have been made to formulate theories on the functioning of value-based decision-making. Classical models state that VDM consists of three phases: option identification, evaluation, and choice (Baron, 2000; Lipshitz et al., 2001), which partially overlap with the generic framework proposed in this dissertation (Figure 1). While this framework is a useful starting point, it is also overly simplified and not wholly informative. An evolution of this model can be found in the work of Rangel et al. (2008). According to their view, VDM processes are articulated into five computational stages: first, the decision problem is represented by taking into account the internal state of the subject, the external state of the environment and potentially viable courses of action. Secondly, the different actions or options are evaluated according to different "valuation systems" (i.e., Pavlovian, Habitual, Goal-directed systems) (O'Doherty et al., 2007). Then, the values associated with these actions or options are compared and a response is selected. The fourth process consists of evaluating the outcome or feedback. While the wording might be similar, the second and fourth stages are markedly different, because the evaluation of an outcome occurs *after* the decision has been made, not to mention that it is the driving force behind the final phase, i.e., learning. While there is overlap between the "classical" model and this updated version, certain aspects have been expanded or included, e.g., the importance of feedback and learning processes to guide subsequent decisions.

Nevertheless, Rangel et al. (2008) are also acutely aware of the limitations of their model. First of all, the first stage (i.e., the representation of the decision problem) has received little attention in the literature, so that its computational and

neurobiological bases are still largely unknown. Moreover, it is not clear whether the five stages are strictly serial or not, a question that concern specifically the second and third stages (i.e., option evaluation and action selection) (Cisek, 2012). Other questions concern the exact nature, number, and neural underpinnings of the so-called "evaluation systems" (Balleine, 2005; Kable & Glimcher, 2009; Murray et al., 2007). The Pavlovian system is considered to be innate and to have a limited behavioural repertoire that is mostly concerned on consummatory or avoidance responses (i.e., outcome-specific responses related to rewards or punishments) (Gallagher et al., 1999), while the Habitual system is involved in slowly learning how to assign values to a large number of actions (Yin & Knowlton, 2006); finally the Goal-directed system focuses on action-outcome associations as it quickly updates the value of an action based on the value of its consequences (Wallis, 2007). However, it remains unclear which elements are shared among these systems, how factors such as long-term goals, cultural and moral norms are integrated into these systems, and whether their supposed differences are a consequence of their theoretical formulations or of their intrinsic characteristics.

This picture is further complicated by another interpretation that divides the concept of value amongst different "classes", rather than systems (Peters & Büchel, 2010). The authors, in this case, explain that the subjective value of an option can be classified as "outcome value", "goal value", "decision value", and "action value" depending on the features of the computation, such the integration of costs and risks associated with a decision. Despite having different names, at least two of these definitions can be mapped onto the division advanced by Rangel et al. (2008), i.e., "outcome value" and "action value" are essentially the same as the Pavlovian system and the Goal-directed system. Again, the lack of a consistent nomenclature prevents the construction of an overarching theory of value-based decision-making. Nonetheless, an effort can be made to bring together these different approaches.

One critical notion that unites these frameworks is that of the "common currency", which is crucial for the "information processing" stage. This concept is of fundamental importance in neuroeconomics, and it refers to how the different values attached to multiple options (e.g., apples and oranges) are translated into a common scale to allow the individual to make a decision (Fehr & Rangel, 2011; Levy & Glimcher,

2011, 2012; Peters & Büchel, 2010; Samuelson, 1937). It is important to note that, in the work of Rangel et al. (2008), there is no explicit mention of this concept, yet the authors acknowledge that option values need to be compared and combined to be transformed into a unitary course of action, which corresponds to the definition of "common currency". In Peters & Büchel's (2010) framework this idea is encapsulated in the definition of "goal value", which refers to a more abstract representation of a stimulus value that permits to compare items across different domains.

The second key concept that emerges from the available literature concerns the so-called "modulators", that is factors like the risks, delays, social context, costs, uncertainties, and ambiguities that impact in one way or another the value of an option. While both Rangel et al. (2008) and Peters & Büchel (2010) recognize the importance of these external factors, they differ on how these modulators are incorporated into the decision-making process. The former point out how the implementation of different modulators can be ascribed to different, often competing theories. For instance, the risk of a gamble could be either computed in a statistical fashion (Preuschoff & Bossaerts, 2007) – i.e., the brain assigns a value to the gamble by considering the magnitude of the reward, its variance, and skewness and then aggregates these attributes – or by relying on the expected utility theory (Von Neumann & Morgenstern, 1944) or the prospect theory (Kahneman & Tversky, 1979), explored in Sections 2.1.2.2.1 and 2.1.2.2.2. On the other hand, Peters & Büchel (2010) ascribe this aspect to the so-called "decision value" and focus more on interindividual differences in levels of risk aversion, thus taking a less normative approach and positing the existence of a "subject-specific value function" that integrates individual preferences and how potential costs might affect them. Nevertheless, the two approaches are not mutually exclusive, as one could argue that the norms established by different theories can be assimilated and computed on an individual basis, thus allowing for differences amongst decision-makers.

One alternative interpretation of VDM that could resolve the debates and the inconsistencies in the nomenclature discussed so far is the one advanced by Nakao et al. (2012). In their work, they distinguish between externally-guided (EDM) and internally-guided decision-making (IDM). Externally-guided decisions include those

where a single correct answer exist, whereas internally-guided decisions are based on personal preferences and judgments and no clear choice exists. We consider this classification to be the best one to distinguish between types of value-based decisions, because it offers clear guidelines on how VDM processes could be operationalised and approached in an experimental setting. Therefore, we will henceforth talk about external value-based decision-making (EDM), which includes all those decisions where the value of the options is set externally (e.g., by the experimenter) and an objective answer is present, and internal value-based decision-making (IDM), which instead refers to decisions based on the individual's internal criteria (e.g., preference judgments). Examples of tasks used in EDM paradigms are, for instance, gambling tasks or tasks where a stimulus is associated with a cue that indicates the prospect of a reward. IDM paradigms, on other hand, rely on tasks where participants are asked to rate a certain item in terms of its desirability or to choose between options to which they have attached different subjective values. Because of their underlying assumptions (i.e., individuals attach different values to different options and choose accordingly), IDM tasks can be included in the research field that studies 'consumer behaviour' or 'economic choices'. Experiments in this field include so-called 'willingness-to-pay' tasks, where participants are asked how much money they would be willing to spend on a certain item. The amount of money is then considered an indirect indicator of the individual's personal preference. Therefore, in Chapter 3, we included keywords that reflect this aspect of IDM processes as well (see Section 3.2.1).

To summarise, value-based decision-making is a multifaceted and multistage process in which an agent is required to make a choice between multiple options, by computing and comparing their values based on internal and external demands. The final section of this chapter will link the concepts discussed so far with their putative neurobiological bases.

2.2.3 Neural Bases of Value-based Decision-making

Evidence on the neural substrates of value-based decision-making comes from neuroimaging studies, electrophysiological experiments on animals and lesion studies on patients. Most of the attention has focused on the role played by prefrontal regions,

such as the orbitofrontal/ventromedial prefrontal cortex (OFC/vmPFC), which has been implicated in value comparison and computing the 'common currency' discussed in the previous section (Brosch & Sander, 2013; Gross et al., 2014; Padoa-Schioppa, 2011). However, since decision-making is a highly integrative process, multiple cortical and subcortical areas seem to contribute as well. A study by Brosch & Sander (2013) suggests that the OFC/vmPFC, the striatum, and the insula are part of a network involved in the computation of the 'common currency'. Specifically, the OFC/vmPFC interacts with the insula to conduct a cost-benefit analysis of the different options (Talmi et al., 2009), which is closely linked to the "decision value", and with the ventral striatum during temporal discounting tasks (McClure et al., 2004). Parietal areas and the cingulate cortex have also been associated with the computation of an option's subjective value (Chaudhry et al., 2009; Hunt et al., 2012; Kim et al., 2011; Levy & Glimcher, 2012).

Given that we have divided VDM processes into external and internal value-based decisions based on Nakao et al.'s (2012) work, it is important to address the neural substrates of these two categories as well. To that end, Nakao et al. (2012) conducted a fMRI meta-analysis on studies they classified as either EDM or IDM. Their findings suggest that EDM processes rely on the task-positive network (TPN), which includes the dorsomedial and dorsofrontal PFC, the insula, the thalamus, and the inferior parietal lobule (IPL), whereas IDM decisions depend on the activity of the default mode network (DMN), which has been implicated in intrinsic brain activity and the processing of internally generated info, a role that is consistent with the definition itself of internal value-based decision-making. The brain regions involved in the DMN are the inferior frontal gyrus (IFG), the vmPFC, the posterior anterior cingulate cortex (pACC), the posterior cingulate cortex (PCC), and the superior temporal gyrus (STG). The widespread distribution of these networks further supports the integrative nature of decision-making. Moreover, the findings by Nakao et al. (2012) reflect the current understanding of the neural bases of VDM in the wider literature, thus providing us not only with a plausible theoretical framework to divide value-based decisions into external and internal but also with sound neurobiological evidence.

3 A Systematic Review of MEG/EEG studies on human value-based decisions: experimental paradigms and spatiotemporal characteristics

3.1 Introduction

As established in Chapter 3, decision-making is a ubiquitous process in daily life that relies on the integration of perceptual, attentional, mnemonic, affective and executive inputs to result in a choice, i.e., an overt behavioural response (Fellows, 2004). Researchers across multiple fields, such as economics, psychology, neuroscience, and computer science, have tackled different aspects of this cognitive function. This has resulted into the emergence of neuroeconomics and decision neuroscience (Bossaerts & Murawski, 2015; Glimcher & Fehr, 2014; Rangel et al., 2008; Rustichini, 2009; Smith & Huettel, 2010). However, most of the focus has been on the localisation of the neurobiological substrates of decisional processes, both when considering primary scientific articles, meta-analyses, and systematic reviews. This means that studies carried out with magneto- or electroencephalography, which instead offer insights into the temporal unfolding of decision-making, as well as the paradigms used in those experiments, have received less systematic attention. Therefore, open questions remain on the spatiotemporal dynamics of decision-making processes and on the specifics of the experimental paradigms used so far in this niche of the scientific literature.

The aim of the present chapter is to address this gap by reviewing the MEG/EEG literature on a specific type of decision-making, i.e., value-based decisions. These are reframed in the context of the framework dissected in Chapter 2, i.e., the one proposed by Nakao et al. (2012), which divides value-based decisional processes in either intrinsic (i.e., internal or subjective) or extrinsic (i.e., external) ones. Again, the main difference rests on whether the value of the available options is set according to an internal, subjective criterion or an external, objective one.

There are three key reasons behind our choice to zero in on MEG/EEG studies on value-based decisions. First, MEG and EEG allow researchers to examine cognitive processes with high temporal resolution (in the order of milliseconds), meaning that they are the best non-invasive methods to unravel the temporal profiles of value-based decisions. Secondly, the processes underlying value-based decision-making (VDM) have been the subject of much research and scholarly debate. This means that it is crucial to revisit models and theories on VDM in light of new evidence, thus opening the way to more advanced and more thorough frameworks. Finally, value-based choices are amongst the ones with the most personal relevance and the most far-reaching consequences in real life (e.g., choosing a pension plan or choosing a spouse). As a result, their study has important implications for the understanding of human behaviour (Glimcher & Fehr, 2014).

The overarching goal of this chapter is to provide a comprehensive and systematic review of the current literature that links the psychological and the biological aspects of VDM, as well as to establish whether there is a convergence between extant findings and the MEG/EEG data collected in this review. Finally, the review is meant to provide a summary of tasks used in MEG/EEG research on VDM and, potentially, inspire new experimental designs in this field.

The rest of the chapter is thus organised: first, Section 3.2 elucidates the inclusion criteria we used to select the MEG/EEG studies, and how we extracted the temporal and sensor-space data. Then, in Section 3.3, the findings of the literature search are presented, alongside the findings relating to the temporal and topographical distribution of EDM and IDM processes. The different paradigms used across studies are classified and outlined in detail. Finally, Section 3.4 addresses the main contributions of the current work, its limitations and the potential directions for future research.

3.2 Methods

3.2.1 Study Selection and Inclusion Criteria

We identified studies that used either EEG or MEG to investigate value-based decision-making in healthy adult human participants. We followed the PRISMA guidelines (Moher et al., 2015) to conduct a literature search on the PubMed and PubMed Central (PMC) databases. We considered both databases to account for potential differences in their records. The following keyword combinations were used during the literature search: (“MEG” OR “EEG” OR “magnetoencephalography” OR “electroencephalography” OR “ERP” OR “event-related potentials”) AND ("value-based" OR "value-based decision" OR "subjective value" OR "subjective preference" OR "preference-based" OR “consumer behavior” OR “reward-based” OR “probabilistic reward” OR “reward probability” OR "willingness-to-pay" OR "buying decisions" OR "reward value" OR “reward”). We set the filters to “Title/Abstract” to restrict the search to mostly relevant results. As of May 2021, in PubMed, the search resulted in 1,088 publications, while in PMC, the search amounted to 437 publications.

We inspected each of these publications and applied the following inclusion/exclusion criteria**:**

1 We included only studies that recruited healthy adults as participants. From PubMed records, 687 of the 1088 publications met this criterion. From PMC records, 246 of the 437 publications met this criterion.
2 We included only articles that reported original findings and excluded review articles. This criterion gave 513 papers from PubMed and 187 papers from PMC.
3 We included only publications that used value-based decision-making tasks and reported the cue-locked or stimulus-locked MEG/EEG activity. By cue-locked and stimulus-locked, we refer to those tasks that recorded MEG/EEG activity during the display of a cue or stimulus. The reason behind this is to focus only on that brain activity that occurs prior to a motor response (see 3.2.2 for details) From PubMed records, 91 of the 513 publications met this criterion. From PMC records, 49 of the 187 publications met this criterion.

Search results from the two databases were merged and duplications were removed. Five more articles were added manually (Harris et al., 2011; R. Qiu et al., 2020; Telpaz et al., 2015; Tyson-Carr et al., 2018; Zajkowski et al., 2020). A total of 100 studies met the criteria. Table 1 summarizes the key information of each article.

3.2.2 Data Extraction for Quantitative Summaries

In addition to the synthesis of experiment paradigms and main findings, we provided quantitative summaries of the main MEG/EEG findings. This information serves two purposes. First, we explored post-stimulus time intervals that are commonly observed across studies and task paradigms, during which MEG/EEG evoked activities were modulated by internal or external values. Second, we identified common sensor locations from which those value-sensitive electrophysiological activities were observed.

Our literature search included publications that reported MEG/EEG activities time-locked either to the cue or to the main target stimulus. The reasons for this choice are rooted in the conceptual framework of value-based decision-making. As explained in Chapter 2, VDM processes entail different phases, commonly involving input identification, information processing, and output production, and, in the case of external value-based decisions, outcome evaluation. Here, we are focused on the option identification and evaluation phases, during which participants need to evaluate and compare the values of multiple items. This process occurs when a cue or a target stimulus becomes available to participants. The "choice" phase, instead, refers mainly to overt motor responses, while the "outcome evaluation" phase is carried out *after* a decision has been made. However, not all studies examined response- or feedback-locked activities, which correspond to the latter two phases. Hence, we chose to exclude those types of event-related activity from our quantitative summaries, as they are uninformative for the scope of the present review.

For each publication, we first identified the main contrast of interest, focusing on conditions that were sensitive to a *difference* in value. For instance, in rating tasks or willingness-to-pay tasks, we considered contrasts between high-value and low-value

items. In gambling tasks, we considered contrasts between high-reward and low-reward cues/stimuli. Table 1 lists the contrast of each study that entered the systematic summary.

We then extracted three types of information from each study: (1) the statistically significant time intervals of the chosen contrast; (2) the definition of the baseline (i.e., cue- or stimulus-locked); and (3) the EEG electrodes or MEG sensors associated with those same intervals.

Regarding the reporting of time intervals, researchers used three strategies to identify time points of interest, which are also reported in **Table *1***:

1 ***A priori* identification:** In this case, the time windows were defined based on methods such as visual inspection and on previous related works.
2 **Extrapolated peaks:** In some instances, only a peak was reported. If that was the case, we added an interval of 100 milliseconds for illustrative purposes, an approach used by Munding et al. (2015).
3 **Inferential identification:** A number of studies used specific analysis protocols to identify the time intervals of interest, without relying on previous works.

3.2.3 Alignment of Sensor-space Data across Studies

To identify EEG electrode locations that are prevalently associated with value-based decision-making, we summarised the topographies of relevant electrophysiological activities across all EEG studies. For each EEG study, we mapped the EEG electrodes of interest onto a 32-channel montage according to the international 10–20 system. For studies using high-density EEG systems, we interpolated electrodes of interest to the 32-channel montage using Fieldtrip (Oostenveld et al., 2011). Given the low number of MEG studies and the lack of sensor-level MEG analyses, we did not summarise the topographies of MEG sensor-level activities.

3.3 Results

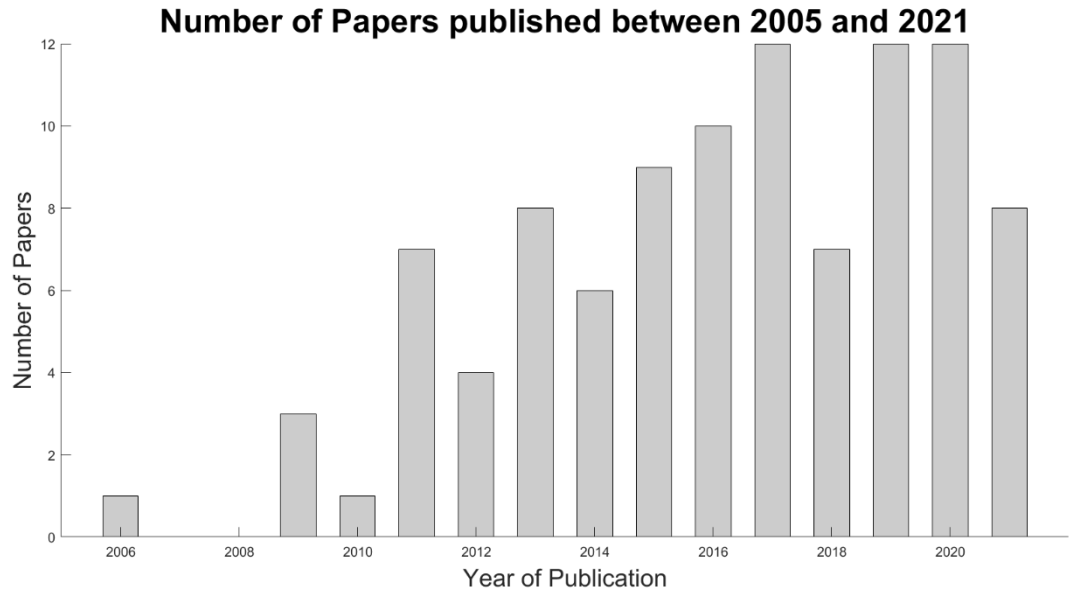
3.3.1 Results of the Literature Search

The literature search resulted in 100 MEG/EEG studies on value-based decision-making (see 3.2.1 for details). **Table *1*** lists the key information of each study, including the number of subjects, the modality (MEG or EEG), the experimental paradigm, and the time interval of interest. Three papers (Krugliakova et al., 2018; Langeslag & van Strien, 2013; MacLean & Giesbrecht, 2015) reported statistically non-significant results for the contrasts of interest and were excluded from our quantitative summaries, but they are included in **Table *1*** for completeness.

All the 100 studies are published after 2006. In the last decade, there is a steady trend of new studies on human value-based decision-making (Figure 8(A)), and an increase of the sample size in studies over the years (Figure 8(B)), up to 114 participants in a recent study (Pegg et al., 2021). The average number of participants in a single study was 28±15 (s.d.). Among the 100 studies, 92 used EEG and 9 used MEG, with one study (Doñamayor et al., 2012) using both EEG and MEG. There is also an imbalance between the category of decision-making tasks use in the current literature: 78 studies investigated external value-based decision-making (EDM), and 22 examined internal value-based decision-making (IDM).

Below, we describe VDM paradigms identified by the literature search and relevant ERP/ERFs reported in those studies. We separated EDM and IDM studies and further classified the experimental paradigms into different categories, according to their design characteristics (see Sections 3.3.2 and 3.3.3).

A



B

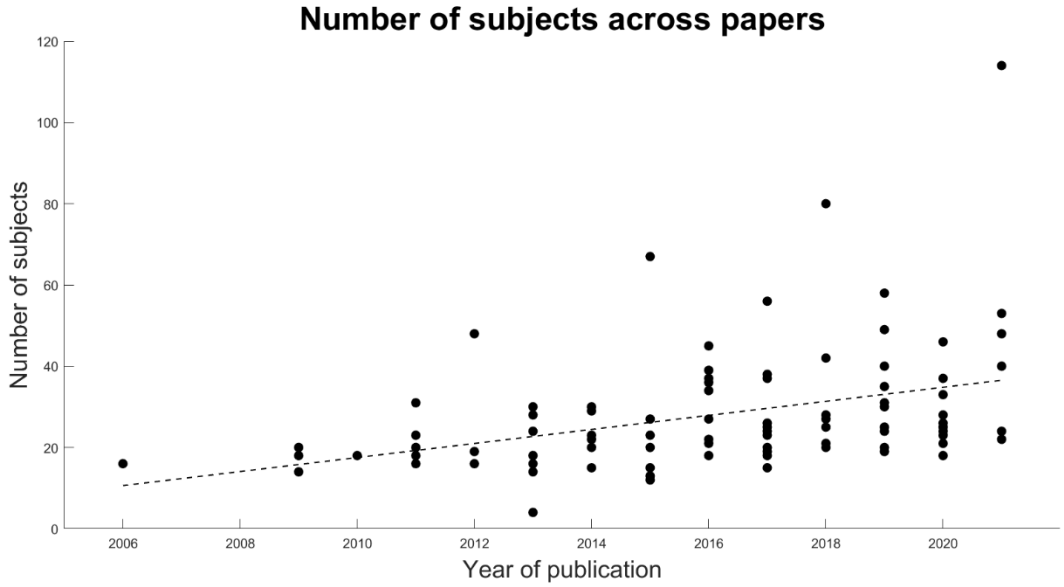


Figure 8 ***Panel A:*** Number of papers published between 2005 and 2021. ***Panel B:*** Number of subjects across papers.

Study	N. Subjects	Modality	Paradigm	Type of value task [EDM, IDM]	Sensors of interest	Interval of interest	Time window identification method
Angus et al., 2017	20	EEG	Money incentive delay task	EDM	P2, Cz, PO7	Cue-locked, incentive vs no incentive cues: [132:136, 276:280, 360:364]	Inferential
Apitz & Buzneck, 2012	16	MEG	Value-directed recognition memory (VDR) paradigm	EDM	MRF44	Stimulus-locked, reward predicting vs not-reward predicting: [300:600]	A priori
Bach et al., 2017	18	MEG	Reward learning task	EDM	N/A	Source-level, cue-locked, reward magnitude: [250:2000]; reward variability: [540:1500]	Inferential
Bachman et al., 2020	28	EEG	Visual search task with associated reward	EDM	PO7, PO8, POz, Pz, PO3, PO4, CPz, Cz, CP1, CP2, P1, Pz, P2	Stimulus-locked, baseline vs equal vs selective reward blocks: [140:180, 150:350, 350:550]	A priori
Bielser et al. 2016	22	EEG	food preference task	IDM	FCz, FC1, F3, F7, FC5	Stimulus-locked, High vs Medium vs Low liking: [135:180]	Inferential

Bland & Schaefer, 2011	31	EEG	Reward learning task	EDM	N/A	Stimulus-locked, high vs low volatility: [200:350, 350:500, 500:800]	A priori
Blangero & Kelly 2017	15	EEG	Rewarded cued-saccade task	EDM	PO7, PO8	Stimulus-locked, High-value on Left vs Right: [280:400]	Inferential
Bowyer et al., 2021	40	EEG	Effort-Doors task	EDM	Pz	Cue-locked, high vs low effort: [300:450]	A priori
Buzneck et al., 2009	14	MEG	Value-directed recognition memory (VDR) paradigm	EDM	N/A	Stimulus-locked, reward predicting vs not-reward predicting: [200:500]	A priori
Buzneck et al., 2011	16	MEG	Reward anticipation paradigm	EDM	MR051	Stimulus-locked, reward probability cues (high vs low vs nil): [100:200]	A priori
Capa et al., 2013	28	EEG	Switching task with associated reward	EDM	FCz	Cue-locked, 1cent vs 50cent: [1100:1750]	A priori
Chen et al. 2019	31	EEG	Speed-Rewarded GO/NO-GO Task	EDM	FCz, CPz	Stimulus, locked Reward x Go-probability: [180:250, 420:800]	A priori

Diao et al. 2021	24	EEG	Preference Judgment Task	IDM	F1, Fz, F2, FC1, FCz, FC2, P5, P7, PO5, PO7, P6, P8, PO6, and PO8	Stimulus-locked, High-value vs Low-value: [230:280; 290:340]	A priori
Diao et al., 2016	18	EEG	Modified Go/No-Go task with associated reward	EDM	FCz, FC1, FC2, Cz, C1, C2, CPz, CP1, CP2	Stimulus-locked, high vs low-value cue reward: [460:600]	A priori
Doñamayor et al. 2012	19	MEG/EEG	Monetary incentive delay task	EDM	Cz, Pz, Fz	Cue-locked, reward vs non-reward cue: [70:170, 150:250]	Inferential
Dong et al., 2016	39	EEG	Iowa Gambling Task	EDM	F3, FZ, F4, C3, Cz, C4, P3, PZ, P4	Stimulus-locked, advantageous vs disavantageous decks: [300:500]	A priori
Elliott et al., 2020	33	EEG	Value-directed recognition memory (VDR) paradigm	EDM	Pz	Stimulus-locked, value conditions: [450:650]	A priori
Flores et al., 2015	23	EEG	Monetary incentive delay task	EDM	Fz, Cz, Pz	Cue-locked, prospective reward conditions (low vs high vs nil): [100:140, 180:220, 440:540]	A priori

Forester et al., 2020	46	EEG	Reward incentive task	EDM	F3, Fz, F4, C3, Cz, C4, P3, Pz, P4	Stimulus-locked, reward vs no reward: [500:700, 800:1200]	A priori
Frömer et al., 2021	53	EEG	Rewarded Stroop Task	EDM	Pz, P3, P4, Fz, FCz, Cz	Cue-locked, High vs Low reward: [250:550, 1000:1500]	A priori
Gluth et al. 2013	30	EEG	Sequential decision making task with probabilistic outcomes	EDM	Cz	Stimulus-locked, High vs Low cost trials: [250:750]; High vs Low evidence (for or against buying): [1000:1500]	A priori
Goldstein et al., 2006	16	EEG	Monetary incentive task	EDM	CPz	Cue-locked, High vs Low vs Nil conditions: [250:450]	A priori
Goto et al. 2017	38	EEG	Rating task + buying task	IDM	Fz, Cz, Pz	Stimulus-locked, High vs Low preference: [250:350, 400:800, 800:3000]	A priori
Goto et al. 2019	40	EEG	Viewing task + Preference task + WTP	IDM	F3, Fz, F4, C3, Cz, C4, P3, Pz, P4	Stimulus-locked, High vs Low preference [200:400, 400:800, 800:3000]	A priori

Gui et al., 2016	34	EEG	Temporal discounting task	IDM	Fz, F3, F4, FCz, FC3, FC4	Stimulus-locked, small vs large reward: [150:250]	A priori
Halsband et al., 2012	48	EEG	Value-directed recognition memory (VDR) paradigm	EDM	F3, Fz, F4, C3, Cz, C4	Stimulus-locked, high vs low reward: [400:700, 700:1000]	A priori
Hammerschmidt et al., 2018	42	EEG	Rewarded associative learning paradigm	EDM	Pz, P1, P2, CPz, POz	Stimulus-locked, consolidation phase, reward vs no reward: [350:700]	A priori
Harris & Lim, 2016	27	EEG	Effort expenditure task for food	IDM	N/A	Stimulus-locked, effort - value: [100:200, 450:650, 750:850]	Inferential
Harris et al. 2011	23	EEG	BDM Bidding task + Rating task	IDM	CP1, CP5, CP2, CP6,P4, P8, P3, P7, Pz, Cz, Fz, AFz, Fpz	Stimulus-locked, Like vs Dislike: [150:250, 400:550, 700:800]	Inferential
Heritage et al., 2018	80	EEG	Rewarded memory-guided visual search task	EDM	Pz	Cue-locked, no vs small vs large reward: [400:600]	A priori

Hinault et al., 2019	19	EEG	Rewarded Working memory task	EDM	N/A	Stimulus-locked (distractor), old reward vs novel in relation trials: [180:210]	A priori
Hughes et al., 2013	16	EEG	Rewarded rapid visual detection task	EDM	Cz, Pz	Cue-locked, reward vs no-reward: [300:500, 700:1000]	A priori
Hunt et al. 2013	18	MEG	Risky value-guided task with probabilistic outcomes	EDM	N/A	Stimulus-locked, Vcontra - VIpsi: [325:425]	Peak
Itthipuripat et al. 2015	27	EEG	Probabilistic Binary-choice task	EDM	P3, P7, PO3, P4, P8, PO4	Stimulus-locked, Differential choice value (selected - unselected) VS Distractor value: [160:185, 215:300, 300:500]	A priori
Jia et al., 2021	24	EEG	Rewarded face-word Stroop paradigm	EDM	F3, Fz, F4, FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4, P3, Pz, P4	Cue-locked, reward vs no-reward: [100:200, 300:600, 800:1500]	A priori
Jin et al., 2018	21	EEG	Willingness to pay task	IDM	F1, Fz, F2, FC1, FC2, FCz	Stimulus-locked, eco-label vs no-label: [160:220, 300:400]	A priori & Inferential

Kaltwasser et al., 2013	24	EEG	Rewarded semantic categorization task	EDM	Fz, Cz	Cue-locked, no reward vs loss vs gain expectancy: [100:500]	A priori
Kawasaki & Yamaguchi. 2012	19	EEG	Color Preference Judgment Task	IDM	O1, O2	Stimulus-locked, Control task vs Preference judgment: [200:350, 700:1000]	A priori
Kelley et al., 2019	58	EEG	Rewarded time estimation task	EDM	Pz	Cue-locked, incentive vs no incentive: [300:600]	A priori
Kiss et al., 2009	18	EEG	Rewarded visual search task	EDM	PO7, PO8	Stimulus-locked, high-reward vs low-reward color: [180:230, 360:500]	A priori
Krebs et al., 2013	14	EEG	Rewarded Stroop Task	EDM	Fz, FCz, F1a, F2a, Pz, POz, P1a, P2a, PO7, PO9, PO8, PO10	Stimulus-locked, potential reward Wc vs no-reward Wc: [200:280, 280:400]	A priori
Krugliakova et al., 2018	27	EEG	Auditory Monetary incentive delay task	EDM	N/A	N/A	N/A
Langeslag & van Strien, 2013	24	EEG	Reward regulation task	EDM	N/A	N/A	N/A

Li et al., 2018	20	EEG	Rewarded time estimation task	EDM	Fz	Cue-Locked, 100% vs 75% vs 50% reliability: [240:340]	A priori
Lin et al., 2019	35	EEG	Monetary gambling task	EDM	O1, O2, Oz, PO3, PO4, PO7, PO8, F1, F2, F3, F4, Fz, FCz, P1, P2, Pz, POz	Stimulus-locked, small vs large reward: [110:150]; risky vs ambiguous context: [290:350, 300:450]	A priori
Lindsen et al. 2010	18	EEG	face preference decision (two alternative forced-choice paradigm)	IDM	Oz, Cz, Pz, Fz	Stimulus-locked, preferred vs non-preferred item: [200:400]	Inferential
Lockhofen et al., 2021	40	EEG	Rewarded visual search task	EDM	PO3, P7, PO4, P8	Source-space analysis, Stimulus-locked, distractor group, high vs low rewards: [238:338]	Inferential
Luo et al., 2019	24	EEG	Monetary incentive delay task	EDM	Fz, FCz, CPz, Pz	Cue-locked, 3 cue conditions (hedonic vs eudaimonic vs neutral): [180:220, 260:300, 300:500]	A priori
Luque et al., 2017	24	EEG	S-R-O reward learning task	EDM	Oz	Stimulus-locked, RL trials, high- vs low-value stimuli: [75:200]	A priori

MacLean & Giesbrecht, 2015	15	EEG	Reward association task + Attention task	EDM	N/A	N/A	N/A
Marini et al., 2011	16	EEG	Value-directed recognition memory (VDR) paradigm	EDM	FCz, Cz, F3, FC3, Fz, F4, FC4, CP3, P3, CPz, Pz, CP4, P4	Stimulus-locked, encoding, incentive vs no incentive: [150:200, 200:300, 300:500, 500:700]	A priori
Molinero et al., 2021	48	EEG	S-R-O reward learning task	EDM	O2, Pz	Stimulus-locked, high- vs low-value: [350:400]	A priori
Morie et al., 2014	23	EEG	Rewarded cue task	EDM	FCz, C1, C2	Cue-locked, very high vs very low probability: [200:250, 600:800]	A priori
Nadig et al., 2019	30	EEG	Navon Monetary Incentive Delay task	EDM	Cz, CPz	Cue-locked, incentive vs no incentive: [140:260, 300:550]	A priori
Novak & Foti, 2015	67	EEG	Monetary incentive delay task	EDM	Fz, FC1, FC2, Cz, CP1, CP2, Pz, C3	Cue-locked, [Exp. 1], potential gain vs neutral vs potential loss: [275:325, 350:450, 2200:2400]; [Exp. 2], incentive vs no incentive: [275:325, 350:450, 2200:2400]	A priori

Oemisch et al., 2017	26	EEG	Value-based reversal learning task	EDM	PO3, PO4, PO7, PO8	Stimulus-locked, chosen vs non-chosen stimulus: [200:300]	A priori
Pegg et al., 2021	114	EEG	Monetary incentive delay task	EDM	Cz, FC1, FC2	Cue-locked, incentive vs non-incentive: [136:236, 384:434]	Peak & Inferential
Pornpattananangkul & Nusslock, 2015	23	EEG	Rewarded time estimation task	EDM	Cz, Fz, FCz, Pz, CPz	Cue-locked, reward vs no reward: [200:350, 350:500]	A priori
Pornpattananangkul & Nusslock, 2016	37	EEG	Rewarded time estimation task	EDM	CPz	Cue-locked, reward vs no reward: [100:500]	Inferential
Qiu et al., 2020	25	EEG	Rating task + wanting task	IDM	Fz, FCz, Pz, Poz	Stimulus-locked, Favourite bundle vs Disliked bundle: [80:140, 160:250]	A priori
Reinhart & Woodman, 2014	30	EEG	Rewarded working memory and attention task	EDM	Fz, F4	Cue-locked, reward vs no reward: [100:1000]	Inferential
Roberts et al. 2018	28	wireless EEG	Rating task + BDM auction task (Willingness to pay)	IDM	Pz	Stimulus-locked, low value items vs intermediate+high value items: [150:250]	Peak & Inferential

San Martín et al., 2016	45	EEG	Probabilistic decision-making task	EDM	PO7, PO8	Cue-locked, reliable gain-cue vs neutral cue vs reliable loss-cue: [200:400]	A priori
Sawaki et al., 2015	13	EEG	Incentive array task	EDM	PO7, PO8, PO4	Cue-locked, high vs low incentive trials, contra vs ipsilateral cue position: [250:300, 325:375]	A priori
Schevernels et al., 2014	22	EEG	Rewarded attention task	EDM	C1, C2, Cz, CPz, FC1, FC2, F1, F2, FCz, Fz, P1, P2, PO3, PO4, Pz, POz	Cue-locked, reward vs no reward cues: [200:250, 250:300, 300:500, 700:1100, 1100:1500]	Inferential & A priori
Schevernels et al., 2016	21	EEG	Rewarded Go/No-Go task	EDM	Pz, P1, P2	Cue-locked, win vs avoid-loss vs neutral cues: [400:600]	Inferential & A priori
Schutte et al., 2019	49	EEG	Cued Go-NoGo task (monetary rewards)	EDM	Afz, FPz, FCz, CPz, Pz	Cue-locked, Reward vs No-reward: [234:254, 429:449, 671:691]	A priori
Silvetti et al., 2014	15	EEG	Modified Money incentive delay task	EDM	FCz	Cue-locked, easy vs hard trials: [200:650]	A priori

Steffen et al. 2011	20	MEG	Gambling task	EDM	N/A	Cue-locked, Reward value conditions - 10c vs 50c: [150:230]	A priori
Sun et al., 2020	18	EEG	Willingness to pay task	IDM	CPz, CP1, CP2, Pz, P1, P2	Stimulus-locked, positive vs negative ratings: [500:1000, 1000:15000]	A priori
Tankelevitch et al., 2020	37	MEG + classifier	S-R learning task + Visual attention task	EDM	N/A	S-R & Attention task, cue-locked, high vs low reward cues: [250:500]	Inferential & A priori
Tashiro et al. 2019	19	EEG	Rating task (food stimuli)	IDM	C3	Stimulus-locked, Favourite food vs Disliked food: [140:322]	Inferential
Telpaz et al. 2015	N/A	EEG	Two-alternative forced-choice task + Rating task	IDM	Fz, Pz	Stimulus-locked, Low preference vs High preference: [200:300]	A priori
Thomas et al. 2013	8 (4 excl)	MEG	Gambling task (slot machines)	EDM	MLO11, 11, 22	Stimulus-locked, Reward probability conditions: [90:260]	Inferential
Toepel et al. 2009	20	EEG	Rating task (judge fat content of foods - high vs low)	IDM	Pz, Oz, POz	Stimulus-locked, Food Category (High vs Low): [160:220, 330:370]	Inferential

Trimber & Luhmann, 2017	25	EEG	Probabilistic choice task	EDM	Fz, F1, F2, FCz, Pz, P1, P2, CPz	Cue-locked, pre-win/win vs pre-loss/loss vs control/neutral: [300:650, 650:1000]	A priori
Tyson-Carr et al. 2018	25	EEG	Willingness to pay task + Rating task	IDM	F2, Fz	Stimulus-locked, High vs Low value items: [195:205, 228:238]	A priori
Tyson-Carr et al. 2020	24	EEG	WTP task	IDM	Pz, Fz	Stimulus-locked, High vs Low value items: [50:70; 85:103, 158:165]	Inferential
Tzovara et al. 2015	12	EEG	Gambling task	EDM	Pz, POz	Stimulus-locked, Accept vs Reject decisions: [240:285, 395:440]	Inferential
van den Berg et al., 2014	29	EEG	Rewarded Stroop Task	EDM	O1, O2, Oz, F1, F2, Fz, FCz	Cue-locked, reward vs no reward: [140:180, 200:300, 700:1200]	Inferential & A priori
Wang & Han 2014	20	EEG	Two-alternative buying task	IDM	P1, PZ, P2, PO3, POZ, PO4, O1, OZ, O2	Stimulus-locked, Expected (Preferred) vs Unexpected (Non-preferred) attributes: [300:400]	A priori

Wang et al., 2019	20	EEG	Gambling task	EDM	F3, Fz, F4, FC3, FCz, FC4, CP3, CPz, CP4, P3, Pz, P4	Cue-locked, Low vs High magnitude: [250:350]; Cue-locked, Low vs High probability: [150:250, 250:350, 450:650]	A priori
Wang et al., 2020	26	EEG	Risky temporal discounting task	IDM	F3, Fz, F4, P3, Pz, P4	Stimulus-locked, high vs low probability rewards: [150:250, 250:350, 280:420, 500:700]	A priori
Wang et al., 2020	21	EEG	Rating task	IDM	P3, Pz, P4, PO3, POz, PO4	Stimulus-locked (S2), monetary vs social reward: [300:450]	A priori
Wei & Ji, 2021	22	EEG	Rewarded visual search task	EDM	Fz, Cz, Pz	Cue-locked, incentive vs no-incentive: [140:210, 300:500, 600:1000]	A priori
Wei et al., 2016	36	EEG	Rewarded semantic categorization task	EDM	F3, Fz, F4, FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4, P3, Pz, P4	Stimulus-locked, incentive vs no-incentive: [50:150, 150:250, 220:230, 300:380, 380:450, 500:700]	A priori

Wu et al., 2019	40	EEG	Rewarded face categorization task	EDM	F3, Fz, F4, FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4, P3, Pz, P4	Cue-locked, incentive vs no-incentive: [310:680, 800:1500]	A priori
Yan et al., 2017	20	EEG	Value-directed recognition memory (VDR) paradigm	EDM	CP3, CPz, CP4, P3, Pz, P4	Stimulus-locked, incentive vs no-incentive: [260:330, 330:500, 500:700]	A priori
Yang & Zhang, 2011	18	EEG	Card Gambling task	EDM	FCz, Cz, CPz	Stimulus-locked, high- vs low-risk: [300:500]	A priori
Yu et al., 2011	16	EEG	Card Gambling task	EDM	Fz	Cue-locked, 9 probability conditions: [275:325]	A priori
Yu et al., 2020	46	EEG	Temporal discounting task	IDM	Fz, F3, F4, FCz, FC3, FC4, Pz, P3, P4, CPz, CP3, CP4	Stimulus-locked, monetary vs food rewards: [200:300]; short vs long delay: [110:210, 200:300, 320:340]	A priori

Zajkowski et al. 2020	23	EEG	Probabilistic reward task	EDM	POz, Cz, Pz	MVPA, Cue-locked, Preferred vs Non-preferred: [316:472]; Certain vs Uncertain choices (100 vs 80 vs 20): [100:150, 300:400]	A priori
Zhan et al., 2016	18	EEG	Rewarded face categorization task	EDM	FCz, Pz	Stimulus-locked, reward vs no reward: [150:220, 220:300, 300:400, 450:600]	A priori
Zhan et al., 2017	19	EEG	Rewarded face categorization task	EDM	CP3, CPz, CP4, P3, Pz, P4	Stimulus-locked, high vs low value reward: [350:450]	A priori
Zhang et al., 2017	23	EEG	Gambling task	EDM	Fz, FCz, Cz	Cue-locked, 0% vs 50% vs 100% cue: [250:350, 800:1000]	A priori
Zhang et al., 2017	56	EEG	Monetary incentive delay task	EDM	P1, Pz, P2, POz, C1, Cz, C2, FCz	Cue-locked, gain vs loss vs neutral cue: [400:550, 2800:3000]	A priori
Zhao et al. 2015	20	EEG	Two-alternative buying task (buy or not buy) + questionnaire	IDM	AF3, AFz, Fz, F1, F3, F5, FCz, FC1, FC3	Stimulus-locked, High vs Low value stimuli: [520:660]	A priori

Zheng et al., 2017	37	EEG	Gambling task	EDM	Pz	Cue-locked, gain vs loss / small vs large cue: [350:550]	Inferential
Zheng et al., 2020	25	EEG	Card Gambling task	EDM	P3, Pz, P4, Fz, FCz	Cue-locked, 9 probability conditions: [202:242, 302:342, 400:650]	Inferential
Zhu et al. 2019	25	EEG	Ambiguous choice task	EDM	Pz	Cue-locked, Big vs Small reward: [400:600]	Peak & Inferential

Table 1 Details of the 100 papers included in the analysis. From left to right: authors and year of publication; number of subjects; neuroimaging modality; overview of the task; type of value-based task (EDM, i.e., External vs. IDM, i.e., Internal); sensors and interval of interest; method of identification of the time window (a priori, inferential, peak).

3.3.2 Summary of External Value-based Decision-making Paradigms

All EDM paradigms share a common aspect: the values of choice options are set *externally* by the experimenter and are therefore an objective feature of the experiment. Below, we categorise them according to the specifics of the different paradigms whilst emphasising the role of external values. Examples of some of these paradigms are included in Figure 9.

3.3.2.1 Probabilistic Reward Tasks

Twenty-five EVDM papers identified from the literature search used probabilistic reward tasks (Bach et al., 2017; Bland & Schaefer, 2011; Bowyer et al., 2021; Dong et al., 2016; Gluth et al., 2013; Hammerschmidt et al., 2018; Hunt et al., 2013; Itthipuripat et al., 2015; Lin et al., 2019; Luque et al., 2017; Molinero et al., 2021; Oemisch et al., 2017; San Martín et al., 2016; Steffen et al., 2011; Thomas et al., 2013; Trimber & Luhmann, 2017; Tzovara et al., 2015; Wang et al., 2019; Yang & Zhang, 2011; Yu et al., 2011; Zajkowski et al., 2020; Zhang et al., 2017; Zheng et al., 2017, 2020; Zhu et al., 2019). These tasks involve an element of reward uncertainty: decision outcomes were determined in a probabilistic manner, and participants could receive different rewards or losses according to their choices. Below we describe the specific subcategories of probabilistic reward paradigms.

3.3.2.1.1 Gambling Tasks

Gambling tasks often involve a loss scenario. Across 17 MEG/EEG papers used gambling tasks, participants were instructed to choose whether to make a bet, choose between options associated with different reward probabilities and magnitudes, or to choose between options associated with unknown reward probabilities (Dong et al., 2016; Gluth et al., 2013; Hunt et al., 2013; Y. Lin et al., 2019; San Martín et al., 2016; Steffen et al., 2011; Thomas et al., 2013; Trimber & Luhmann, 2017; Tzovara et al., 2015; G. Wang et al., 2019; J. Yang & Zhang, 2011; R. Yu et al., 2011; Zajkowski et al., 2020; Zhang et al., 2017; Zheng et al., 2017, 2020; Zhu et al., 2019). EEG studies in this category reported significant ERP components, with their amplitudes differing between reward probabilities or magnitudes, including the P200 (G. Wang et al., 2019; Zheng et

al., 2020), the P300 (Dong et al., 2016; Y. Lin et al., 2019; Trimber & Luhmann, 2017; Zajkowski et al., 2020; Zheng et al., 2017, 2020; Zhu et al., 2019), the P100 (Y. Lin et al., 2019), the N100 (Zajkowski et al., 2020), the N2pc (San Martín et al., 2016), and the Medial Frontal Negativity (G. Wang et al., 2019). Other significant ERP components occurred at later latencies, such as the Lateralised Readiness Potential (LRP) (Gluth et al., 2013), the Slow Negative Wave (SNW) (Zhang et al., 2017), and the Late Positive Potential (LPP) (Trimber & Luhmann, 2017), which were linked to motor preparation, decision uncertainty, and the motivational relevance of prospective rewards, respectively. Furthermore, several studies reported amplitude differences in ERPs specific to value processing, including the cue-evoked Feedback Related Negativity (FRN) associated with outcome expectations (R. Yu et al., 2011; Zhang et al., 2017); and the Reward-related Positivity (RewP) associated with reward probability (Li et al., 2018).

3.3.2.1.2 Value-based Learning Tasks

We refer to value-based learning tasks as an umbrella category of EDM paradigms that comprises S-R-O (stimulus-response-outcome) learning tasks (Bland & Schaefer, 2011; Hammerschmidt et al., 2018; Luque et al., 2017; Molinero et al., 2021), value-based reversal learning tasks (Oemisch et al., 2017), and instrumental reward learning tasks (Bach et al., 2017). Tasks in this category require participants to learn the associations between stimuli and values, and these often were linked to different levels of reward magnitude and variability. Stimuli used in those studies included faces (Hammerschmidt et al., 2018), abstract characters (Luque et al., 2017; Molinero et al., 2021), and coloured/geometric drawings (Bach et al., 2017; Bland & Schaefer, 2011; Oemisch et al., 2017). Like the studies on the gambling task, the main contrast of interest was between different values (high vs. low) or reward probabilities (high vs. low). Under this contrast, significant MEG/EEG activity was reported within a range starting from 75 milliseconds (Luque et al., 2017) up to 2000 milliseconds (Bach et al., 2017) after stimulus onset. ERP analyses of this contrast showed significant amplitude difference in the P100 (Luque et al., 2017), the N200 (Bland & Schaefer, 2011), the N2pc (Oemisch et al., 2017), the N400 (Bland & Schaefer, 2011), the P300 (Molinero et al., 2021) and the Late Positive Component (Bland & Schaefer, 2011; Hammerschmidt et

al., 2018). One paper (Bach et al., 2017) reported the a priori time intervals of interest but did not link them to specific ERP/ERF components.

3.3.2.1.3 Other Probabilistic Reward Tasks

We highlighted two studies that cannot be readily assigned to the two common categories above. In a binary choice task (Itthipuripat et al., 2015), participants choose between two options associated with different values while a task-irrelevant distractor was present on screen. The distractor itself was presented with the same visual feature as the previous high-, medium- or low-value stimulus, allowing the researchers to examine how value-based attentional capture towards the distractor influences value-based decisions. Between trials with different distractor's values, this study reported significant amplitude changes in the N100, the N2pc, and the P300 components.

In a binary choice task used by Bowyer et al. (2021), participants had to press a button several times in high- or low-effort conditions, then choose between two options associated with probabilistic rewards. This design allowed the researcher to explore how effort expenditure impacts the anticipation and the evaluation of a reward, which resulted in a change in ERP amplitude close to the P300 between high and low effect conditions.

3.3.2.2 Auxiliary Value Tasks

We define the second type of EVDM paradigms as the auxiliary value task. Here, "auxiliary" reflects a key characteristic that external values, or rewards, in those tasks do not dictate the correct decision option, but their presence may influence participants' behaviour. Most studies of this type examined how the presence of an incentive (i.e., value) cue impacts subsequent cognitive processing.

In total, 49 papers from our literature search used auxiliary reward tasks (Angus et al., 2017; Apitz & Bunzeck, 2012; Bachman et al., 2020; Blangero & Kelly, 2017; Bunzeck et al., 2011; Capa et al., 2013; X.-J. Chen et al., 2019; Diao et al., 2016; Doñamayor et al., 2012; Elliott et al., 2020; Flores et al., 2015; Forester et al., 2020; Frömer et al., 2021; Goldstein et al., 2006; Halsband et al., 2012; Heritage et al., 2018;

Hinault et al., 2019; Hughes et al., 2013; Jia et al., 2021; Kaltwasser et al., 2013; Kelley et al., 2019; Kiss et al., 2009; Krebs et al., 2013; Li et al., 2018; Lockhofen et al., 2021; Luo et al., 2019; Marini et al., 2011; Morie et al., 2014; Nadig et al., 2019; Novak & Foti, 2015; Pegg et al., 2021; Pornpattananangkul & Nusslock, 2015, 2016; Reinhart & Woodman, 2014; Sawaki et al., 2015; Schevernels et al., 2014, 2016; Schutte et al., 2019; Silvetti et al., 2014; Tankelevitch et al., 2020; van den Berg et al., 2014; Wei et al., 2016; Wei & Ji, n.d.; Wu et al., 2019; Yan et al., 2017; Zhan et al., 2016, 2017; Zhang et al., 2017) Below, we summarize the eight main categories of auxiliary value paradigms used in the literature.

3.3.2.2.1 Value-driven Delay (VDD) Tasks

The VDD task (also referred to as the monetary incentive delay task in some studies) consists of two stages: a cue is presented first indicating the amount of incentive or loss a given trial, and the cue is followed by a target stimulus. Participants need to respond to the onset of the target as soon as possible, and their responses are followed by feedback of rewards or losses. Eleven MEG/EEG studies used the monetary incentive delay (MID) task (Angus et al., 2017; Doñamayor et al., 2012; Flores et al., 2015; Goldstein et al., 2006; Luo et al., 2019; Morie et al., 2014; Nadig et al., 2019; Novak & Foti, 2015; Pegg et al., 2021; Silvetti et al., 2014; Zhang et al., 2017).

A common contrast of all 11 VDD studies was between trials with different incentive cues, i.e., between different auxiliary values. Significant MEG/EEG activity of this contrast were reported within a range from 70 milliseconds (Doñamayor et al., 2012) to 3000 milliseconds (Zhang et al., 2017) after the incentive cue onset. In 9 out of 11 MID studies, this contrast led to significant changes in ERP components: the N100 (Angus et al., 2017; Flores et al., 2015), the P200 (Flores et al., 2015; Luo et al., 2019; Nadig et al., 2019), the N200 (Luo et al., 2019; Novak & Foti, 2015), the P300 (Angus et al., 2017; Flores et al., 2015; Goldstein et al., 2006; Luo et al., 2019; Nadig et al., 2019; Novak & Foti, 2015; Pegg et al., 2021; Zhang et al., 2017) and the contingent negative variation (CNV), a slow negative wave that has been associated with outcome anticipation, attention, and motor preparation (Novak & Foti, 2015; Silvetti et al., 2014; Zhang et al., 2017).

3.3.2.2.2 Value-driven Recognition (VDR) Tasks

In the VDR task, incentive cues are commonly presented during the encoding or familiarisation phase of standard recognition memory paradigms. During this phase, participants need to remember individual items, and their recognition memory performance is tested in a subsequent retrieval phase. Seven MEG/EEG studies used the VDR task (Apitz & Bunzeck, 2012; Bunzeck et al., 2009, 2011; Elliott et al., 2020; Halsband et al., 2012; Marini et al., 2011; Yan et al., 2017). The incentive cues in those studies indicate reward/no-reward or reward with different magnitudes that are paired with individual items to be remembered (e.g., faces or scenes).

Across the VDR studies, a consistent behavioural finding is that the presence of incentive cues boosts recognition memory performance. The contrasts between conditions with different incentive cues (reward/no-reward, or reward with different probabilities or magnitudes) revealed significant changes in MEG/EEG activity from 100 milliseconds (Bunzeck et al., 2011) to 1000 milliseconds (Halsband et al., 2012) following cue onset. Two studies reported significant ERP components associated with incentive cues. Elliott et al. (2020) observed a significant amplitude change in P300 following cues of different magnitudes. Marini et al. (2011) reported significant amplitude changes in N170, LPP, and the Vertex Positive Potential (VPP) when participants remember face stimuli at the presence of incentive.

3.3.2.2.3 Value-driven Attention and Working-memory (VDAW) Tasks

In the VDAW tasks, incentive cues are paired with attention or working-memory tasks to examine the effect of external values on those cognitive processes. Twelve studies used the VDAW tasks (Bachman et al., 2020; Blangero & Kelly, 2017; Heritage et al., 2018; Hinault et al., 2019; Hughes et al., 2013; Kiss et al., 2009; Lockhofen et al., 2021; MacLean & Giesbrecht, 2015; Reinhart & Woodman, 2014; Sawaki et al., 2015; Schevernels et al., 2014; Tankelevitch et al., 2020; Wei & Ji, n.d.). Most VDAW paradigms start with a cue and a target stimulus. Participants then need to identify the target from distractors or identify an item with same features as the target (e.g., colour, orientation, spatial position). Four VDAW studies used slightly different task designs. Bachman et al. (2020) and Lockhofen et al. (2021) integrated incentive cues with target stimuli. Hinault

et al. (2019) presented the incentive cues after the main stimuli in a spatial working memory task. In Hughes et al., (2013), targets and distractors were presented in a rapid serial visual presentation format following incentive cues.

We systematically summarised cue-evoked MEG/EEG activity changes between conditions with different incentive cues, because this is the common contrast in all studies. The significant time intervals of this contrast ranged from 140 milliseconds (Bachman et al., 2020; Wei & Ji, n.d.) to 1500 milliseconds (Schevernels et al., 2014) after cue onset. Several VDAW studies reported ERP amplitude changes between different incentive cues, including the N100 (Bachman et al., 2020), the P200 (Schevernels et al., 2014; Wei & Ji, n.d.), the N200 (Schevernels et al., 2014), the N2pc (Bachman et al., 2020; Hinault et al., 2019; Kiss et al., 2009; Sawaki et al., 2015), the PD (distractor positivity) (Lockhofen et al., 2021; Sawaki et al., 2015), the P300 (Bachman et al., 2020; Heritage et al., 2018; Hughes et al., 2013; Schevernels et al., 2014; Wei & Ji, n.d.), and the CNV (Hughes et al., 2013; Schevernels et al., 2014; Wei & Ji, n.d.). Two studies (Reinhart & Woodman, 2014; Tankelevitch et al., 2020) did not report specific ERP components and one study (MacLean & Giesbrecht, 2015) did not find significant main effects of reward cues.

3.3.2.2.4 Value-driven Go-NoGo (VDG) Tasks

In the VDG task, incentive cues were followed by a Go/No-Go decision, during which participants need to respond to a target or withhold their responses. Four papers used this paradigm (X.-J. Chen et al., 2019; Diao et al., 2016; Schevernels et al., 2016; Schutte et al., 2019).

MEG/EEG activities that differ between different incentives ranged from 180 milliseconds (Chen et al., 2019) to 800 milliseconds (Chen et al., 2019) and the reported ERP components were the P200 (Chen et al., 2019), the RewP (Schutte et al., 2019), the P300 (Diao et al., 2016; Schevernels et al., 2016; Schutte et al., 2019), and the P3b (Chen et al., 2019).

3.3.2.2.5 Value-driven Time Estimation (VDT) Tasks

Four papers used the VDT task (Kelley et al., 2019; Li et al., 2018; Pornpattananangkul & Nusslock, 2015, 2016), which introduced incentive cues during time estimation. Participants need to reproduce an instructed time interval, and their timing precision dictates the delivery of reward according to the incentive cue. One paper (Li et al., 2018) used a modified version of the task, where participants received a visual cue after their time estimation responses, and the cues indicate different probabilities of correct feedback. Significant MEG/EEG differences between different incentives ranged from 100 milliseconds (Pornpattananangkul & Nusslock, 2016) to 600 milliseconds (Kelley et al., 2019) after the cue onset. The related ERPs were the N200 (Pornpattananangkul & Nusslock, 2015), the RewP (Li et al., 2018) and the P300 (Kelley et al., 2019; Pornpattananangkul & Nusslock, 2015, 2016)

3.3.2.2.6 Value-driven Stroop (VDS) Tasks

Four experiments used the VDS tasks with different paradigm designs (Frömer et al., 2021; Jia et al., 2021; Krebs et al., 2013; van den Berg et al., 2014). Van den Berg et al. (2014) presented an incentive cue at the beginning of the standard Stroop task to indicate prospective outcome (reward or no reward). In a similar word colour/naming Stroop task, Krebs et al. (2013) associated certain word colour with reward or no-reward conditions, such that the word stimulus itself serves as an incentive cue. In Frömer et al. (2021), the incentive cue before the Stroop task indicates both the expected value of the reward and whether the reward is contingent on participants' performance. In Jia et al. (2021), the incentive cue is presented before a Stroop task with its congruency introduced by face stimuli and gender words.

Significant MEG/EEG differences between different incentives ranged from 100 milliseconds (Jia et al., 2021) to 1500 milliseconds (Frömer et al., 2021; Jia et al., 2021). The reported ERPs that differ between different incentives were the N100 (van den Berg et al., 2014), the P100 (Jia et al., 2021), the N200 (van den Berg et al., 2014; Krebs et al., 2013), the P300 (Frömer et al., 2021; Jia et al., 2021; Krebs et al., 2013; van den Berg et al., 2014), and the CNV (Frömer et al., 2021; Jia et al., 2021; van den Berg et al., 2014).

3.3.2.2.7 Value-directed Categorisation (VDC) Tasks

In the VDC task, an incentive cue proceeds a categorization task, during which participants categorise either words (e.g., positive or negative valence) or face stimuli (e.g., friends or strangers). Five studies used VDC tasks (Kaltwasser et al., 2013; Wei et al., 2016; Wu et al., 2019; Zhan et al., 2016, 2017). Significant MEG/EEG differences between different incentives ranged from 50 milliseconds (Wei et al., 2016) to 1500 milliseconds (Wu et al., 2019). The reported ERPs that differ between different incentives were the N200 (Zhan et al., 2016), the P200 (Kaltwasser et al., 2013), the VPP (Zhan et al., 2016), the P300 (Wei et al., 2016; Wu et al., 2019; Zhan et al., 2016, 2017), the CNV (Wu et al., 2019) and the LPP (Zhan et al., 2016).

3.3.2.2.8 Other Auxiliary Value Tasks

Three auxiliary value studies (Capa et al., 2013; Forester et al., 2020; Langeslag & van Strien, 2013) do not belong to the categories above. In Capa et al. (2013), incentive cues were presented either subliminally or supraliminally on a block-by-block basis, and the main task was arithmetic operations. They reported significant change of the CNV component between reward magnitudes, with a latency between 1100 and 1750 milliseconds after cue onset.

In Forester et al. (2020), the incentive cue was followed by a sematic decision task: choosing an option that is more appropriate according to a scenario (e.g., “broom” or “mirror” in a house moving scenario). The P300 and the Frontal Slow Wave (FSW) showed significant changes between incentive cues (reward vs no-reward).

In Langeslag & van Strien (2013), the incentive cues (a blue square or a yellow square, which yielded no reward or a small reward, respectively) were used to elicit up-regulated or down-regulated emotion responses. No main effect of reward was found.

3.3.3 Summary of Internal Value-based Decision-making Paradigms

In all IDM studies, participants made choices based on their subjective preferences or endogenous values. The 22 MEG/EEG IDM studies from the literature search can be categorized into four main types: temporal discounting tasks,

willingness-to-pay tasks, rating tasks, and forced-choice evaluation tasks. Examples are depicted in Figure 9.

3.3.3.1 Temporal Discounting (TD) Tasks

The classical TD task requires participants to choose between a small, but immediate, reward or a larger, but delayed, one (Green & Myerson, 2004; Samuelson, 1937). Consistent findings suggest that humans prefer the immediate reward but with high inter-individual variability in the rate at which rewards are discounted over time (Berns et al., 2007; Peters & Büchel, 2011). Three studies used MEG/EEG with the TD task (Gui et al., 2016; Wang et al., 2020; Yu et al., 2020). These studies reported ERPs that were sensitive to the delay or the magnitude of the prospective reward after stimulus onset. These ERPs occurred at latencies that are consistent with the P200, the N200 and the P300. Yu et al. (2020) also reported changes in the N200 amplitude between different types of reward (monetary vs food).

3.3.3.2 Willingness-To-Pay (WTP) Tasks

The WTP task is often used in financial decision research and based on the Becker-DeGroot-Marschak auction paradigm (Becker et al., 1964). In this experimental design, the participant is shown an item and is asked to "bid" a certain amount of money by choosing among the available options. The amount of money that a person is willing to spend is considered an indirect measure of preference: the bigger the amount of money, the more that item is desirable. This task is often preceded by a rating phase, meaning that some of the studies that use a BDM task belong to both the "Willingness-to-pay" and "Rating" categories (Harris et al., 2011; Roberts et al., 2018; Tyson-Carr et al., 2018). Seven of the studies included in our analysis used a BDM auction task (Goto et al., 2019; Harris et al., 2011; Jin et al., 2018; Roberts et al., 2018; L. Sun et al., 2020; Tyson-Carr et al., 2018, 2020), and the objects shown to the participants included mainly household items and food items. Three studies (Jin et al., 2018; L. Sun et al., 2020; Tyson-Carr et al., 2020) carried out EEG recordings during the BDM task, while the remaining four (Goto et al., 2019; Harris et al., 2011; Roberts et al., 2018, 2018) required the participants to carry out the WTP task during a behavioural phase of the

experiments. Nevertheless, these studies were included because they investigated VDM processes and recorded relevant brain activity with either EEG or MEG.

The most common contrast in these experiments focuses on the difference between high- and low-value items. Significant intervals range from 50 milliseconds up to 400 milliseconds and the most frequently reported ERP components are the N200, the P200 (Jin et al., 2018; Tyson-Carr et al., 2020) and the LPP (L. Sun et al., 2020).

3.3.3.3 Rating Tasks

Rating tasks require the participant to indicate which value on a scale (e.g., a Likert scale) most closely reflects the internal value they have attached to a certain item or object. Depending on how the task is framed, the individual's response can reflect different aspects, such as wanting, liking, familiarity, or pleasantness (Goto et al., 2017). These tasks are usually carried out in combination with others, such as forced-choice or BDM tasks, but in some cases they constitute the primary focus of the experimental investigation. In total, eight papers included in our analysis (Bielser et al., 2016; Goto et al., 2017; Harris et al., 2011; Harris & Lim, 2016; R. Qiu et al., 2020; Roberts et al., 2018, 2018; Tashiro et al., 2019; Tyson-Carr et al., 2018) used a rating task in their design, and in three of them (Qiu et al., 2020; Sun et al., 2020; Tashiro et al., 2019), the rating task was the main focus of the experiment.

Similar to the WTP studies, the most frequent contrast between conditions concerns the difference between high- and low-value items, which, in rating tasks, is reflected by the rating value associated to each item rather than by the size of the bid. Occasionally (Goto et al., 2017), the contrast also included medium-value items as well.

Significant intervals ranged from 135 milliseconds up to 3000 milliseconds (Goto et al., 2017), and some of the reported latencies reflect ERP components such as the P100 (R. Qiu et al., 2020; Tyson-Carr et al., 2018), the P200 (Tyson-Carr et al., 2018), the N200 (Goto et al., 2017; R. Qiu et al., 2020; Tyson-Carr et al., 2018), the P300 (Tyson-Carr et al., 2018), and the LPP (Goto et al., 2017). The remaining papers reported significant time intervals that reflected a difference in value but did not link them to

known ERP components and one paper (Roberts et al., 2018) required participants to carry out the rating task as part of the behavioural phase of the experiment, with EEG signals being recorded during a previous viewing task.

3.3.3.4 Forced-choice Preference Tasks

The last category of IDM tasks comprises so-called 'forced-choice' preference tasks, where participants are asked to choose which out of two or multiple items they prefer. In most cases, the choice is binary (e.g., 'yes' or 'no', 'want to buy' or 'don't want to buy'), but it is possible to ask participants to choose between more than two options. In our analysis, twelve papers (Bielser et al., 2016; Goto et al., 2017; Goto et al., 2019; Harris & Lim, 2016; Kawasaki & Yamaguchi, 2012; Lindsen et al., 2010; Telpaz et al., 2015; Toepel et al., 2009; Wang & Han, 2014; Wang et al., 2020; Zhao et al., 2015) used a forced-choice task, sometimes in combination with rating or WTP tasks, which is why some papers are included in multiple task categories in the current review. One paper (Telpaz et al., 2015) required participants to carry out the forced-choice task during a behavioural phase of the experiment. EEG signals were instead recorded during a previous viewing task. Most of the papers used stimuli such as food or household items, clothes, or electronic devices. In two cases (Kawasaki &Yamaguchi, 2012; Lindsen et al., 2010), the chosen stimuli were coloured circles and faces, respectively. Another paper (Harris & Lim, 2016) used a particular kind of forced-choice task called 'effort expenditure task', where participants were asked whether they wanted to exert a certain amount of effort ('high', 'medium', 'low') in order to obtain the food item displayed on the screen.

Significant contrasts concerned mainly chosen vs unchosen items, or preferred vs not-preferred items, or high vs low-value items. The associated time intervals ranged from 135 milliseconds (Bielser et al., 2016) up to 3000 milliseconds (Goto et al., 2017). Three papers (Bielser et al., 2016; Harris & Lim, 2016; Toepel et al., 2009) did not associate the significant intervals with specific ERPs. For the remaining nine studies, the reported ERP components were the N200 (Goto et al., 2017; Goto et al., 2019; Telpaz et al., 2015, *during the viewing task*), the Late Positive Potential (LPP) (Goto et al., 2017; Goto et al., 2019; Lindsen et al., 2010; Zhao et al., 2015), the Positive Slow Wave

(PSW) (Goto et al., 2017; Goto et al., 2019), the N2pc (Kawasaki & Yamaguchi, 2012), the Sustained Posterior Contralateral Negativity (SPNC) (Kawasaki & Yamaguchi, 2012), and the P300 (Wang & Han, 2014; Wang et al., 2020).

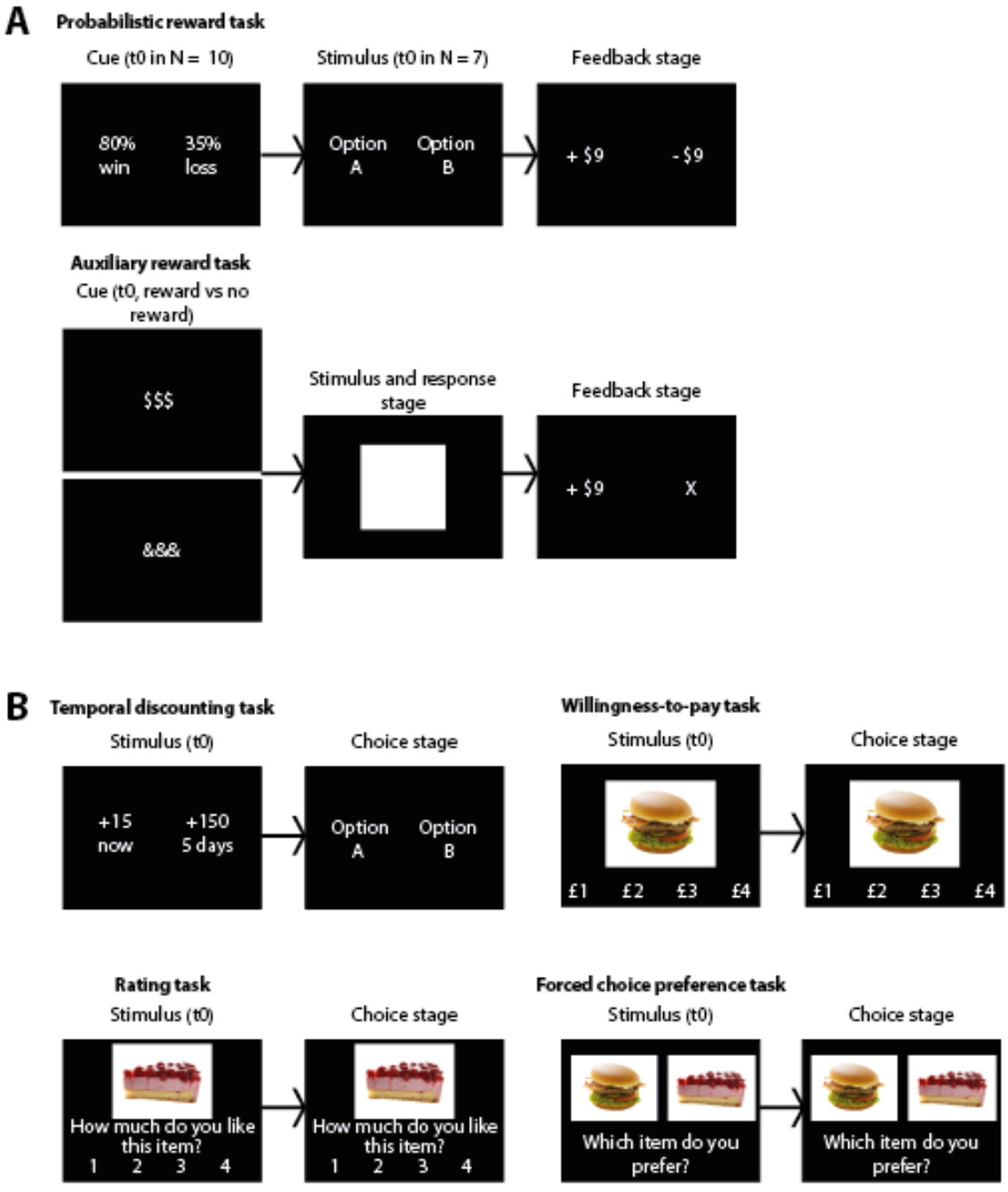


Figure 9 Examples of EDM (A) and IDM (B) paradigms.

3.3.4 Summary of Brain Areas involved in EDM and IDM Tasks

Different papers across the EDM and IDM paradigms also reported different brain areas as being involved in value-based decisions, such as: the cuneus (Doñamayor et al., 2012), the cingulate cortex (Doñamayor et al., 2012; Harris et al., 2011; Morie et al., 2014; Toepel et al., 2009; Yu et al., 2011), the motor cortex (Hunt et al., 2013), temporal (Harris et al., 2011; Tankelevitch et al., 2020) and temporo-parietal regions (Bach et al., 2017; Steffen et al., 2011), the calcarine sulcus and the cuneus (Thomas et al., 2013), frontal and prefrontal regions (Bach et al., 2017; Bielser et al., 2016; Harris et al., 2011; Reinhart & Woodman, 2014; Tankelevitch et al., 2020; Toepel et al., 2009), the orbitofrontal cortex (Bach et al., 2017; Harris et al., 2011; Harris & Lim, 2016; Reinhart & Woodman, 2014; Tyson-Carr et al., 2018), the medial frontal cortex (Silvetti et al., 2014), the insula (Bielser et al., 2016; Harris et al., 2011; Lockhofen et al., 2021; Tyson-Carr et al., 2018), the putamen (Morie et al., 2014), and the superior parietal cortex (Bielser et al., 2016).

3.3.5 Time-course across EDM and IDM Studies

We illustrate the temporal unfolding of external and internal value-based decision-making in **Figure *10***. EDM processes were divided in cue- and stimulus-locked (see Section 3.2.2 for details), while IDM tasks only reported stimulus-locked activity. Relevant M-EEG activity is reported up to 1000 milliseconds after stimulus onset.

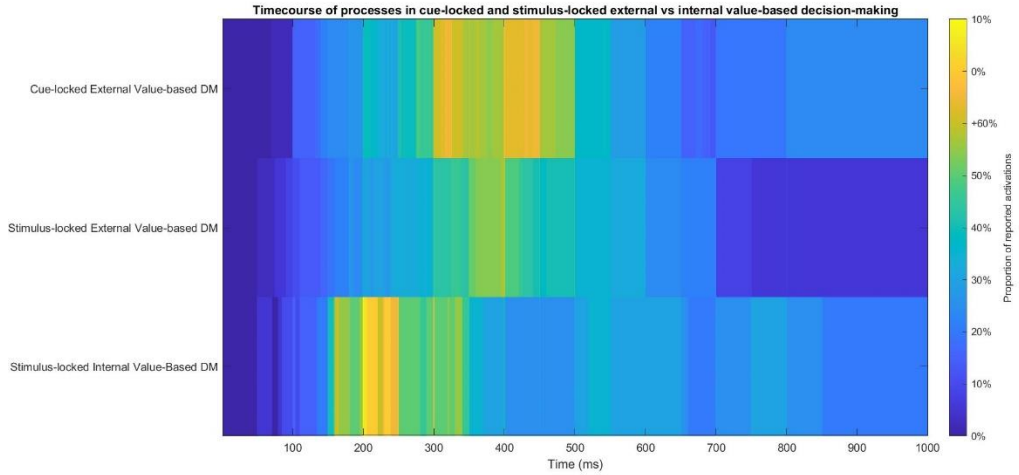


Figure 10 Time course of cue- and stimulus-locked external and internal value-based decision-making. Warmer colours indicate that a greater percentage of papers reported those time intervals as significant, whereas colder colours refer to a smaller percentage of reported activations.

Given the exploratory nature of the present review and the impossibility of conducting statistical analysis on the data, we can only make descriptive summaries on the findings. Over 60% of EDM papers reported significant intervals occurring over a larger time window (between 300 to 500 milliseconds) compared to IDM studies. This latency is consistent with ERP components such as the P300 (Apitz & Bunzeck, 2012; Dong et al., 2016; Jia et al., 2021; Schevernels et al., 2014; Zheng et al., 2017). On the other hand, more IDM papers report activations up until 1000 milliseconds (Goto et al., 2017, 2019; Harris et al., 2011; Harris & Lim, 2016; Kawasaki & Yamaguchi, 2012; L. Sun et al., 2020). Additionally, between 40% and 50% of IDM papers report significant intervals at earlier latencies than EDM studies, around 200-250 milliseconds.

3.3.6 Topographical Distribution of EDM vs IDM Processes

As explained in Section 3.2.3, we went through a process similar to the one employed to create Figure 10 in order to assess the degree of consistency with which specific electrodes were reported across EDM and IDM studies. The results of this analysis are displayed in Figure 11.

Based on the available data, in EDM studies, frontal, central, and parietal electrodes such as Fz, Cz, and Pz are the ones most consistently reported and

associated with significant cue-locked or stimulus-locked intervals. Other electrodes that are reported with a frequency between 10-15 times are F3, F4, P3 and P4. IDM studies primarily report brain activity underlying electrodes Fz and Pz, with a frequency of over 10 times. In contrast with EDM papers, Cz is not as frequently reported in IDM studies (only between 4-6 times).

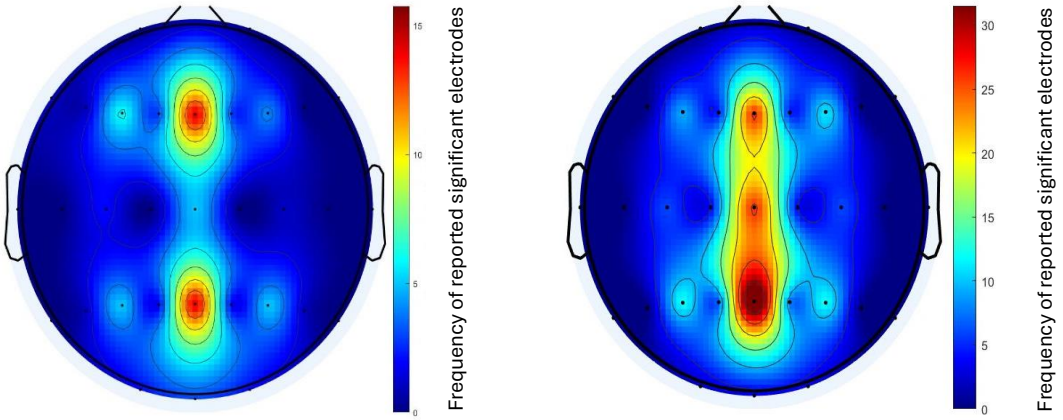


Figure 11 Topographical distribution of EEG sensors in IDM (left) and EDM tasks (right). Warmer colours indicate a higher frequency of reported activations, while colder colours refer to fewer reported activations.

3.4 Discussion

The systematic review summaries MEG/EEG evidence on human value-based decision-making. We highlighted two different types of VDM: (1) EDM, where the value of choice options is defined by an external agent (e.g. the experimenter); and (2) IDM, where decisions are based on the individual's subjective preferences. This division is based on a precedent in the literature (Nakao et al., 2012) and it is not only a useful way to categorise the tasks that have been used in the literature so far, but it also based on neurobiological evidence (see Section 2.2.2). Additionally, we have also classified EDM and IDM paradigms into subcategories and provided summaries of their characteristics and findings. One peculiar aspect concerns the 'Auxiliary reward' category, which includes those papers that did not use classical decision-making tasks, but still assessed how the value of a prospective reward affects a wide range of cognitive

processes, such as attention, working memory, categorisation, recognition memory, and executive functions.

We also reported the findings of seventeen papers that applied source-space analysis to their MEG/EEG data. Their conclusions are largely consistent with the wider fMRI and neuropsychological literature on the brain areas that have been most frequently linked to value-based decisions and they are also reflected in the sensor-space data, as frontal, central and parietal sensors are the ones most commonly implicated in EEG studies on VDM. Frontal, prefrontal, orbitofrontal and medial frontal regions, specifically, have been shown to play an important role in the computation of the single values and in their integration into the so-called 'common currency' process, which is crucial for value comparison (Bach et al., 2017; Bielser et al., 2016; Harris et al., 2011; Harris & Lim, 2016; Reinhart & Woodman, 2014; Silvetti et al., 2014; Tankelevitch et al., 2020; Toepel et al., 2009; Tyson-Carr et al., 2018). As explained in Section 2.2.3, the review by Nakao et al. (2012) suggests that these different brain areas involved in EDM and IDM tasks are part of two networks, the 'task-positive network' and the 'default mode network'. Both include the dorsomedial (dmPFC) and ventromedial prefrontal cortices (vmPFC), thus pointing to the two types of decisions as lying on the two ends of a continuum rather than being two discrete categories. The level of engagement or activation of either network seemingly depends on the specifics of the decision-making situation and on the level of attention that the individual needs to pay towards either the external or the inner environment (Nakao et al., 2012).

Therefore, our systematic findings are largely in line with the wider literature on VDM processes, concerning both their temporal dynamics and the underlying neurobiological mechanisms, thus strengthening the conclusions reached by different experiments across the field.

3.4.1 Contributions

While there are several fMRI meta-analyses and critical reviews on decision-making in general and, more specifically, on value-based decision-making (Acikalin et al., 2017; Bartra et al., 2013), there is a resounding absence of similar works in the M-

EEG literature. This is due to a few critical factors, such as the lack of standardised protocols for data acquisition, pre-processing, and data analysis in the context of MEG/EEG research, as well as the lack of strong protocols for potential meta-analytic reviews. Conversely, fMRI research benefits from a long tradition of meta-analytic methods like the Activation Likelihood Estimate (ALE) and from a certain uniformity concerning, for example, the consistent use of coordinate-based systems, which enables researchers to precisely localise the neural substrates of different neural functions across experiments. Following from this premise, the present work is original both in its scope and, partially, in its methodology, which was based on the work of Munding et al. (2015). Given this originality and the limitations intrinsic to the methods we investigated, we acknowledge that the findings presented in this chapter do not meet the strictest criteria for a systematic review.

3.4.2 Future directions

Although the present review attempts to approach M-EEG evidence on value-based decision-making data in a systematic and meaningful manner, some limitations, as well as potential future directions in this line of research, need to be addressed.

First, the current work aimed to provide a *summary* of the available M-EEG evidence on the temporal dynamics of value-based decision-making, meaning that we did not conduct any statistical analysis on the data. We are aware that there are alternative approaches, however these go beyond the scope of this review. One such approach tries to address the lack of consistency in how MEG/EEG data is reported, especially pertaining to how measurements are conducted and how the intervals of interest are defined. This method was proposed by Sambrook & Goslin (2015) who conducted a meta-analysis to examine the ERP component known as the Feedback Related Negativity (FRN) across EEG studies and developed the 'great grand average' (GGA) method. This approach relies on extracting the grand average waveforms (i.e., the average waveform computed from all the subjects of a study) from all the studies included in the analysis and averaging them to obtain 'great grand average' waveforms. The GGA approach is a good candidate for future meta-analyses of EEG data, and it could be expanded to include ERF components from MEG studies. Nonetheless, the

use of this technique was not in line with the aims of the present review, since our work focuses on the temporal evolution of EDM and IDM processes, rather than on the discrete components.

Another limitation of the present review concerns the disparity in the numbers of papers that have been classified as EDM or IDM studies, with 76 and 21 papers, respectively. This means that internal value-based decision-making processes are potentially understudied in the current literature. We therefore encourage researchers to focus on this particular type of decisions, since experiments on this topic would help deepen our understanding of decision-making and might lead to the development of novel tasks, as well.

A third limitation concerns the difficulties of linking significant ERP components to putative brain processes. One frequent issue we have encountered during the analysis is the lack of consistency in the ERP nomenclature. In fact, there is very little accord across papers over the exact names of the functions that different ERPs supposedly reflect, which invariably affects any attempts to draw commonalities across papers. For example, the P300 component has been associated with attention (Polich, 2003) , event memorability (Donchin, 1981), stimulus uncertainty (Sutton et al., 1965), conscious perception (Rutiku & Bachmann, 2017), and context updating (Donchin & Coles, 1988), to name only a few. Consequently, we have not dived into this specific aspect of the ERP literature and, instead, narrowed our focus to those experimental contrasts that reflected differences in internal or external value, without drawing inferences about which cognitive processes underlie the time intervals of interest.

In addition to highlighting the limitations of the present work, future directions should also be stressed. Since techniques such as fMRI, MEG, EEG, single- or multi-cell recordings only allow researchers to draw correlational conclusions, we believe that the field of decision-making research would benefit from the development of works similar to the current one that focus on methodologies such as transcranial magnetic stimulation (TMS) or transcranial electrical stimulation (TES), which might enable

scientists to make stronger casual inferences about how different brain areas contribute to decisional processes.

We also believe that our approach could open new avenues of systematic research on the topic, as the focus of the present review could be further expanded by considering the temporal dynamics of decision-making processes in clinical populations affected by disorders such as Attention-deficit and Hyperactivity Disorder (ADHD), Parkinson's disease and schizophrenia. Some works have been published on differences on ERP/ERF components between patients and healthy controls (Bramon et al., 2004; Y. Qiu et al., 2014) but, to our knowledge, no reviews or meta-analyses have specifically examined these differences in the specific context of decision-making.

Finally, it is worth highlighting that Chapters 5, 6, and 0 will address some of the key questions raised here, namely how external and internal values interact with one another at the behavioural and neural level (Chapters 5 and 6) as well as expanding upon the neural substrate of one of the IDM categories identified in this review, i.e., forced-choice preference tasks (Chapter 0).

3.5 Conclusion

MEG/EEG data, with its high temporal resolution, can offer useful complementary evidence on the temporal dynamics of value-based decision-making processes, thus enriching the available fMRI evidence on the topic. This review aims to be one of the first works to assess electro- and magneto-physiological evidence on said processes in a systematic manner.

Our theoretical framework is based on a precedent in the literature (Nakao et al., 2012) , where value-based decisions were divided into 'externally-guided' and 'internally-guided'. We slightly changed this nomenclature into 'external' and 'internal' value-based decision-making processes, to indicate whether the values of the available options are set by an external agent or by the individual themselves depending on their personal preferences. We further classified the paradigms included in each of these two categories depending on their specific characteristics and the underlying rationales. This in-depth description shows, on the one hand, how diverse the literature

on the topic is and, on the other hand, which specific paradigms have been most consistently used to inform our understanding of decisional processes. The next Chapters will focus on exploring the behavioural and neural correlates of both externally and internally-guided decisions.

4 Does size matter? Investigating the roles of size and value in food preference choices

4.1 Introduction

In Chapter 2 we established, many studies have examined perceptual and value-based decision-making separately, where individuals are asked to respond either according to an objective criterion (perceptual decisions) or according to higher-order factors, such as the probability of gaining a reward and/or their personal preferences (value-based choices) (Cohen et al., 2007; Dutilh & Rieskamp, 2016; Nakao et al., 2012). Compared to perceptual decisions, value-based decisions can be influenced by a multitude of more complex factors, e.g., the cost and effort that one must employ to gain something, the probability of a positive or negative outcome, the uncertainty and ambiguity of the decision context, as well as the internal value that an individual attaches to the available options, which might not be a static feature of decision processes nor be driven by purely rational computations as one might intuitively think (Hamlin, 2010; Polanía et al., 2019; Roefs et al., 2018; Voigt et al., 2019).

As will be seen also in Chapters 5, 6, 0, the type of value-based decisions at the centre of this chapter concerns food-related choices, which are especially important because of how significant they are to the continued survival of an organism. Unsurprisingly, food is considered a primary reinforcer that drives motivated behaviour (Burger et al., 2011; Kumar et al., 2016; Spetter et al., 2020; Zald, 2009). As such, food choices have been investigated by multiple disciplines that span from consumer science to (neuro)marketing, economics, psychology, and medicine (Bartels & Johnson, 2015; Chater, 2015; Gere et al., 2020; Golnar-Nik et al., 2019), and with different methodologies, namely surveys and questionnaires, eye-tracking equipment and

neuroimaging techniques (Cherubino et al., 2019; Moya et al., 2020; Nelson et al., 1994).

This multidisciplinary approach has enabled researchers to investigate different facets of food-related choices, relating to both their value-based and perceptual characteristics (e.g., features of the packaging, such as size, colour, and labels, and portion size perception) (Aydinoğlu & Krishna, 2011; Beran et al., 2008; Dai et al., 2020; Parrish et al., 2015; Peschel & Orquin, 2013; van Koningsbruggen et al., 2011; Vandenbroele et al., 2019). This illustrates how the study of food choices often sits at the crossroads between perceptual and value-based decision-making, therefore, further studies on the topic could inform ongoing debates on the degree of overlap between the two processes. However, despite the wealth of information accumulated so far, some features of food choices have not been explored as frequently as others previously mentioned in this section. One such aspect concerns whether the subjective value associated with a food item and its perceived surface size have an impact on decision-making behaviours, either as single factors or in an interactive manner (Parrish et al., 2015; Peschel & Orquin, 2013). Addressing this will constitute an ulterior step towards assessing the potential interactions between the perceptual and the value-based decisional domains (see Section 2.2.1). To that end, the present chapter attempts to answering the same question, in different ways, in Experiment 1 and Experiment 2: do these two sources of information (size and value) interact to influence accuracy (i.e., the consistency between choices and initial ratings)?

4.2 Experiment 1

The aim of the first experiment is to investigate whether value-based and perceptual features have a separate or joint influence on decisional processes. To do so, we designed a rating task where we asked participants to indicate how much they prefer one item over the other, while we manipulated the surface size of the stimuli.

4.2.1 Hypotheses

Our hypotheses are encapsulated in the following statements: first, as the difference in subjective values between two food items increases, the preference rating towards the more preferred item increases. Secondly, as the size difference between two food items increases, the preference rating for the bigger item increases (Chen et al., 2013; Draper & Menzel, 1965; Menzel, 1960; Peschel & Orquin, 2013). Thirdly, the subjective value difference between the two items interacts with the total value magnitude (i.e., the sum of the preference ratings) with regards to preference ratings. Finally, the subjective value difference interacts with the size difference between the two items to influence preference ratings.

4.2.2 Method

Ethical permission for both experiments was obtained from the University of Cardiff Research Ethics Committee. The experiment was preregistered on the Open Science Framework – (https://osf.io/tg3h9) – and the anonymised data and code can be found in the project repository – (https://osf.io/8jvrf/). Where relevant, we report deviation from preregistration plans.

4.2.2.1 Participants

Participants were recruited via the Prolific platform (https://www.prolific.com/). The participants had to be English-speaking adults, with no chronic or long-term illnesses or mental health conditions. Participants, including those that were prematurely rejected for not meeting the preregistered inclusion criteria, were paid the equivalent of £6.50/h.

We aimed to recruit 130 participants, as per our preregistered plan (see Section 4.5.3). 199 participants started the task, of which 38 were prematurely rejected during the experiment and a further 31 were excluded after data collection (see 4.5.4 for exclusion criteria), ending up with the desired 130 participants (Age: Mean = 27.27, SD = 8.61; Gender: 78 male, 79 female, 4 unknown; Height, in cm: M = 170.29, SD = 19.37; Weight, in kg: M = 75.69, SD = 21.35; BMI: M = 26.18; SD = 7.64)

4.2.2.2 Design

We conducted a within-subjects design with the size difference between food items as the critical experimental manipulation. The size of each food item is defined as the proportion of the area taken by the actual food picture (i.e. non-white pixels, given that the background is white[1]. Each food item picture had eight sizes: 0.10, 0.16, 0.22, 0.28, 0.34, 0.40, 0.46, 0.52 (see **Figure *12***). Using these sizes for each image in the test trials, we manipulated the difference between the sizes of the two items, such that it corresponded to one of seven values: 0, 0.06, 0.12, 0.18, 0.24, 0.30 or 0.36.

4.2.2.3 Stimuli

The experiment used food pictures from the Food-Pics database (Blechert et al., 2019). To select the images for the current experiment, we looked at the size category of the original image (calculated by the original authors of the database). We only selected images with a size category of 0.35 (+/-0.007). Thirty-five food images from the Food-Pics database were found, of which we selected 30 for the current experiment. Each selected image was modified to have nine different sizes: one for each of the eight size categories and one additional size, set to 0.31 (Panel A - **Figure *12***). The 0.31 size was not used in the main decision task (Stage 2), but only displayed during Stages 1 and 3 when the participants rated their preference for individual items. Each food picture was displayed on a white background, forming an image with a width-to-height ratio of 4:3. During the experiment, each image was presented with a fixed width such that it represented a fixed percentage of the user's screen (see Section 4.2.2.4).

4.2.2.4 Procedure

The experiment followed a procedure consisting of three main stages (Figure 12). In the first stage (Panel B), the participants rated their preference for each of the 30 food

[1] We acknowledge that count of non-white pixels is likely not the most accurate measure of size of food item relative to background as some food items might contain background-coloured pixels in themselves (e.g. bread), but upon a visual inspection of all images, we did not find this to be a significant issue.

pictures, twice. In the second stage (Panel C), participants made multiple comparative judgements on a continuous scale to indicate their preference for 15 items from the first stage. In the third stage, participants again rated their preference for each of the 30 food items. The experiment was written and conducted in jsPsych v6.3.0 (de Leeuw, 2015).

The minimum screen size that was allowed for the experiment was set to 768 pixels width and the minimum allowed height was set to 40% of the participant's screen width plus 150 pixels, in order to ensure that the experiment's content appeared smoothly without the need to scroll.

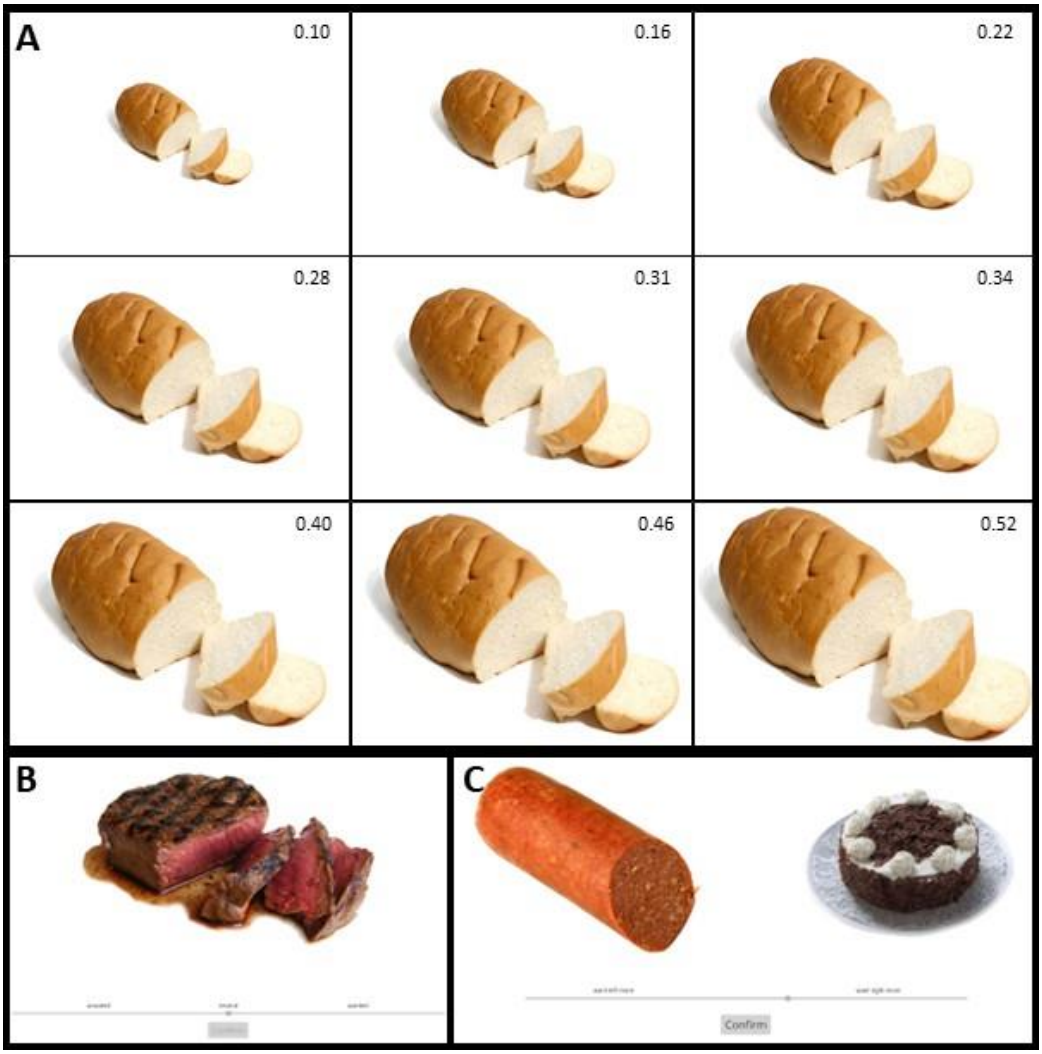


Figure 12 Experimental design. Panel A shows an example of an image in all its different size versions. Panels B and C depict different stages in the experiment. Panel C shows Stages 1 and 3, respectively, in which participants rated their level of preference for each individual food item. Panel B depicts Stage 2, in which participants made preference choices between two food items of varying sizes.

Stage 1: Initial Rating. Participants performed two consecutive rounds of preference ratings of the 30 images on a continuous scale from 1 to 100. Item presentation was randomized between participants and also for each of the two iterations within-participant. The participants were informed that their ratings between repetitions had to be similar enough. If the ratings were not similar enough, defined by a Spearman rho <.20, the participant was rejected prematurely.

On each rating trial, a food stimulus was presented in the centre of the screen, such that the entire image width (including the white background) represented 55% of the user's screen. During this stage, the image size category was fixed to 0.31, meaning that the food picture represented 31% of the entire image (which in turn represented 55% of the user's screen). A rating scale, spanning 70% of the user's screen, was presented below the image with equidistant labels above the scale. The labels were "unwanted", "neutral", and "wanted". Participants used a mouse to drag or click on the scale. After making their selection on the scale, participants had to click a "confirm" button to continue to the next trial. There was no time limit for the response.

Stage 2: Main Task. 15 images out of the 30 total images rated in Stage 1 were selected. To select the images the following algorithm was used: first, all items from Stage 1 whose average rating was between 5 and 95 were selected, thus excluding if those items that received extreme ratings. If there were fewer than 15 items matching this condition, the participant was prematurely rejected. Then the selected items were ordered in ascending order according to their distance from their mean. The first (up to) 20 items that were closest to the mean were selected and a random set of 15 from those 20 items was selected as the final items to be shown in Stage 2. The reason for this level of control was to introduce a degree of variability in the rated items across participants. During the choice task, the seven size difference categories were each shown 50 times, resulting in 350 test trials.

To create a single test trial, the following conditions had to be met: 1) the two randomly selected food items (out of the 15) could not be the same, 2) the current trial did not already exist (i.e. trials are unique), and 3) the previous three trials did not

contain any of the two current trial's food items. Another set of 50 trials was added as distractor trials. These contained random food items from the Food Pics database, which were selected based on the condition that they were different from the 30 items shown in Stage 1. The 50 trials were interspersed throughout Stage 2 such that they appeared in a random position on every seven trials. The final number of trials in Stage 2 was 400, which were divided into five blocks with self-paced breaks.

On each trial, two side-by-side images were presented in the centre of the screen, such that each image's width (including the white background) represented 45 of the user's screen. Participants were asked to make a choice between the two items on a continuous scale from -100 to 100 (the numbers were not displayed to participants), which spanned 70% of the user's screen with equidistant labels placed above. The labels were "want left more" and "want right more". Similar to the rating phase, participants used mouse clicks to move left and right along the scale. The trial was completed after pressing a "confirm" button. Participants had a time limit of 5000 ms to make a judgement. If no response was provided in time, a prompt saying "Please respond faster" was presented for 500 ms, after which the next trial was presented.

Stage 3: Final Rating. Identical to Stage 1, where participants provided their preference ratings on the 30 individual food items.

Stage 4: Questionnaires. Participants were asked to provide their weight (in kg) and height (in cm). Then they completed the full Adult Eating Behaviour Questionnaire (Hunot et al., 2016), which is a 32-item questionnaire tapping into eight appetitive traits (hunger, food responsiveness, emotional over-eating, enjoyment of food, satiety responsiveness, emotional under-eating, food fussiness and slowness in eating), of which we use three (food responsiveness, enjoyment of food, and food fussiness) in the current analyses.

4.2.2.5 Analytical Strategy

Analyses were conducted using the R programming language (Ripley, 2001). The core packages used were tidyverse (Wickham et al., 2019), lme4 (Bates, 2010), psych (Revelle, n.d.), and ggplot2 (Wickham, 2016). To test our hypotheses, we constructed a

linear mixed effects model. For advantages of these models over traditional analyses of variance, see Baayen et al. (2008), Bates et al. (2018), Kliegl et al. (2010, 2011). There were three independent variables:

1 Value conflict, defined as 100 (i.e., the maximum value) minus the absolute difference between the average preference ratings given in Stage 1 of the two images;
2 Value magnitude, defined as the sum of the average preference ratings given in Stage 1 of the two images;
3 Size conflict, defined as 0.36 (i.e., the maximum value; or 0.42 for Experiment 2 in order to scale to the 0.06-0.36 range) minus the absolute difference between the sizes of the two images (for why we decided to use absolute difference see[2]).

In building each model, we had the same core structure for fixed and random effects: the fixed effect structure included all three independent variable and their interactions, while the random effect structure included a by-participant random intercept and a by-participant random slope for each of the main effects of the three independent variables.

The first model we built attempted to provide insights into why participants provide the ratings that they give[3]. To that end, we used the absolute value of the slider rating as a dependent variable, transformed so that positive and negative values represent correct and incorrect responses, respectively, while the value itself is the absolute value of the rating provided on the scale. The fixed and random effects structures were the same as the core ones specified above.

[2] Using absolute transformation was not preregistered but was added subsequently as otherwise the modelling was non-sensical (see Appendix A).

[3] This model was partly preregistered, but further transformations were done as the preregistered plan was not sensibly specified (see Appendix A).

The second model we built attempted to assess how accurate participants are in their comparative judgements[4]. To do that we constructed a new variable, called choice bias. This measure allowed us to estimate how much participants over- or under-estimated their preference on each test trial compared to their initial preference given in Stage 1. Choice bias (CB) was calculated as a function of the raw slider rating and the participant's Stage 1 ratings, as follows:

$$CB_t = \begin{cases} R_t - (IR_{right} - IR_{left}), & \text{if } preferred_t = right \\ -(R_t - (IR_{right} - IR_{left})), & \text{if } preferred_t = left \end{cases}$$

Equation 1 Choice bias equation

where at trial *t*, CB_t is the choice bias, R_t is the slider rating response, and *IR* is the initial rating of the right or left item based on Stage 1. Positive and negative values represent over- and under-estimation, respectively, based on Stage 1 ratings.

For each model, model comparisons were conducted to identify the most parsimonious model that accounted for the data. To prevent model overfitting, three raw statistics were used: the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), both of which are punishing indices (i.e. lower values indicate better fit), and the log likelihood (where higher values indicate better fit). Moreover, the percent of explained variance of each random effects factor was estimated (using the rePCA function in *lme4*) and those that explain little to no variance were considered as candidates for removal. Model comparisons were conducted between nested models (Pinheiro & Bates, 2006), using the ML algorithm, as recommended by the *lme4* package. Significance was evaluated using a chi^2-distributed likelihood ratio and its associated p-value (if two nested models are not significantly different, then the simpler one is preferred).

[4] We did not preregister this model.

Concerning the plotting of the results of the models, the slope for each main effect, predicted from the model, is plotted. Although all variables are scaled and centred when inputted in the models, they are back transformed before plotting. All fitted values are limited to [-100; 100]. When plotting interaction between two continuous variables, one of them is fixed at specific values, i.e., the mean, one standard deviation above and one below the mean (as recommended by Aiken et al. (1991)) as well as minimum and maximum values.

4.2.3 Results

The two mixed-effects models specified in Section 4.2.2.5 were run. The results of the final models are displayed in Table 2.

Predictors	**Absolute model**			**Bias model**		
	Estimates	95% CI	*p*	Estimates	95% CI	*p*
Value magnitude	0.23	0.17 – 0.29	**<0.001**	0.24	0.18 – 0.31	<0.001
Value conflict	-0.57	-0.61 – -0.53	**<0.001**	-0.24	-0.28 – -0.20	<0.001
Size conflict	0.00	-0.01 – 0.01	0.631	0.00	-0.01 – 0.01	0.470
Value magnitude x Size conflict	0.00	-0.01 – 0.00	0.293	-0.01	-0.01 – 0.00	0.277
Value magnitude x value conflict	-0.15	-0.16 – -0.13	**<0.001**	-0.14	-0.15 – -0.12	<0.001
Size conflict x value conflict	0.00	-0.01 – 0.01	0.921	0.00	-0.01 – 0.01	0.446
Value magnitude x size conflict x value conflict	0.00	-0.01 – 0.00	0.277	-0.01	-0.02 – 0.00	0.127

Table 2 Results of the Absolute and Bias model on predicted slider ratings.

4.2.3.1 Model 1 – Absolute Model

Upon running the model, it failed to converge, and it was noted that one of the by-participant random slope, namely the size conflict one, accounted for little to no variance (≈0.1%), hence it was considered for removal. Removing this slope did not lead

to a significant loss of explanatory power, $\chi 2(4) = 2.41$, $p = .661$. There were no other identifiable reasons to further reduce the model.

The final model included three significant effects (Figure 13). The first one was a main effect of value magnitude, $\beta = 0.23$, $p < .001$, suggesting that as the value magnitude on a given trial increases, so does the participant's slider rating, meaning that their responses are more accurate with respect to the Stage 1 ratings. The second significant effect was a main effect of value conflict, $\beta = -0.57$, $p < .001$, suggesting that as the value conflict on a given trial increases (i.e., the difference in ratings between items becomes smaller), the participant's slider rating decreases, indicating lower accuracy. These two main effects were qualified by a significant value conflict by value magnitude interaction, $\beta = -0.15$, $p < .001$, suggesting that even if we keep one of the two variables (value conflict or value magnitude) constant, the other displays a negative relationship with the slider rating. All other effects, including any effects related to size conflict, were not significant.

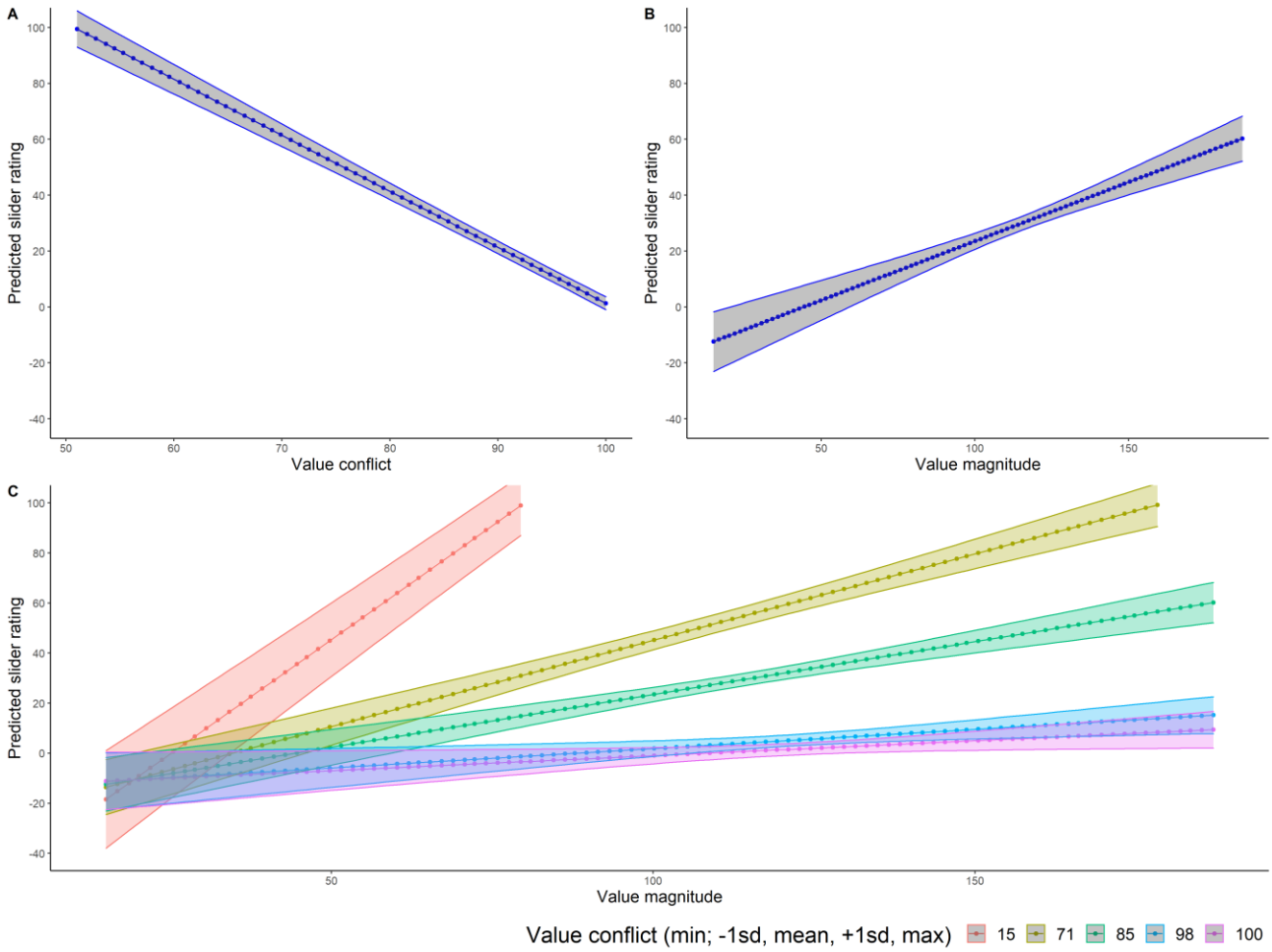


Figure 13 Plots depicting the 3 significant effects on predicted slider rating from Model 1 – Absolute model in Experiment 1. Lines depict predicted values from the model with 95% CIs. Panel A shows the main effect of value conflict, Panel B shows the main effect of value magnitude and Panel C represents the value conflict by value magnitude interaction.

4.2.3.2 Model 2 - Bias Model

Upon running the model, it failed to converge and was noted that one of the by-participant random slope, namely the size conflict one, accounted for little to no variance (≈ 0%), hence it was considered for removal. Removing this slope did not lead to a significant loss of explanatory power, $\chi^2(4) = .88$, $p = .927$. There were no other identifiable reasons to further reduce the model.

The final model included three significant effects (see Figure 14). The first one was a main effect of value magnitude, $\beta = 0.24$, $p < .001$, suggesting that as the value magnitude on a given trial increases, so does the participant's bias to overestimate the true value difference. The second significant effect was a main effect of value conflict, β

= -0.24, $p < .001$, suggesting that as the value conflict on a given trial increases, so does the participant's bias to underestimate the true value difference. These two main effects were qualified by a significant value conflict by value magnitude interaction, $\beta = -0.14$, $p < .001$, suggesting that even if we keep one of the two variables (value conflict or value magnitude) constant, the other still has a significant relationship with the participants' bias to underestimate the true value difference. All other effects, including any effects related to size conflict, were not significant.

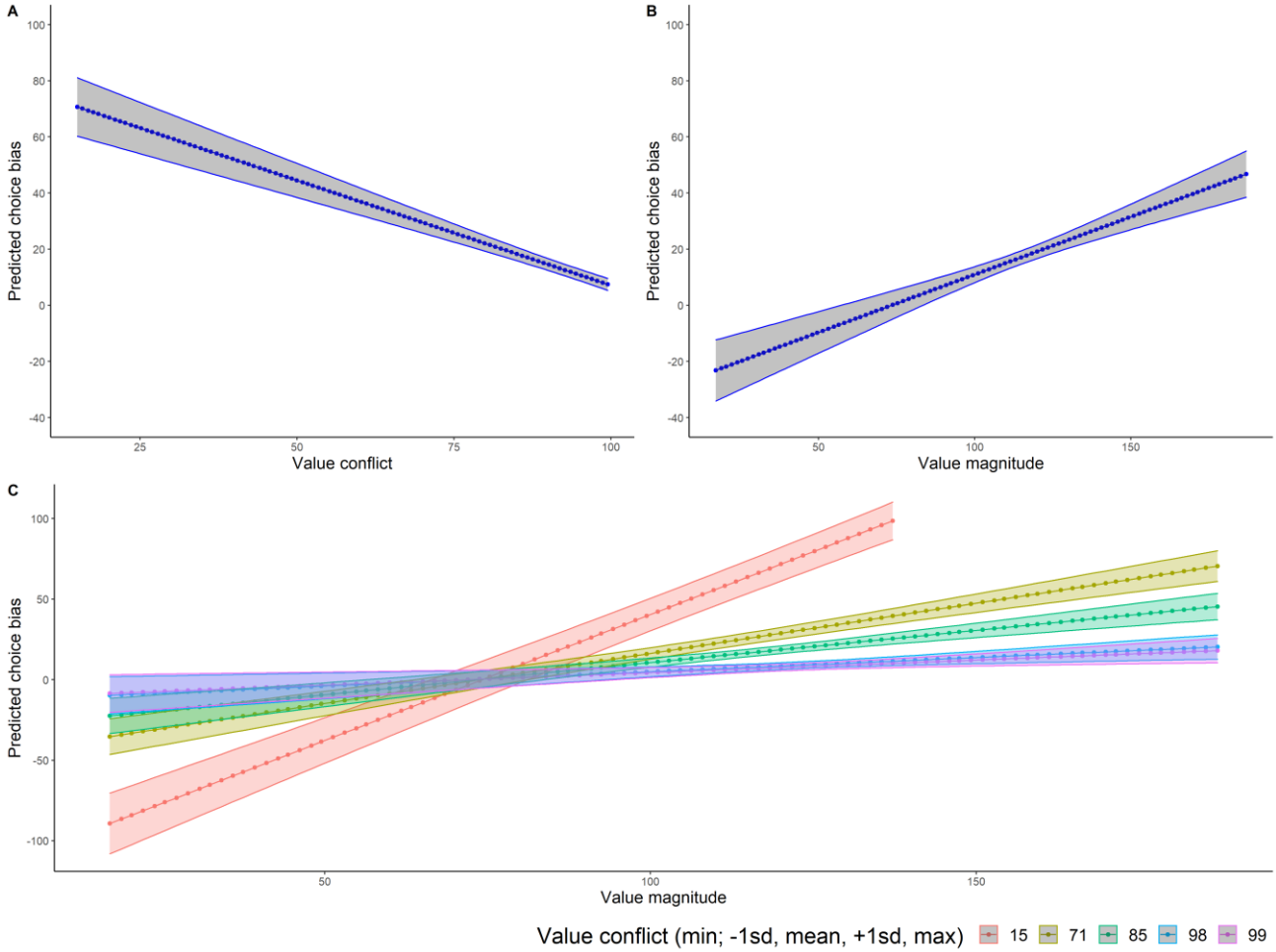


Figure 14 Plots depicting the 3 significant effects from Model 2 – Bias model in Experiment 1. Lines depict predicted values from the model with 95% CIs. Panel A shows the main effect of value conflict, Panel B - the main effect of value magnitude and Panel C – the value conflict by value magnitude interaction.

4.2.4 Summary

The findings of Experiment 1 show a clear picture, namely that participants were unaffected by the surface size of the stimuli and that the bottom-up perceptual

information did not play a role during the decision-making process. This is evidenced by a lack of size-related significant main effects or interactions with value-related information. Consequently, we cannot reject the null hypothesis that there is no relationship between a bigger surface size and an increase in preference ratings. Similarly, our data leads us to reject the hypothesis that there would be an interaction between the differences in subjective values and the size difference of the two items.

Preference-based variables, on the other hand, were statistically significant, including the interaction between value magnitude and value conflict. This suggests that value-related information was the main parameter that guided the participants' decisions, implying a dissociation between the two domains.

With regards to the research question we posed in the Introduction - i.e., do these two sources of information (size and value) interact to influence accuracy (i.e., the consistency between choices and initial ratings)? - Model 1 shows that value magnitude, value conflict and their interaction were all statistically significant in relation to the participants' predicted slider ratings. The positive relationship between value magnitude and the ratings means that participants tend to confirm their preferences, especially when faced with two stimuli that are both highly rated (i.e., a situation with both high value magnitude and value conflict), in order to reduce the uncertainty provoked by these ambiguous choices (O'Hora et al., 2016; Voigt et al., 2019; Zajkowski et al., 2019). On the other hand, we also see that higher value conflict results in lower predicted ratings, suggesting that participants become less accurate when two items are very close in value, regardless of the size difference.

Model 2, instead, introduces the choice bias variable to assess the participants' consistency with their Stage 1 preference judgements. Again, value magnitude and value conflict, as well as their interaction, were statistically significant effects. Concerning value magnitude, we see once again a positive relationship, whereby the participants' have a tendency to overestimate the true value difference between items and to attach a higher than before rating to one of the two items, especially in ambiguous contexts. Conversely, in the context of value conflict and its interaction with

value magnitude, participants tended to underestimate the true value difference between items. Surface size did not play a role in either model, highlighting a dissociation between the perceptual and value-based decisional domains.

4.3 Experiment 2

The results of Experiment 1 seem to point towards a dissociation between the two decisional domains, at least when we consider whether the perceptual domain affects the value-based one. Therefore, this begs the question of whether this is a single or a double dissociation between decisional processes. In Experiment 2, we investigate whether value-related information plays a role when participants are asked to make size-based perceptual decisions. The structure of the task is identical as in Experiment 1, to ensure a good degree of comparability between the two experiments, but participants are instead asked to rate the size difference between the two items rather than their preference.

4.3.1 Hypotheses

The hypotheses of Experiment 2 are expressed in the following statements: As the size difference between two food items increases, the size rating for the bigger item increases. As the size magnitude (the sum of the sizes of two images) increase, the size rating for the bigger item increases. Moreover, the size difference and the size magnitude interact to influence size ratings. The value difference and the size difference interact to influence size ratings. Finally, the value difference and the size magnitude interact to influence size ratings.

4.3.2 Method

The experiment was preregistered on the Open Science Framework – https://osf.io/hq4nb - and the anonymised data and code can be found in the project repository – https://osf.io/8jvrf/. Where relevant, we report deviation from preregistration plans in the footnotes.

4.3.2.1 Participants

Participants were recruited and reimbursed in the same way as Experiment 1.

We aimed to recruit 130 participants, as per our preregistered plan. 202 participants started the task, of which 34 were premature rejected during the experiment and further 38 were excluded after data collection, ending up with the desired 130 participants (Age: *M* = 31.2, *SD* = 10.3; Gender: 91 male, 39 female; Height, in cm: *M* = 174.6, *SD* = 9.0; Weight, in kg: *M c*= 75.1, *SD* = 17.4; BMI: *M* = 24.5; *SD* = 4.7)

4.3.2.2 Design

In Experiment 2, participants were asked to make size judgments instead of preference ones.

4.3.2.3 Stimuli

Same as Experiment 1.

4.3.2.4 Procedure

Same as Experiment 1, with the only difference being that in Stage 2 participants were now asked not to rate their preference between two items, but rather to rate which food item was bigger relative to a thin black border around the image. Participants were explicitly instructed to consider the size of the image as it appeared on the screen relative to its border, not the size of the item in real life.

4.3.2.5 Analytical Strategy

Same as Experiment 1, with the only difference being that for Model 2 the dependent variable was not choice bias, but a functionally similar variable, which we call discriminability bias. This measure, same as choice bias, allowed us to estimate how much participants over- or under-estimated the true size difference between the two food items on each test trial in Stage 2. Discriminability bias (DB) was calculated as a function of the raw slider rating and the true size difference between the two images, as follows:

$$DB_t = \begin{cases} R_t - (scale(true\ size\ difference)), & \text{if } bigger_t = right \\ -(R_t - (scale(true\ size\ difference))), & \text{if } bigger_t = left \end{cases}$$

Equation 2 Discriminability bias equation

where at trial *t*, DB_t is the discriminability bias, R_t is the slider rating response, and scaling function transforms the true size difference between the images to [-100; 100] (same as the slider rating response). Identically to choice bias, positive and negative values represent over- and under-estimation, respectively, relative to the true size difference.

4.3.3 Results

The results of the final mixed-effects models, as specified in the Analytical strategy, are in Table 3.

Predictors	**Absolute model**			**Bias model**		
	Estimates	95% CI	*p*	Estimates	95% CI	*p*
Size magnitude	-0.02	-0.04 – -0.01	**0.003**	-0.02	-0.04 – -0.01	**0.003**
Size conflict	-0.45	-0.47 – -0.42	**<0.001**	0.51	0.49 – 0.53	**<0.001**
Value conflict	-0.01	-0.01 – 0.00	0.239	-0.01	-0.01 – 0.00	0.239
Size magnitude x Size conflict	-0.01	-0.02 – 0.00	**0.014**	-0.01	-0.02 – 0.00	**0.014**

Size magnitude x value conflict	-0.01	-0.02 – 0.00	0.282	-0.01	-0.02 – 0.00	0.282
Size conflict x value conflict	0.00	-0.01 – 0.01	0.461	0.00	-0.01 – 0.01	0.461
Size magnitude x size conflict x value conflict	0.00	-0.01 – 0.01	0.742	-0.01	-0.01 – 0.01	0.742

Table 3 Results of the Absolute and Bias model on predicted slider ratings.

4.3.3.1 Model 1 – Absolute model

Upon running the model, it failed to converge and was noted that one of the by-participant random slope, namely the value conflict one, accounted for little to no variance (≈ 0.3%), hence it was considered for removal. Removing this slope did not lead to a significant loss of explanatory power, $\chi^2(4) = 9.12$, $p = .058$. There were no other identifiable reasons to reduce the model any further.

The final model included three significant effects (**Figure *15***). The first one was a main effect of size magnitude, $\beta = -0.02$, $p = .003$, but the beta coefficient is quite small and negative. Additionally, Panel B of Figure 13 shows that the data points do not reflect a linear relationship, but rather a nonlinear one, suggesting that our model was not successful in capturing the actual dynamics of perceptual information in decision-making. The second significant effect was a main effect of size conflict, $\beta = -0.45$, $p < .001$, suggesting that as the size conflict on a given trial increases, the participant's slider rating decreases, indicating that participants had overall lower accuracy (negative values here represent incorrect responses). These two main effects were qualified by a very small but statistically significant size conflict by size magnitude interaction, $\beta = -0.01$, $p = .014$. All other effects, including any effects related to value conflict, were not significant.

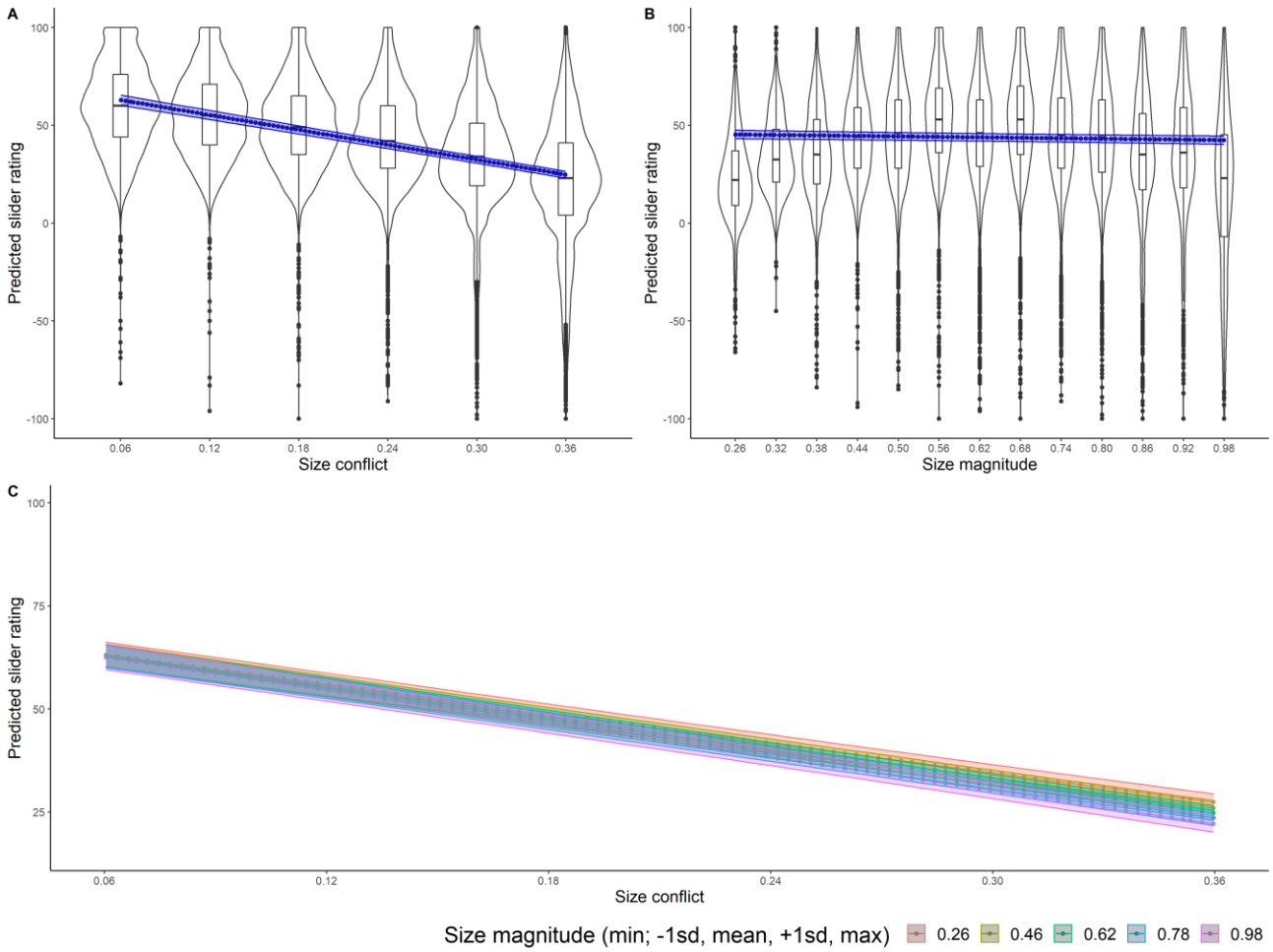


Figure 15 Plots depicting the 3 significant effects from Model 1 – Absolute model in Experiment 2. Violin boxplots show the raw data. Lines and points depict predicted values from the model with 95% CIs. Panel A shows the main effect of size conflict, Panel B shows the main effect of size magnitude and Panel C reflects the size conflict by size magnitude interaction.

4.3.3.2 Model 2 – Bias model

Upon running the model, it was noted that one of the by-participant random slope, namely the value conflict one, accounted for little to no variance (≈0.3%), hence it was considered for removal. Removing this slope did not lead to a significant loss of explanatory power, $\chi^2(4) = 9.12$, $p = .058$. There were no other identifiable reasons to further reduce the model.

The final model included three significant effects (see **Figure *16***). The first one was, once again, a very small but statistically significant main effect of size magnitude, $\beta = -0.02$, $p = .003$. The second significant effect was a main effect of size conflict, $\beta = 0.51$, $p < .001$, suggesting that as the size conflict on a given trial increases, so does the

participant's bias to overestimate the true size difference. These two main effects were qualified by a very small but significant size conflict by size magnitude interaction, β = -0.01, p = .014. All other effects, including any effects related to value conflict, were not significant.

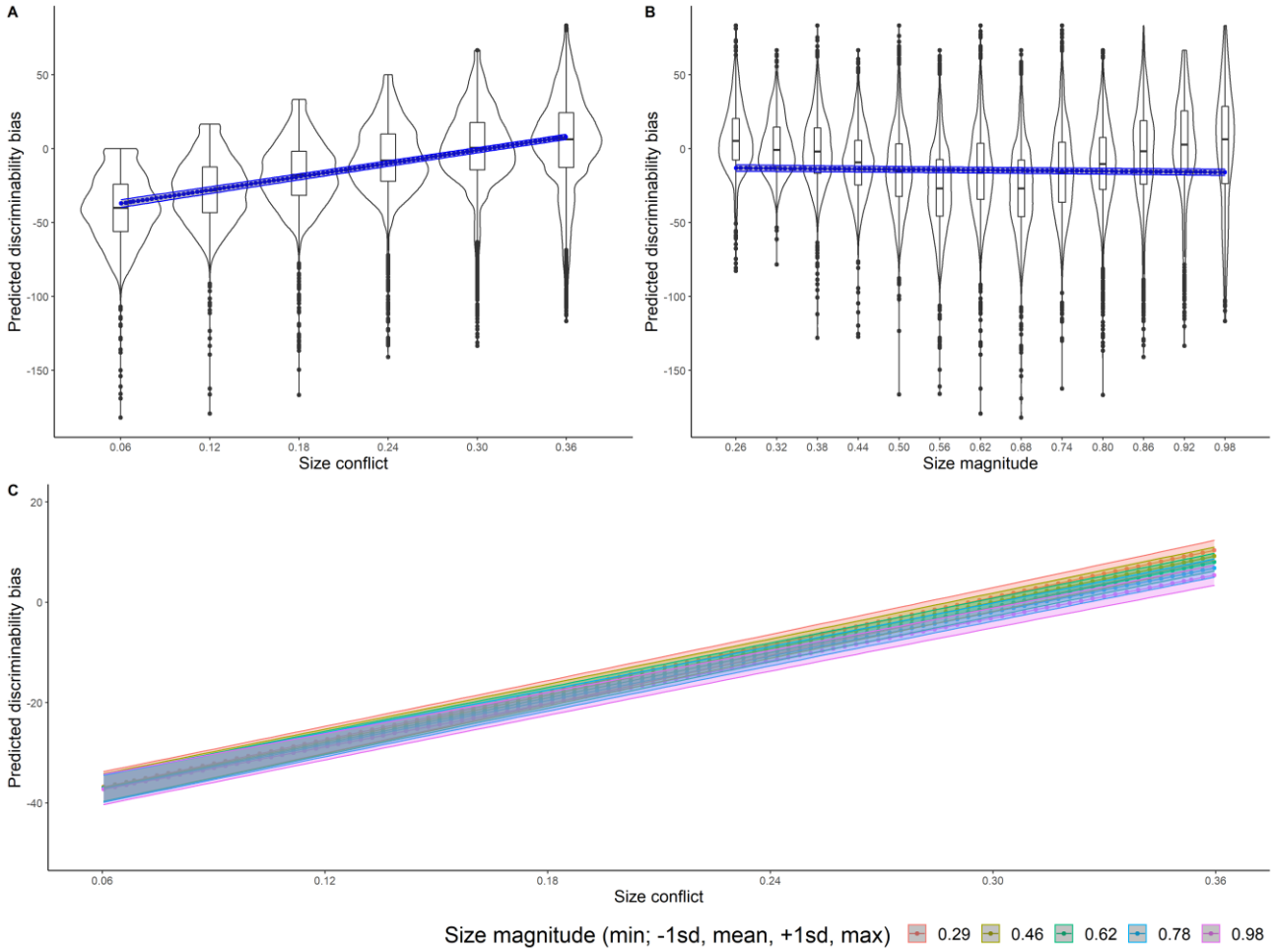


Figure 16 Plots depicting the 3 significant effects from Model 2 – Bias model in Experiment 2. Violin boxplots show the raw data. Lines and points depict predicted values from the model with 95% CIs. Panel A shows the main effect of size conflict, Panel B shows the main effect of size magnitude and Panel C represents the size conflict by size magnitude interaction.

4.3.4 Summary

The results confirmed that, in the context of this experimental paradigm, there is a double dissociation between perceptual and value-based decisions. Size magnitude,

size conflict, and their interaction are all statistically significant effects, whereas value conflict, value magnitude, and their interaction have negligible or non-existent effects.

The overall picture suggests that participants are able to differentiate between relevant and irrelevant sources of information in order to perform the task at hand. Further reasons for this dissociation, limitations of the current paradigm, and open questions are addressed in the general discussion.

4.4 General Discussion

The findings from Experiment 1 and 2 show that, depending on the task demands (i.e., to select an item depending on their preference or on the stimulus size), participants are able to isolate the relevant sources of information (i.e., intrinsic value or perceptual features) without being influenced by irrelevant features of the stimulus during the decisional process. In Experiment 1, where participants selected one of the two items based on their preferences, we found significant effects of value conflict, value magnitude, and a significant interaction between the two. Instead, in Experiment 2, where participants were asked to indicate which of the two items was bigger in surface size, size conflict, size magnitude, and their interaction were statistically significant. This highlights how decisions are shaped by task demands and are therefore flexible and context-dependent, an aspect that is reinforced by previous examples in the literature (Milosavljevic et al., 2012; Summerfield & Tsetsos, 2012; Trueblood et al., 2013; Vanunu et al., 2020; Voigt et al., 2019).

The role of magnitude is especially significant as highlighted by a recent review on its role in decision-making processes (Pirrone et al., 2022). Magnitude is defined as the total sum of the values of available options, and it is argued to be crucial in driving performance regardless of the decisional domain (e.g., perceptual, value-based, economic, etc.). This seems to apply especially in deadlock or stalemate situations, where the individual has to choose between equal alternatives. Magnitude-sensitivity then allows the subject to resolve these scenarios by prioritising value maximisation over accuracy. This provides a suitable explanation for the current findings, as indicated by the significant role of value/size magnitude on choice and by its interaction with

value/size conflict. On a behavioural level, this magnitude-sensitivity is reflected in the participants' tendency to re-affirm their preferences or size judgements as the magnitude (i.e., the sum of the average Stage 1 ratings) increases. The role of magnitude-sensitivity could also be inserted in the context of conflict monitoring and choice bias, as a mechanism that attempts to resolve the conflict induced by deadlock choices by prompting an overestimation in the participants' preferences or judgements (Milosavljevic et al., 2012; O'Hora et al., 2016; Zajkowski et al., 2019). This is in line with the conceptualisation of decision-making as a flexible and adjustable process that depends on multiple factors such as the degree of difficulty or uncertainty elicited by a choice (see also Chapter 2). On the other hand, while our results show an important role of magnitude and conflict in decision-making, we did not find any cross-domain effects between perceptual and value-based information in either experiment. This puts our findings in contrast with the extant literature where said influences have instead been found (Draper & Menzel, 1965; Peschel & Orquin, 2013).

One key aspect of the current design that differs from similar studies (Gluth et al., 2018; Lee & Coricelli, 2020; Milosavljevic et al., 2012; Vanunu et al., 2020; Voigt et al., 2019; Wyart et al., 2012; Zajkowski et al., 2019) is the lack of constraints that might affect the participants' decisions. Specifically, we did not enforce a short time limit (e.g., under 1.5 seconds) for the response, and while we added distractor trials, those did not seem to have any marked effects on the participants' accuracy. According to the current literature, these differences might be at the heart of our findings: in the absence of external pressures, such as time constraints, individuals are able to direct their attention only to the task-relevant features. This points towards a more dominant role of top-down attentional factors (Van Osselaer et al., 2005) even when different degrees of saliency are embedded in the stimulus' features.

Moreover, given the purely behavioural nature of the current study, there might be additional processes that do not necessarily translate to an overt behavioural response. Several eye-tracking studies propose that bottom-up features such as size or colour influence gazing behaviour (i.e., number of saccades and fixation counts), which is considered an indirect measure of attention (Gere et al., 2020; Jantathai et al., 2013;

Orquin & Lagerkvist, 2015; Peschel & Orquin, 2013; Towal et al., 2013). It would be worth addressing this question in a follow-up study to examine whether covert attentional processes are indeed influenced by the stimulus surface size - which would be in line with the literature - or not, which would instead provide further support to our results.

To conclude, decision-making is a flexible and context-dependent process and, in the absence of tight time constraints or added cognitive load, individuals are able to differentiate between relevant and irrelevant sources of information relating to value or perceptual features.

4.5 Supplementary Methods

4.5.1 Absolute Value Transformation

In our initial preregistration of Experiment 1, we specified that we would not be applying an absolute transformation to our dependent variable, namely slider rating, or any independent variables, but instead keep all variables coded as "right item" minus "left item" value. Upon reflection, however, this coding scheme resulted in the estimates for the value magnitude becoming meaningless. For instance, a negative beta coefficient in Experiment 1 for value magnitude would imply that as the value magnitude in a trial increases, the participants are more likely to give a response favouring the item to the left, rather than to the right. This, then, answers a question whether a participant has a left/right bias, rather than why participants provide the ratings they do. To answer the latter we reverted back and applied an absolute transformation to all variables, as described in the main text.

4.5.2 AEBQ Subscales

Initially we specified that we would include the three subscales from the AEBQ, namely enjoyment of food, food responsiveness and food fussiness, as independent variables but upon further reflection, we considered that these are better suited as random effects in order to examine if they capture enough meaningful variance that could explain the participants' responses. However, inputting all three of the subscales

led to an overparameterized model and collinear random effects (given that the three subscales share a lot of common variance), hence we decided to conduct a principal components analysis to extract factor scores for each participant. The three subscales shared 59% common variance, which is similar to the 64% shared variance for the entire scale (Hunot et al., 2016). Therefore, we used the factor scores for each participant from the principal components analysis in the random effects structure.

4.5.3 Sample Size and Power Analysis

We followed the preregistered plan when planning our sample size. Specifically, to power our primary mixed model to answer the key hypotheses, we conducted a power analysis via the *simr* package in R. To determine the effect size for which we wanted to power the study, we used the standardized estimates from pilot data. In our pilot data, the effects of subjective value difference (hypothesis 1) and the interaction between subjective value difference and value magnitude (hypothesis 3) were both very large, with estimates of .73 and .15, respectively. The smallest marginally non-significant effect size was the one for the main effect of size difference (hypothesis 2) and it was 0.008. The size difference by value difference interaction (hypothesis 4) was non-significant in the pilot data with an estimate at approximately 0. Hence, we decided to attempt to power both the main size difference effect and the interaction at .010. We decided to use this threshold as it was a relatively small effect size and if the effects were not significant for that effect size, they are unlikely to be practically or theoretically useful. We sought to achieve at least 80% power with an alpha probability of .05, although the exact power was subject to practical constraints – given our tight exclusion criteria, we had to set aside additional funding for paying rejected participants which limited our power for the interaction. The power analysis showed that with a sample size of 130, we achieve 82% power for the main effect of size conflict and 72% power for the size conflict by value conflict interaction. To power the interaction at 80% power we required 30 additional participants and decided against it due to financial constraints. See the OSF repository for the pilot data used for the simulation, as well as code to run the power analysis.

4.5.4 Exclusion Criteria

The preregistered report also outlined our strategy for data exclusion. Specifically, data were excluded at two key stages:

1 During the runtime of the experiment. Participants were prematurely rejected from the study if they failed to meet one of four criteria:

1.a The preference ratings they have provided during the initial rating of individual items were too extreme (i.e. too many ratings <=5 or >=95). Participants completed those initial ratings twice and if the two ratings are too different (Spearman correlation of <=0.2), they were also rejected.

1.b Using the initial preference ratings for each item, participants had an accuracy score calculated during the test trials – if, based on the initial items, they should prefer the right item and preference rating on the test trial in Stage 2 signified that they prefer the right item, the response that was coded as accurate. If the preference rating on the test trial in Stage 2 signified that they prefer the left item, that was coded as an inaccurate trial. After each of the 5 blocks of test trials, the cumulative accuracy thus far on the test trial was calculated and if it was below 0.55 (where 0.50 is chance), they were rejected.

1.c If participants failed to respond to more than 5% of the test trials (each of which had a time limit of 5 seconds), they were rejected.

1.d If, based on the preference ratings provided during stage 1, there was an expectation that 50% or more of the test trials ratings would be between -5 and 5, the participant was rejected prematurely.

The second stage for data exclusion occurred during the analysis. The criterion used was as follows: if a participant's ratings on the test trials were too close, the data were be discarded. This was defined as the average of 1) the standard deviation of all ratings being >= 5 and 2) the standard deviation of all ratings <= -5. If this average of the two standard deviations is 12 or below, the response was excluded.

5 The interplay between internal and external value-based decision-making: evidence from three online behavioural experiments

5.1 Introduction

As established so far, decision-making is a multifaceted process that involves different functions to work in concert in order to achieve a goal. In Chapter 3, we explored how value-based decisions, specifically, have been studied in the M/EEG literature and subsequently, in Chapter 4, we broadened our scope to consider whether there are any interactions between perceptual and value-based sources of information. In this chapter and the next (Chapter 6), we will instead assess a lingering question stemming from Chapter 3: since externally-guided and internally-guided value-based decisions have been studied, for the most part, in isolation from each other, what happens when both types of value information are present in the same task? Do these sources of information interact with one another? If so, what are the behavioural effects of this interaction? Do they occur under specific conditions? The current chapter will present three online behavioural experiments that attempt to answer these questions, while Chapter 6 will investigate the underlying neural substrate of one of these experiments (Experiment 1) with the use of magnetoencephalography.

In Experiment 1, we investigated whether EDM and IDM information has an interference-like effect across the two sub-domains by manipulating the congruency between the two types of information on a trial-by-trial basis. By congruency, here, we refer to whether the value levels (high or low) were the same between the two types of information (reward and preference). In practice, this means that on congruent trials, a high reward would be paired with the high-value item, whereas on incongruent trials there would be a mismatch between the two. Additionally, since the task demands (i.e., whether participants had to make an EDM or IDM decision) changed on a trial-by-trial basis, this added an element of uncertainty to the decisional process. Moreover, participants in Experiment 1 and 2 were required to respond within a time limit, meaning

that time-pressure was also a consistent external factor. In order to explore the boundaries of the 'spill-over' effect, in Experiment 2, we removed the uncertainty component to examine whether the cross-domain interference still occurred, while in Experiment 3, we introduced a fixed delay before participants could make a choice, thus eliminating the urgency component. The results of all three experiments are presented in section 1.1.

5.1.1 Overarching Hypotheses

Across all experiments, we test the same set of hypotheses, which are separate for type of trial (reward and preference) and dependent variable of interest (accuracy and reaction times). The core effects we are interested in can be encapsulated in the following statements: 1) For reward and preference trials, we hypothesise that the effect of congruency will result in higher accuracy and lower reaction times in congruent trials and that the effect will be reversed for incongruent ones, 2) For reward and preference trials, we hypothesise that an increase in value conflict will result in accuracy decreasing and reaction times increasing, 3) For reward and preference trials, we hypothesise that an increase in value magnitude will result in an increase in accuracy and a decrease in reaction times, 4) For reward and preference trials, we hypothesise that differences in reward probability (high versus low probability) will result in either an increase or decrease in accuracy and reaction times.

5.2 Studies Overview

All studies were preregistered before data collection. Experiment 1 was preregistered first and after seeing its results, we conceptualised, preregistered and ran Experiments 2 and 3 simultaneously. All materials etc are available on OSF (**Exp 1**, **Exp 2**, **Exp 3**). Unless otherwise noted, all design and analyses are part of the preregistration plan.

5.3 Experiment 1

5.3.1 Aims

In Experiment 1, the aim is to investigate the interplay between external and internal value during decisional processes. Specifically, participants need to encode both types of value-related information in order to perform the task effectively, which also requires switching between the two sources of information according to the type of trial (reward vs preference).

5.3.2 Methods

5.3.2.1 Participants

Participants were recruited via the Prolific platform. The participants had to be English-speaking adults in the 18-35 age range, with no chronic/long-term illness or mental health condition and must not have participated in related study (i.e., one participant could not have completed all experiments; participants who completed various related pilots were also excluded). Participants were paid the equivalent of £6.50/h, with an additional bonus payment, depending on their performance, of up to £1.00. Overall, 80 participants passed the exclusion criteria and were included in the final analyses (M_{age} = 26.60, SD_{age} = 4.49; Gender: 49 Male, 32 Female, 4 Unknown).

5.3.2.2 Power Analysis

Before running Experiment 1, we ran a pilot with 31 participants. We used the effect sizes from the significant hypothesised effects from the pilot data as a starting point for our power analysis. The smallest significant estimate from those models where accuracy was the dependent variable was a main effect of value conflict on reward trials at -.17, while the smallest significant estimate from those models with reaction time as the dependent variable was the main effect of value magnitude on reward trials at -.05. Although, to our knowledge, the models we are constructing are unique in the literature, similar designs have been used in the past to test the effect of value conflict. Compared to other similar results, both these estimates are much smaller than what has been previously found (e.g. Frömer et al., 2019). Still, we maintained a conservative

outlook and hence considered even these effects as overestimations given the small sample size for the pilot. Thus, to replicate these effects we used a "small-telescope" approach (Simonsohn, 2015). This approach allows us to both achieve power to reject a zero-effect null hypothesis, assuming there is a true effect, and to detect an effect much smaller than the pilot could have detected. To achieve this, it is recommended to use a sample 2.5 times that of the pilot. Hence, we opted to use a target sample size of 80 participants.

5.3.2.3 Apparatus

The experiment was programmed in JavaScript using the jsPsych v6.3.1 (de Leeuw, 2015) framework. We used food pictures from the Food-Pics database (Blechert et al., 2019). Each food picture was displayed on a white background with a width to height ratio of 4:3. To select the images for the current experiment, we used four criteria: 1) the picture depicts a single food item; 2) there are no plates or containers in the picture; 3) there are no brands in the picture; 4) there are no items that are too similar to each other. 81 food images from the Food-Pics database were found, of which we selected 40 at random for the current set of experiments.

5.3.2.4 Procedure

Experiment 1 followed a procedure consisting of three main stages. In the first stage, the participants rated their preference for each of the 40 food pictures, twice. In the second stage, participants made a binary choice between two alternatives either based on their preference for the food items or based on the reward probability of each option in order to win points. Participants were told that the points they win will be converted to a monetary bonus. In the third stage, participants again rated their preference for each 40 food items.

The minimum screen size allowed for the experiments was set to 768 pixels width and 800 pixels height to ensure that the experiments' content appeared smoothly without the need of scrolling.

Stage 1: Initial rating. Participants performed two blocks of preference ratings of the 40 images on a continuous scale from 0 to 100. Item presentation was randomized for each of the two blocks and also between-participants. The participants were informed that their ratings across blocks had to be consistent with each other. If the ratings were not similar enough, as defined by a Spearman rho <0.50, the participant was rejected prematurely. On each rating trial, a food stimulus was presented in the centre of the screen, such that the entire image width (including the white background) was set to 500 pixels (resulting in a height of 375 pixels due to the 4:3 ratio), with a rating scale of the same width below the image with labels above the scale. The labels of the scale were “Dislike”, “Neutral”, and “Like” from left to right. Participants used a mouse to drag or click on the scale. After making their selection on the scale, participants had to click a “confirm” button to continue to the next trial. There was no time limit for response.

Stage 2: Main task. There were 4 blocks of 90 trials each, thus yielding a total of 360 trials. On each trial, two random food items were drawn from the whole set of 40 images with the only constraint that those items' subjective value (calculated by taking the mean of the two ratings of the item based on Stage 1 ratings) could not be equal. Throughout the trials, there was a progress bar at the top of the screen, indicating the progress within the current block.

The timeline of the Stage 2 trials is depicted in Figure 17. At the beginning of each trial, participants were presented with two side-by-side food images, and each filled 35% of the user’s screen in width, including a 10-pixel coloured border (either red or blue). The images were presented for 1200 ms, during which no response was possible. After 1200 ms the food images disappeared, and the colour of both borders changed to black. Between the two borders, a trial type icon (either a heart in preference trials or a dollar symbol in reward trials) appeared at the centre of the screen, together with a text message “Press left or right arrow for selection” underneath the icon. Participants had up to 2000ms to provide a response. Any responses quicker than 200ms and longer than 2000ms were followed by feedback indicating that the response had been either "too slow" or "too quick", respectively, and the response was later discarded. If

participants made more than 5% cumulative too quick or too slow responses, they were prematurely rejected. After participants provided a response, they were given feedback , lasting 1000ms, about whether they had won points (fixed to 100) or not (0 points). To win points on preference trials participants had to correctly select the item that has higher average subjective value, based on Stage 1 ratings.

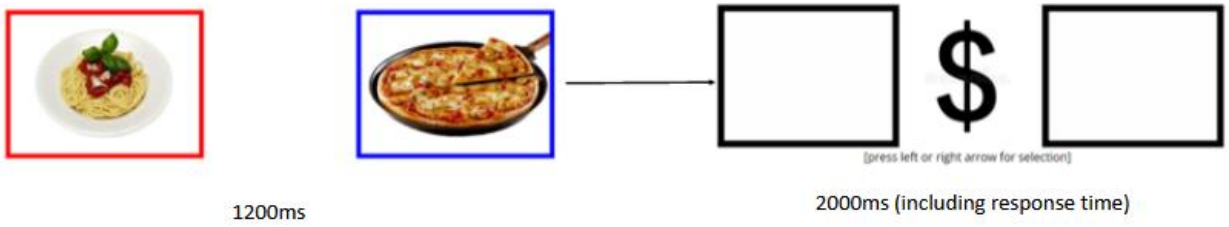


Figure 17 Procedure for Exp 1. In the first stage, participants were shown two stimuli enclosed by coloured borders (red or blue). After 1200ms, the cue was shown (either a dollar sign or a heart-shaped symbol) to indicate the type of decision and the borders turned to black with no picture inside. Participants had up to 2000ms to respond.

To win points on reward trials, the reward probability associated with each border colour was taken and used as the probability to win. The trial ended with an inter-trial-interval randomly drawn from a uniform distribution between 800ms and 1500ms.

Stage 3: Final rating. Same as Stage 1, participants rated their preference on the 40 individual food items; this time they did so once.

5.3.2.5 Design

All experiments used a within-subjects design, in which we controlled three key variables. On the block-level, we manipulated the reward probability condition, such that a block could be either easy, where one border colour is associated with an 80% chance of winning points and the other with a 20% chance, or hard, with a 40% vs 60% chance of winning for each border colour. On the block-level, we also controlled the congruency of the preference (i.e., the subjective ratings) for the food items with the reward probability associated with its coloured border, so that a block could be congruent (the preferred item, i.e. the item with higher average subjective value based on Stage 1 ratings, was always associated with the item that had higher reward probability) or incongruent (the preferred item was always associated with the item that had lower reward probability). On the trial-level, we controlled the trial type, which

could be either preference (wherein the participant had to make a decision about which item they preferred) or reward (wherein the participant had to make a decision which colour has a greater chance of winning them points). The trial type was indicated, as seen in Section 5.3.2.4, by either a heart symbol (preference) or a dollar sign (reward). There were an equal number of preference and reward trials within a block.

Additionally, we exerted the following control measures on the paradigm. First, the location of the red and the blue borders was counterbalanced within blocks, such that for each block, half of the trials had a blue border on the left side of the screen and the other half had a red border on the left. Second, the colour associated with the higher reward probability (80% or 60% in easy and hard trials respectively) was also counterbalanced between blocks, such that in half the blocks red had a higher reward probability and in the other half blue had a higher reward probability. Third, the reward probability condition was counterbalanced for each level of congruency, such that each reward probability condition was once congruent and once incongruent. Fourth, to avoid a reward probability condition appearing twice in a row, blocks 2 and 3 were restricted such that they could not have the same reward probability condition.

5.3.2.6 Data Pre-processing

5.3.2.6.1 Variables

As explained in Section 5.3.2.4 we collected participants' preference ratings on individual food items across Stages 1 and 3. We also collected participants' responses and reaction times on Stage 2 trials.

We combined these ratings and responses with the independent variables we manipulated, namely reward probability condition (easy, i.e., 20% vs 80%, or hard, i.e. 40% vs 60%), congruency (congruent or incongruent), and trial type (preference or reward).

Furthermore, we used the preference ratings assigned to individual items from Stage 1 to construct two additional independent variables from Stage 2 trials: value conflict and value magnitude. Value conflict is defined as the opposite of the absolute

value difference between the subjective ratings of each item for each Stage 2 trial. Specifically, we first calculated the average preference ratings for each item based on Stage 1 ratings. Then, we took the absolute difference of the average preference ratings of the two items on each test trial in Stage 2. Given that the absolute difference can range between 0 and 100, we flipped it (100 minus the absolute difference) to produce a measure of value conflict. Value magnitude was calculated similarly, but instead of taking the difference between the average preference ratings for each of the two items on any given trial in Stage 2, we took their sum.

We also calculated an index of participants' accuracy on Stage 2 trials. On preference trials, participants were accurate if they selected the item that had higher subjective value (again, defined by taking the average of Stage 1 preference ratings), meaning that accuracy corresponded to being consistent with their Stage 1 ratings. On reward trials, an accurate response involved selecting the option (left/right) that had higher reward probability.

5.3.2.6.2 Data Exclusion

There were two points where participants were excluded. As per our preregistration, we re-ran all our analyses on the sample before and after exclusion criteria were applied (as long as the participant finished the study) and found no differences in conclusions.

The first stage of exclusions was during the runtime of the experiment. Participants were prematurely rejected from the study if they failed to meet one of 2 criteria: 1) If the correlation between the two iterations of ratings of food items during Stage 1 was too low (Spearman rho <= .5), then the participant was prematurely rejected; 2) If participants failed to provide a valid response either by responding too fast, i.e. response time less than 200ms, or by responding too slowly, i.e. no response in the 2000ms time limit to more than 5% of the test trials cumulatively, then they were rejected.

The second stage for data exclusion occurred after we collected the data. Here we used two criteria to exclude responses: 1) If accuracy on preference trials was below

60%; 2) If accuracy on reward trials on the congruent, easy (reward probability condition 20% vs 80%) trials was below 50%.

Additionally, for the participants included in the final samples, some trials were rejected due to a response that was either too slow (over 2000ms) or too fast (under 200ms).

5.3.2.7 Data Post-processing

Analyses were conducted using the R programming language. The core packages used were tidyverse (Wickham et al., 2019), lme4 (Bates et al., 2018), psych (Revelle, n.d.), and ggplot2 (Wickham, 2016).

To test our hypotheses, we constructed four mixed level models, with identical fixed and random effects structures (close to maximal ones, see Barr, 2013).

The fixed-effects structure included four independent variables: congruency, reward probability condition, value conflict, and value magnitude as well as all their two-way interactions. Higher-order interactions are not of interest and are likely to needlessly overparametrize the model.

The random-effects structure included both a by-participant random intercept and a by-participant random slopes for the effect of congruency and reward probability condition, as well as their interaction. There will be no by-participant random slope for value conflict and value magnitude as these are likely to overparametrize the model due to very low numbers at certain levels (see Barr, 2013). There will be no by-item random effects, as these are drawn randomly, and we do not expect them to make a difference. To test whether the selected random-effects structure was the most parsimonious one, model comparisons were conducted. Across all experiments and models, the random effects explained a significant amount of variance, thus no removal of any random effect was justified.

Two of the generalised linear mixed models (one for preference trials and one for reward trials) were fit, using a maximum likelihood algorithm with Laplace

approximation, on accuracy as the dependent variable, here coded as a binary variable (correct/incorrect).

The other two linear mixed models (one for preference trials and one for reward trials) were fit, using a restricted maximum likelihood algorithm, with the degrees of freedom for the t-tests defined using the Satterthwaite's adjustment, on reaction time[5] as the dependent variable, which is instead coded as a continuous variable.

Across all models, the continuous variables (value conflict, value magnitude and reaction time) were centred and scaled, while the categorical variables (congruency and reward probability condition) were coded using sum contrasts in order to estimate the difference between the two levels of each variable. For the categorical variables, a positive effect implies going from the grand mean to the congruent or easy condition for the congruency and reward probability, respectively (i.e. OR > 1 or $\beta > 0$).

Plotting the predicted probabilities from the generalized linear mixed models is done using marginal standardization, which has been reliably shown to be a robust method compared to alternatives (Muller & MacLehose, 2014).

5.4 Experiment 2

5.4.1 Introduction and Differences with Experiment 1

In Experiment 2, we assessed whether the cue onset during Stage 2 trials had any effect for the same sets of hypotheses as Experiment 1. Namely, the dollar or heart-shaped symbol was now presented on the screen for 500ms before the food items and the coloured borders appeared, and it was visible for the whole length of the trial. The

[5] As specified in our preregistrations, we did not log-transformed reaction times as these were not skewed in our pilot data. Still, as per our preregistrations, we re-ran all our models using log-transformed RTs and found no differences in conclusions (despite some *p*-value fluctuations) – see Appendix "Results comparison: original vs log-transformed reaction times".

aim was to find the boundaries of the spill-over effect; participants were shown the cue at the start so that they knew in advance on which information to focus.

5.4.2 Methods

5.4.2.1 Participants

Overall, 80 participants passed the exclusion criteria and were included in the final analyses (M_{age} = 24.95, SD_{age} = 4.12; 20% females, 80% males). See Table 3.

5.4.2.2 Procedure

The setup for the main task was close to identical with that of Experiment 1, with the following difference. In the current experiment, the flow of a single trial was changed such that at the start of each trial, the trial type icon (dollar or heart) was first displayed for 500ms (Figure 18). Then the same flow is preserved as for Experiment 1, with the food pictures with the red and blue borders displayed for 1200ms, followed by the black borders for 2000ms, during which a response can be registered. Notably, throughout the entire time, including the initial 500ms, the trial type icon (dollar or heart) is constantly shown at the centre of the screen (unlike Experiment 1, where the trial type icon was show only during the 2000ms time when a response can be registered).

Figure 18 Procedure for Exp 2**.** In the first stage, participants were shown the cue 500ms before the stimulus display. The cue remained on screen for the entire duration of the trial. Like in Exp 1, after 1200ms, the borders turned to black with no picture inside. Participants had up to 2000ms to respond.

5.5 Experiment 3

5.5.1 Introduction and Differences with Experiment 1

In Experiment 3, we examined whether a longer response time would have any effects on the participants' accuracy and on the inter-domain spill-over effect found in

Experiment 1. The hypotheses we tested were the same as in Experiment 1, but we did not take into consideration those regarding reaction times, as the delayed response window would make those meaningless. The design for Experiment 3 was identical to Experiment 1, with the added caveat that participants were given 1500ms to prepare their responses before being prompted to make a choice between the two options. Consequently, the lower limit of 200ms for responding was also removed.

5.5.2 Methods

5.5.2.1 Participants

Overall, 80 participants passed the exclusion criteria and were included in the final analyses (M_{age} = 26.06, SD_{age} = 4.43; 30% females, 70% males). See Table 3.

5.5.2.2 Procedure

The setup for the main task was similar to that of Experiment 1, with the following difference. In the current experiment, the flow of a single trial was changed such that once the trial type and the black borders are displayed, participants were prompted (with a small accompanying text at the top of the screen) to prepare their response for 1500ms (Figure 19). After that, they were prompted (by bigger text in the same place as the previous one) to provide a response, with a time limit of 1500ms. Given the changes in the design, we removed the restriction that responses cannot be quicker than 200ms.

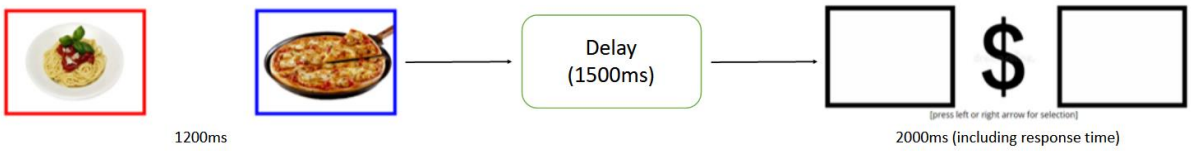


Figure 19 Procedure for Exp 3. It is identical to Exp 1, but between the stimulus display and the cue, we inserted a delay of 1500ms to remove the component of temporal pressure.

5.6 General Results

5.6.1 Descriptive Statistics

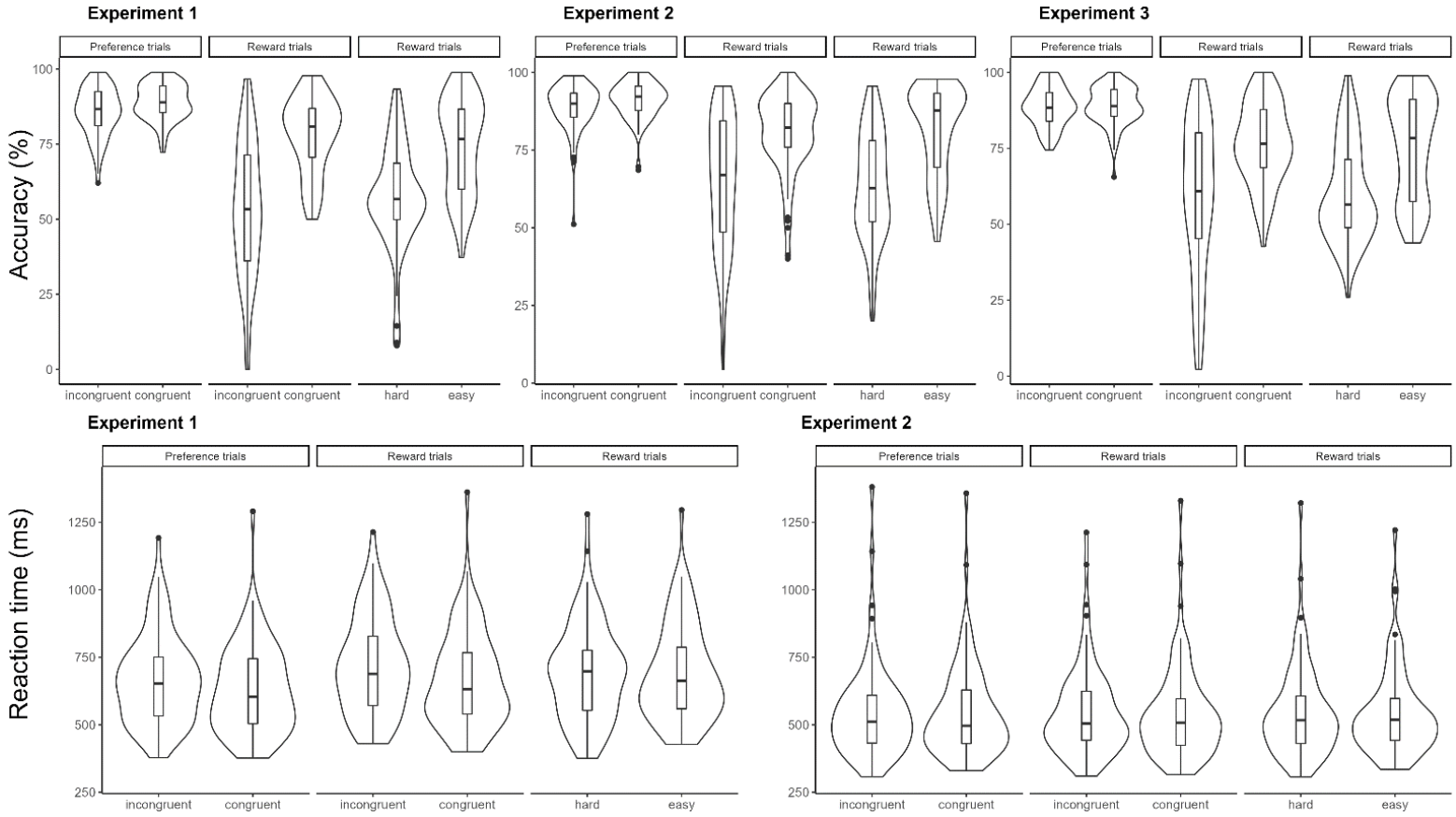


Figure 20 Descriptive violin plots for accuracy (%) and reaction times (ms) separated for Experiment (1 - 2 - 3) and trial type (reward or preference)

The top left panel in Figure 20 shows that in Experiment 1, on Stage 2 preference trials, participants achieved an overall accuracy of *M* = 87.35%, *SD* = 33.24%. Broken down by conditions, the achieved accuracy in the congruent condition was *M* = 89.00%, *SD* = 31.29%, and in the incongruent it was *M* = 85.70%, *SD* = 35.01%. On reward trials, participants achieved an accuracy of *M* = 78.08%, *SD* = 41.37% on congruent trials and *M* = 53.36%, *SD* = 49.89% on incongruent trials. The achieved accuracy on easy reward probability condition was *M* = 74.42%, *SD* = 43.64% and on the hard reward probability condition it was *M* = 57.07%, *SD* = 49.50%. A similar pattern was observed for reaction times, as seen on the bottom left panel of Figure 20. On preference trials, the reaction time on congruent trials was *M* = 628.49ms, *SD* = 278.52ms and on incongruent trials it was *M* = 667.21ms, *SD* = 290.03ms. On reward trials, participants had a reaction time of *M* = 664.85ms, *SD* = 285.43ms on congruent trial and *M* = 716.07ms, *SD* = 285.26ms on

incongruent trials. Broken down by reward probability condition, the reaction time for the easy condition was *M* = 690.24ms, *SD* = 285.99ms and for the hard one it was *M* = 690.60ms, *SD* = 287.00ms. Taken together, the descriptive statistics indicate that, on average, participants engaged the task in the way that it was designed. Specifically, the better performance on both metrics (accuracy and reaction time) on congruent versus incongruent trials and on easy reward probability trials vs hard ones suggest that both manipulations worked as intended.

The top middle panel from Figure 20 shows that, in preference trials in Stage 2, participants achieved an overall accuracy of *M* = 89.97%, *SD* = 30.04%. Broken down by conditions, the achieved accuracy in the congruent condition was *M* = 90.97%, *SD* = 28.66 %, and in the incongruent it was *M* = 88.98%, *SD* = 31.32%. On reward trials, participants achieved an accuracy of *M* = 80.53%, *SD* = 39.60% on congruent trials and *M* = 64.37%, *SD* = 47.89% on incongruent trials. The achieved accuracy on easy reward probability condition was *M* = 81.39%, *SD* = 38.92% and on the hard reward probability condition it was *M* = 63.50%, *SD* = 48.15%. A similar pattern was observed for reaction times, as seen in the bottom right panel of Figure 20. In preference trials, the reaction time on congruent trials was *M* = 543.14ms, *SD* = 269.42ms and on incongruent trials it was *M* = 543.54ms, *SD* = 266.02ms. On reward trials, participants had a reaction time of *M* = 537.30ms, *SD* = 264.20ms on congruent trial and *M* = 542.03ms, *SD* = 266.50ms on incongruent trials. Broken down by reward probability condition, the reaction time for the easy condition was *M* = 535.71ms, *SD* = 262.99ms and for the hard one it was *M* = 543.63ms, *SD* = 267.66ms. Therefore, we see a pattern similar to Experiment 1, where, on average, participants engaged the task in the way that it was designed.

The top right panel in Figure 20 shows that, in Experiment 3, in preference trials in Stage 2, participants achieved an overall accuracy of *M* = 88.79%, *SD* = 31.56%. Broken down by conditions, the achieved accuracy in the congruent condition was *M* = 88.96%, *SD* = 31.34%, and in the incongruent it was *M* = 88.61%, *SD* = 31.77%. On reward trials, participants achieved an accuracy of *M* = 76.51%, *SD* = 42.40% on congruent trials and *M* = 59.08 %, *SD* = 49.17% on incongruent trials. The achieved accuracy on easy reward probability condition was *M* = 75.20%, *SD* = 60.37% and on the

hard reward probability condition it was *M* = 60.37 %, *SD* = 48.92%. We did not consider reaction times data for this experiment, as we had introduced a fixed delay of 1500ms before participants could respond.

5.6.2 Mixed Models

5.6.2.1 Accuracy Rates

Predictors	**Reward trials - Accuracy**						**Preference trials - Accuracy**					
	Experiment 1 Baseline		**Experiment 2 Advance cue**		**Experiment 3 Delay**		**Experiment 1 Baseline**		**Experiment 2 Advance cue**		**Experiment 3 Delay**	
	OR [95% CI]	*p*	OR [95% CI]	*p*	OR [95% CI]	*p*	OR [95% CI]	*p*	OR [95% CI]	*p*	OR [95% CI]	*p*
value magnitude	1.02 [.97, 1.08]	.468	.98 [.92, 1.04]	.550	1.05 [.99, 1.12]	.094	1.42 [1.32, 1.52]	<.001	1.82 [1.63, 2.03]	<.001	1.79 [1.62, 1.97]	<.001
value conflict	.92 [.87, .98]	.009	.99 [.93, 1.06]	.783	.94 [.88, 1.01]	.074	.27 [.24, .30]	<.001	.11 [.10, .13]	<.001	.13 [.12, .15]	<.001
congruency	4.20 [2.98, 5.93]	<.001	2.72 [1.99, 3.71]	<.001	2.79 [1.88, 4.12]	<.001	1.40 [1.18, 1.66]	<.001	1.98 [1.50, 2.62]	<.001	1.20 [.96, 1.50]	.101

reward probability condition	2.88 [2.12, 3.91]	<.001	3.32 [2.54, 4.34]	<.001	2.58 [2.01, 3.33]	<.001	.88 [.73, 1.05]	.150	.84 [.66, 1.06]	.138	1.16 [.94, 1.43]	.161
value magnitude * value conflict	1.00 [.94, 1.06]	.928	1.05 [.98, 1.12]	.141	.95 [.89, 1.01]	.128	.81 [.75, .89]	<.001	.59 [.52, .66]	<.001	.60 [.53, .66]	<.001
value magnitude * congruency	1.11 [1.00, 1.22]	.046	1.13 [1.02, 1.26]	.019	1.01 [.91, 1.13]	.812	1.04 [.94, 1.16]	.464	.99 [.88, 1.12]	.890	.98 [.87, 1.09]	.699
value magnitude * reward probability condition	1.10 [1.00, 1.22]	.053	1.06 [.95, 1.17]	.313	.96 [.86, 1.06]	.399	1.00 [.90, 1.11]	.996	1.00 [.89, 1.12]	.984	1.04 [.93, 1.16]	.510
value conflict * congruency	.65 [.58, .72]	<.001	.66 [.59, .74]	<.001	.74 [.66, .83]	<.001	.97 [.82, 1.16]	.775	.54 [.41, .72]	<.001	.82 [.65, 1.04]	.098

value conflict * reward probability condition	.90 [.81, 1.01]	.063	.83 [.74, .93]	.001	.96 [.86, 1.07]	.465	1.09 [.92, 1.30]	.316	1.20 [.93, 1.55]	.152	.85 [.67, 1.07]	.160
congruency * reward probability condition	1.00 [.68, 1.48]	.996	.81 [.50, 1.33]	.412	1.47 [.90, 2.40]	.123	1.92 [1.38, 2.67]	<.001	.97 [.69, 1.38]	.881	1.22 [.90, 1.66]	.190

Table 4 Mixed Linear Models Effects in Experiments 1-2-3 on Reward and Preference trials with Accuracy as DV.

Table 4 shows the results of the generalised linear mixed model on reward and preference trials with accuracy as the dependent variable across all three experiments. The values of the Odds Ratios column (OR) give an indication of whether the relationship between the predictors and the dependent variable is a positive (OR =>1) or a negative one (OR =<1).

In Experiment 1, the following predictors were statistically significant for reward trials: value conflict, congruency, and reward probability. Value conflict, OR = .92 [.87, .98] has a negative relationship with accuracy, meaning that as value conflict increases, accuracy decreases. Congruency, OR = 4.20 [2.98, 5.93], and reward probability (easy vs hard trials), OR = 2.88 [2.12, 3.91], instead, both have a positive relationship with accuracy, indicating that congruent or easy trials result in an increase in accuracy rates. The statistically significant interaction between value magnitude and congruency, OR = 1.11 [1.00, 1.22], is also a positive one, showing that as value magnitude increases, accuracy rates increase if the trial is a congruent one, compared to an incongruent one. On the other hand, the interaction between value conflict and congruency, OR = .65 [.58, .72], is a negative one, meaning that higher levels of value conflict led to lower

accuracy in congruent trials, compared to incongruent ones (see

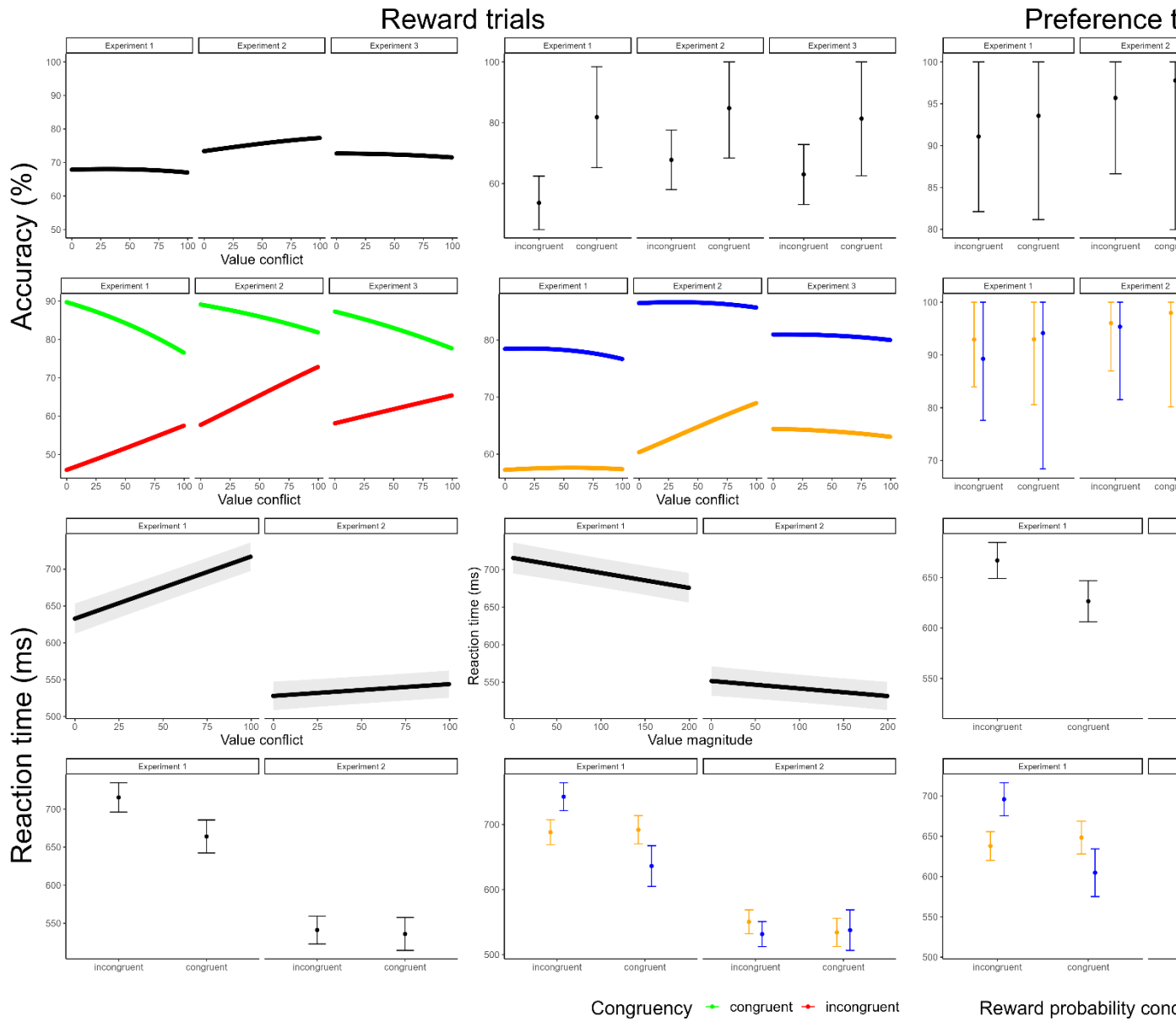


Figure ***21***) suggesting that higher value conflict makes congruency a less reliable cue for the decisional process. This means that participant rely more on preference-related information in reward trials, indicating a spillover effect between the two domains.

For preference trials, instead, we see that value magnitude, OR = 1.42 [1.32, 1.52], is a statistically significant predictor with a positive effect on accuracy rates. Similarly to reward trials, value conflict, OR = .27 [.24, .30], and congruency, OR = 1.40 [1.18, 1.66], are both statistically significant, with a negative and a positive effect on

accuracy rates, respectively. The interaction between value magnitude and value conflict is also significant and qualified by a negative effect, OR = .81 [.75, .89]. Interestingly, the interaction between value conflict and congruency was not significant for preference trials, suggesting that while preference-related information has an effect on reward trials, the reverse does not occur.

In Experiment 2, congruency, OR = 2.72 [1.99, 3.71], and reward probability, OR = 3.32 [2.54, 4.34] are again statistically significant predictors for reward trials. The interactions between value magnitude and congruency, OR = 1.13 [1.02, 1.26], and between value conflict and congruency, OR = .66 [.59, .74], are both statistically significant and qualified by a positive and a negative direction, respectively. The latter indicates that, even when the cue indicating the trial type is presented in advance, in reward trials, participants use preference-related information to guide their decisions, resulting in lower accuracy rates. Finally, there is a negative and statistically significant interaction between value conflict and reward probability, OR = .83 [.74, .93].

For preference trials, value magnitude, OR = 1.82 [1.63, 2.03], value conflict, OR = .11 [.10, .13], and congruency, OR = 1.98 [1.50, 2.62] are all statistically significant. The interaction between value magnitude and value conflict is once again significant, OR = .59 [.52, .66]. Interestingly, the interaction between value conflict and congruency, OR = .54 [.41, .72], is significant for preference trials too.

In Experiment 3, only congruency, OR = 2.79 [1.88, 4.12], and reward probability, OR = 2.58 [2.01, 3.33], are statistically significant predictors in reward trials. Amongst the interactions, only the one between value conflict and congruency, OR = .74 [.66, .83], is statistically significant and indicates that preference information plays a role in reward trials, thus suggesting that across all three experiments, preference-based information (i.e., value conflict) interferes with reward-related decisions when a less preferred item is paired with a higher probability of reward.

For preference trials, instead, only the value-related variables, i.e., value magnitude, OR = 1.79 [1.62, 1.97], and value conflict, OR = .13 [.12, .15], as well as their interaction, OR = .60 [.53, .66], are statistically significant.

5.6.2.2 Reaction Times

Predictors	Reward trials – Reaction Times				Preference trials – Reaction Times			
	Experiment 1 Baseline		**Experiment 2 Advance cue**		**Experiment 1 Baseline**		**Experiment 2 Advance cue**	
	β Estimate	*p*	β Estimate	*p*	β Estimate	*p*	β Estimate	*p*
value magnitude	-.03 [-.04, -.01]	.001	-.02 [-.03, .00]	.084	-.13 [-.15, -.12]	<.001	-.10 [-.12, -.09]	<.001
value conflict	.08 [.06, .10]	<.001	.02 [-.00, .04]	.065	.21 [.20, .23]	<.001	.16 [.14, .18]	<.001
congruency	-.18 [-.25, -.11]	<.001	-.02 [-.10, .06]	.619	-.14 [-.21, -.08]	<.001	.00 [-.06, .07]	.921
reward probability condition	-.00 [-.07, .07]	.955	-.03 [-.08, .03]	.294	.03 [-.03, .09]	.411	.01 [-.04, .06]	.640
value magnitude * value conflict	.01 [-.01, .03]	.290	.01 [-.01, .03]	.155	.01 [-.01, .03]	.227	.05 [.03, .06]	<.001
value magnitude * congruency	-.04 [-.07, -.01]	.010	-.01 [-.04, .02]	.391	.03 [-.00, .06]	.057	-.02 [-.05, .01]	.223

value magnitude * reward probability condition	.01 [-.02, .04]	.352	.02 [-.01, .04]	.313	.02 [-.01, .05]	.180	-.02 [-.05, .00]	.099
value conflict * congruency	.03 [.00, .06]	.036	-.02 [-.05, .01]	.148	-.02 [-.05, .01]	.257	.00 [-.03, .03]	.819
value conflict * reward probability condition	-.02 [-.05, .01]	.138	-.02 [-.05, .01]	.115	.01 [-.02, .04]	.645	.02 [-.01, .05]	.127
congruency * reward probability condition	-.39 [-.53, -.24]	<.001	.08 [-.05, .22]	.220	-.36 [-.49, -.22]	<.001	.13 [.01, .25]	.036

Table 5 Linear Models Effects in Experiments 1-2-3 on Reward and Preference trials with RTs as DV.

Table 5 shows the results of the mixed linear models with reaction times as the dependent variable. Here, we ran the models only on the data from Experiment 1 and 2, thus excluding the data from Experiment 3, where a fixed delay of 1500ms was introduced, making the reaction times data uninformative. In Experiment 1, the following predictors were statistically significant for reward trials: value magnitude, β = -.03, [-.04, -.01], which had a negative effect on reaction times; value conflict, β = .08 [.06, .10], with a positive effect on RTs, indicating that as value conflict increased, RTs also increased and were thus slower; and a negative main effect of congruency, β = -.18 [-.25, -.11]. Additionally, these main effects were qualified by a negative significant

interaction between value magnitude and congruency, β = -.04 [-.07, -.01], a positive significant interaction between value conflict and congruency, β = .03 [.00, .06], and a negative significant interaction between congruency and reward probability condition, β = -.39 [-.53, -.24].

For preference trials, the same predictors as above were statistically significant: a significant negative main effect of value magnitude, β = -.13 [-.15, -.12]; a significant positive main effect of value conflict, β = .21 [.20, .23]; and a significant negative main effect of congruency, β = -.14 [-.21, -.08]. These main effects were qualified by a negative significant interaction between congruency and reward probability condition, β = -.36 [-.49, -.22].

In Experiment 2, the linear mixed model on reward trials with reaction time as the dependent variable showed no significant effects. On the other hand, for preference trials we obtained a significant negative main effect of value magnitude, β = -.10 [-.12, -.09], and a significant positive main effect of value conflict, β = .16 [.14, .18]. These main effects were qualified by a significant interaction between value magnitude and value conflict, β = .05 [.03, .06], and a significant interaction between congruency and reward probability condition, β = .13 [.01, .25].

5.6.2.3 Evidence of Spill-over Effects

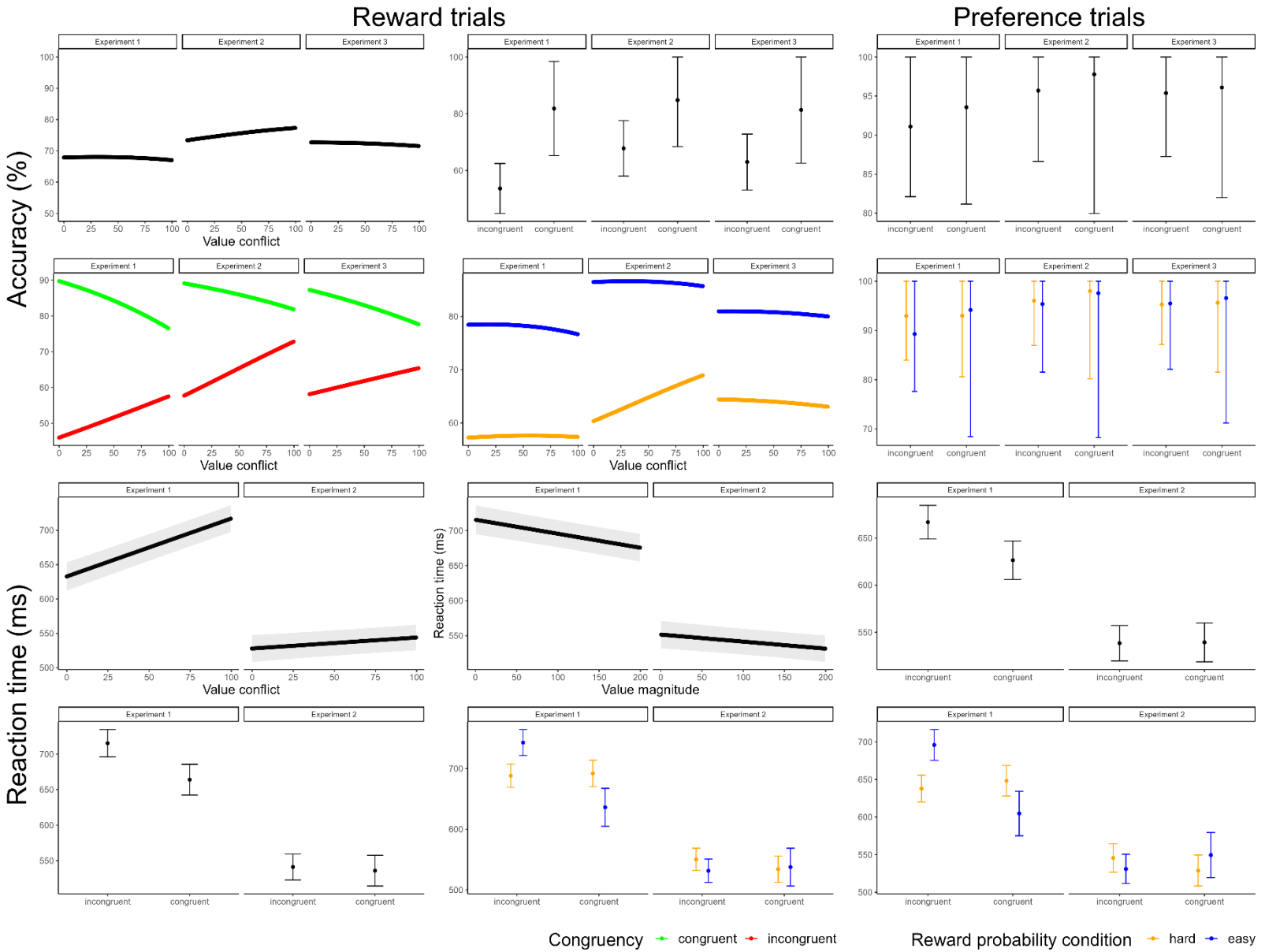

Reward trials
Preference trials
Accuracy (%)
Reaction time (ms)
Experiment 1
Experiment 2
Experiment 3
Value conflict
Value magnitude
incongruent
congruent
Congruency
congruent
incongruent
Reward probability condition
hard
easy

Figure 21 Evidence of spillover effects from Experiments 1-2-3 on accuracy (%) and reaction times (ms) split between reward and preference trials. Error bars represent SE.

The key findings that suggest the existence of a spillover effect between decisional domains reside in the interactions between value conflict and congruency, as depicted in the first panel of the second row of

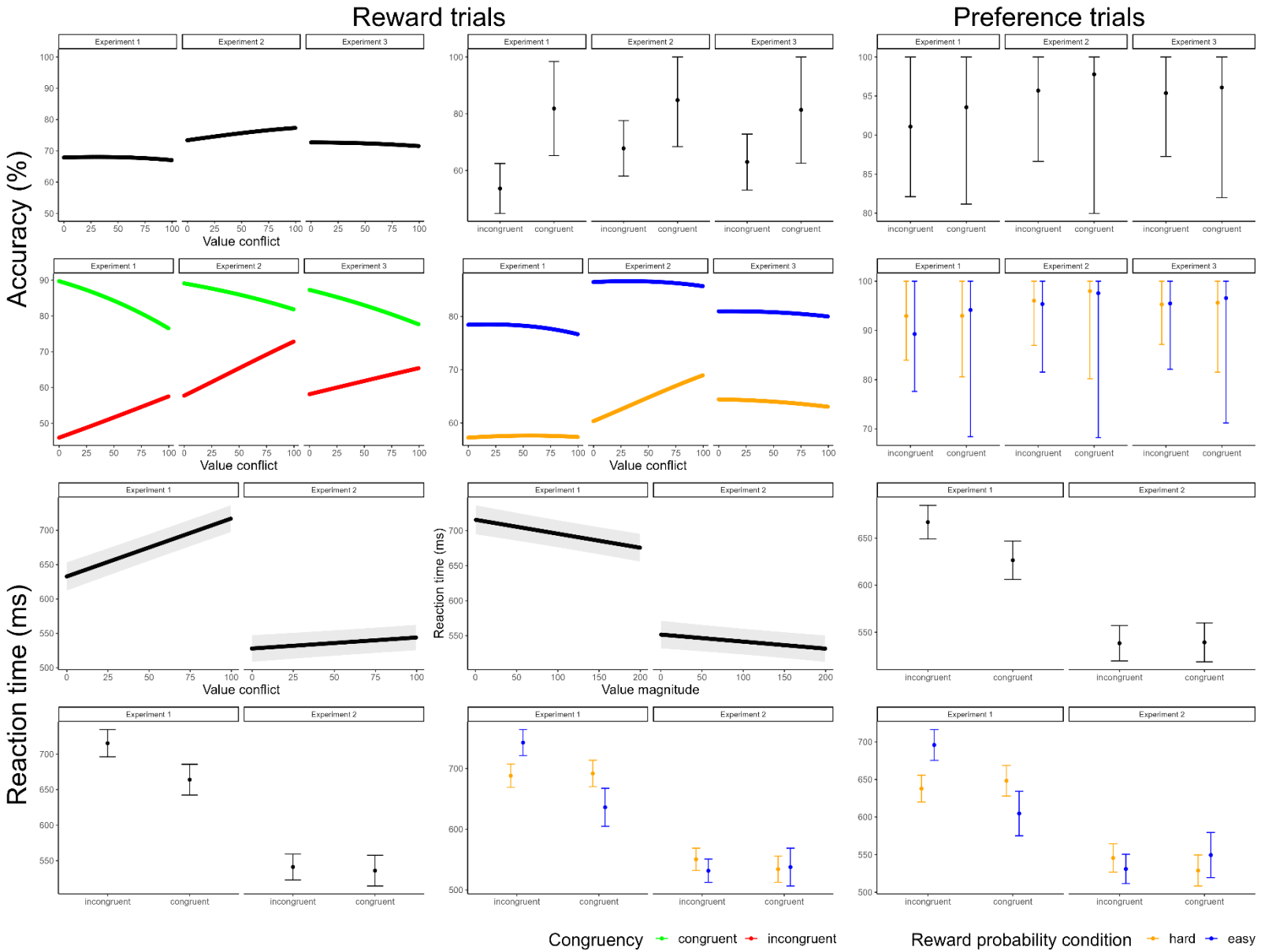

Reward trials
Preference trials
Accuracy (%)
Reaction time (ms)
Experiment 1
Experiment 2
Experiment 3
Value conflict
Value magnitude
incongruent
congruent
Congruency
congruent
incongruent
Reward probability condition
hard
easy

Figure ***21***. Indeed, the results from the linear mixed models (see 5.6.2) show that across all three experiments, in reward trials, we found a negative interaction between congruency (i.e., whether the high-value item was associated with the high-reward colour or not) and value conflict (i.e., a reverse measure of how close the ratings of the two items are). This affects the participants' accuracy especially in the congruent condition, meaning that, as value conflict (i.e., the preference-related information) increases, the congruency between item and reward is not as useful as a cue to solve the ambiguity. Concretely, this highlights how preference-related information – which would be irrelevant in a reward trial if

participants acted as entirely rational agents with the sole goal of reward maximization – interferes with the participants' performance on reward trials when they present ambiguous information. Additionally, in this same panel, we see that participants' accuracy for incongruent trials is almost at or even below chance level. This means that participants were foregoing a reward if it was paired with a particularly disliked item and instead opted for the preferred item even if it was paired with the low reward probability colour. In line with this logic, participants' accuracy increases on par with the value conflict levels, suggesting that, in incongruent blocks, it was easier to go for the high reward probability colour when this did not imply a "cost", i.e., sacrificing one's preferences.

Interestingly, this effect still occurs even when participants are cued in advance about the type of trial (reward or preference) in Experiment 2 and when they are given time to prepare for their responses in Experiment 3. The implications will be examined in Section 5.7.

5.7 General Discussion

In this chapter, we adapted the nomenclature from the work of Nakao et al. (2012) of 'externally-guided' and 'internally-guided' decision-making to provide a simple but effective operationalisation of value-based decisions. Crucially, these two types of decisions have not commonly been studied within the same task, therefore the nature of their potential interaction has not been fully addressed in the extant literature.

Experiment 1 assessed how external and internal value-based decisions would interact with one another. The findings showed an interference effect (i.e., lower accuracy rates and longer RTs) between the two domains, more specifically a spill-over of preference-related information into the reward-based domain. Similar effects were replicated in Experiment 2, despite the participants being cued at the beginning of the trial to eliminate the uncertainty inherent to the decisions made in Experiment 1. The effect was also present in Experiment 3, where the time pressure component was removed by inserting a fixed delay between cue and response, suggesting that, overall,

the interference effect is present across a variety of experimental scenarios and making it quite a robust finding.

The interfering effects that emerge from the data can be linked to different concepts explored in the extant literature, namely cognitive conflict, common currency in decision-making, modulators, reward history and value-directed attentional capture (VDAC) (Braem et al., 2012; Chiew, 2021; Chouiter et al., 2014; Feuerriegel et al., 2021; Gross et al., 2014; Levy & Glimcher, 2011; Moneta et al., 2021; Pearson et al., 2022).

Cognitive conflict can be defined as a state of difficulty and frustration driven by incongruencies in the information being processed by the brain (Pinner & Cavanagh, 2017; Pochon et al., 2008). Its resolution does not necessarily lead to optimal or rational choices, hence the longer reaction times and lower accuracy rates that have been found across several studies (Lin et al., 2018; Senftleben & Scherbaum, 2021). The task we designed was meant to introduce conflicting sources of external and internal value-related information, to assess whether such a conflict would arise in the first place. Additionally, our task also required participants to switch between external and internal value-related information, a process that, similarly to conflict resolution, is mediated by higher-order executive functions. While the two mechanisms might seem closely linked on an intuitive level - since switching task repeatedly could lead to added cognitive load and incongruent information, thus eliciting a cognitive conflict - an exploratory analysis suggests that this is not the case and the two processes are largely independent of each other, pointing towards a finer-grained parcellation within this class of cognitive functions.

Nevertheless, the cognitive conflict that seems to drive the interference effect emerging from our data can find stronger connections with the notion of common currency (Kobayashi & Hsu, 2019; Levy & Glimcher, 2011, 2012; Padoa-Schioppa & Cai, 2011). This concept is one of the key tenets in the decision-making literature and it encapsulates the idea that the values of different options need to be compared and *integrated* on a common scale in order to facilitate the decisional process. Evidence shows that specific brain areas, such as the ventromedial prefrontal cortex, are involved

in value integration across types of tasks, reward modalities, and stages of the decisional process. Integrated values are then fed to the anterior cingulate cortex and the dorsomedial and dorsolateral prefrontal cortices, which are also known for their role in conflict monitoring (Clithero & Rangel, 2014; Flannery et al., 2020; Foo et al., 2014; Sescousse et al., 2013; Wallis & Kennerley, 2010). This suggests that value integration is mediated by distinct networks of brain regions with separate roles. More specifically, an fMRI study by Kahnt et al. (2011) attributed to the dlPFC a sensitivity to attribute variability and to the difficulty of the integration process, e.g., if the attributes of the options suggest conflicting value predictions. While we cannot glean such insights from our behavioural data, we can assume that such a process might be taking place, given that the attributes of the available options in our task change within and across blocks along four important dimensions, i.e., task difficulty (easy vs hard trials), task type (reward vs preference), the congruence between item and colour (with congruent and incongruent blocks), and the individual ratings of the two items displayed on the screen, the latter being crucial for computing predictors such as value magnitude and value conflict. All this information needs to be integrated in order to perform the task effectively, but as suggested by the lower accuracy rates and longer RTs in incongruent reward trials in Experiment 1, variability in these attributes might lead to difficulties in the integration process, and in turn to suboptimal and erroneous choices.

Attribute variability and its behavioural and neural consequences can be further linked to reward history, value updating, and value-directed attentional capture (Bucker et al., 2015; MacLean & Giesbrecht, 2015; Matias et al., 2021). These three concepts all share a key commonality: that reinforcement learning is a dynamic driving force affecting both decisional and attentional processes. For instance, in our task, participants learned over time which colour was the most advantageous one in a specific block, but when the reward probabilities were reversed or changed and the item-colour congruence was modified, their prior learning and value history seem to have bled into their behavioural responses, resulting in changes in average accuracy and reaction times. Indeed, based on prior research, previously rewarded options automatically capture attention and can do so even when the item-reward association is removed (Bucker et al., 2015; Kim & Anderson, 2019). This could provide another

fitting explanation for the patterns observed across blocks and experiments, specifically in reward trials and for the differences seen in congruent and incongruent blocks, since this kind of bottom-up attentional allocation could potentially override optimal top-down control during the decision phase.

Overall, several interconnected factors seem to be at play during the current set of experiments, ranging from attentional to conflict monitoring to integration processes. The inferences that can be drawn from the behavioural data are limited, but still greatly informative in ascertaining that in Experiments 1 and 2, there is indeed a spill-over effect between the external and internal value domains. Consequently, further investigations on the corresponding neural substrates are warranted and needed to elucidate the spatiotemporal dynamics of this phenomenon. This will be explored in Chapter 6.

6 The interplay between internal and external value-based decisions: an MEG experiment

6.1 Introduction

In this Chapter, we aim to replicate and expand upon the findings of Experiment 1 in Chapter 5 by using magnetoencephalography (MEG) to examine the temporal unfolding of the interplay between internal and external value-based information. The reason for using MEG, specifically, is that it offers superior temporal resolution to fMRI, in the order of milliseconds, and it is not affected by the same signal issues as EEG, namely the distortion of the electrical signal as it passes through the meninges, the skulls, the scalp, and the hair. Additionally, by using Multivariate Pattern Analysis (see Section 6.2.4.2 for a detailed explanation of the process), we can also extract information regarding the cortical areas involved during the task. Overall, the experiment detailed in the following pages provides a starting point to further assess the neural correlates involved in complex decisional scenarios with varying levels of conflicting information.

6.1.1 Hypotheses

We hypothesise that the behavioural effects found in Experiment 1, Chapter 5, concerning the influence of congruent or incongruent information and of the different probability reward conditions on accuracy rates and reaction times will be replicated here. Moreover, we hypothesise that the MVPA classification of MEG source-localised data will detect differences between trial types (reward vs. preference), congruency conditions (incongruent vs. congruent), and reward probability conditions (hard vs. easy).

6.2 Methods

6.2.1 Participants

We recruited a total of 47 participants (F = 35, M = 12) through the EMS System (Sona Systems), the CUBRIC Research Digest, and word of mouth. Participants' ages ranged from 18 to 35 years old, and they had no history of neurological or psychiatric disorders, with normal or corrected-to-normal vision. Four participants did not complete the full protocol after the first behavioural session and an additional one completed the two MEG sessions but did not undertake a structural MRI scan. Four more participants were removed during preprocessing due to the poor quality of the structural images. The data from these 9 participants was excluded from further analyses, leaving a sample of 38 participants (F = 28, M = 10, M_{age} = 24.42, SD_{age} = 3.08). Participants provided their informed consent at the start of each experimental session, and they received monetary compensation to take part in the experiment. This applied to all participants, regardless of whether they completed the protocol or not.

The study was approved by the Ethics Committee of the School of Psychology at Cardiff University.

6.2.2 Design

The aim of this study was to examine the neurophysiological correlates of the interplay between externally-guided and internally-guided decision-making, thus expanding the behavioural findings discussed in Chapter 5 with the inclusion of MEG data. To this end, we used the same design as that of Experiment 1 explained in Chapter 5 (see 5.3.2.4 and 5.3.2.5). The main difference concerns the total number of trials, as participants performed 8 blocks of the task across two MEG sessions, meaning the total number of trials was 720 instead of 360.

6.2.3 Procedure

Each participant included in the final sample attended four separate sessions, namely a behavioural "pre-scanning" session, where they could practice the task,

followed by two separate MEG sessions and an MR session. The procedural details of each session are described below.

6.2.3.1 Behavioural Session

During the behavioural session, participants received detailed written and verbal instructions on how to carry out the Stage 1 ratings on a webpage, where they rated 40 food items taken from the *Foodpics_extended* database (Blechert et al., 2019) according to the same criteria used in Chapter 5 (see 5.3.2.3). The Stage 1 ratings consisted of two consecutive rounds of rating to ensure consistency. Following the ratings, participants were asked to practice a short run of Stage 2 trials consisting of 10 trials with food items that were not present within the 40 items already rated.

6.2.3.2 MEG Acquisition

The two MEG sessions followed an identical procedure. The participants carried out the full version of the main task, consisting of 720 trials across the two sessions, with the congruency between item and coloured border, and the reward probability counterbalanced across blocks. Therefore, across the two sessions, participants were presented with the following block configuration, which was randomised within each session of four blocks each:

- 2 congruent blocks with easy reward probability (80% vs 20%)
- 2 incongruent blocks with easy reward probability (80% vs 20%)
- 2 congruent blocks with hard reward probability (60% vs 40%)
- 2 incongruent blocks with hard reward probability (60% vs 40%)

Visual stimuli were displayed on an MEG-compatible screen using PROPixx projector (VPixx Technologies Inc., Canada) with a resolution of 1920 × 1080 pixels and a refresh rate of 120 Hz. Participants were sat at approximately 120cm from the screen.

The MEG data were acquired using a CTF MEG system with 275 axial gradiometer sensors distributed over the whole cortex (CTF MEG Neuro Innovations, Inc., Canada). Before the participant entered the MSR, we acquired the digitized head data from each participant using a Fastrak digitizer (Polhemus, Inc., US). The digitized head data

included the location of the three fiducial points on the nasion, the left and the right preauricular points, as well as the positions of three HPI coils placed on the same points, and at least 200 points of the head shape used for co-registration purposes. We also attached three pairs of EOG electrodes to the participants to record their eye movements in order to filter out the related artifacts during preprocessing. A pair of EOGs were placed above and below the right eye to record blinks, while a second pair was placed about 1 cm away from the lateral canthi on each side to record saccades and the third pair was placed on both mastoids for reference. During the MEG recording, participants rested their chins on a chin rest to minimize any noise generated by head movements. A NATA button box was used to record the responses and participants were instructed to use their right index and middle finger to choose either the option presented on the left side of the screen or the one on the right, respectively.

6.2.3.3 Structural MRI Acquisition

Brain images were collected using a 3T MRI Scanner (Siemens PRISMA, Siemens, Erlangen, Germany). Head motion was minimised by positioning additional foam paddings around the participant's head and they were provided with earplugs to insulate them from the noise of the machine. We acquired structural images for each participant with an MPRAGE sequence (TR = 2.1 s, TE = 3.24 ms, flip angle = 8°, acquisition matrix= 256 ×256, voxel size =1mm^3).

6.2.4 MEG Analyses

6.2.4.1 MEG Preprocessing

Data preprocessing was applied according to the following step: 1) the data was band-pass filtered from 0.1Hz to 90Hz; 2) the data was then down-sampled to 200Hz; 3) independent component analysis (ICA) was run on the down-sampled data with fixed random seeds; 4) we manually identified the components containing ECG/EOG artifacts and 5) attenuated the artifacts by removing said components. We removed between 3 and 5 components, which mainly reflected eye movements and cardiac responses, for each subject. We then 6) segmented the data into epochs aligned with the stimulus presentation with an overall length of 3 seconds, divided into 0.8 seconds

before the stimulus presentation (which corresponds to the shortest ITI between trials and that we use as a baseline) and 2.2 seconds starting from the stimulus presentation.

6.2.4.2 Source-level Analysis

We applied a Linearly Constrained Minimum Variance (LMCV) beamformer to the time domain in order to estimate the level of activation at a given Region of Interest (ROI). After dividing the brain into a regular 3D-grid of equivalent current dipoles (ECDs), we produced a 3D spatial distribution of the neural sources, which was overlaid on a structural image of the subject's brain. The ROIs were based on the Automatic Anatomical Labelling (AAL) Atlas (Tzourio-Mazoyer et al., 2002). After averaging between left- and right-hemisphere ROIs and removing subcortical ones, 39 ROIs remained.

We conducted a time-resolved Multivariate Pattern Analysis (MVPA) decoding on the non-averaged source-localised MEG data in order to decode the spatiotemporal profiles of the information contained in the task. Specifically, we decoded the trial type (reward vs. preference), the congruency condition (incongruent vs. congruent) on both reward and preference trials, and the reward probability condition (hard vs. easy) on reward trials. No trials were left out of the during the 5-fold cross validation applied using all the ECD signals from all ROIs, ensuring the robustness an generalisability of the results while preventing model overfitting (King & Dehaene, 2014). Additionally, source data was averaged every 2 trials in a given condition, in order to enhance the signal-to-noise ratio (SNR) (Baillet et al., 2001).

For each of the five cross-validations, we used 80% of the data as a training set and 20% as a test set. We applied an under-sampling methodology to redress the imbalance between the two datasets, whereby a random number of trials from the training set is picked in order to align with the number of trials in the test set, preventing the decoder from being biased towards the majority class. Moreover, in order to reduce the complexity of the data whilst still being able to explain 99% of the variance in the training data set, we applied a Principal Component Analysis (PCA). Then, the test dataset is projected onto the same reduced dimensional space using the eigenvectors corresponding to the output of the PCA. These steps are then used to train a Linear

Discriminant Analysis (LDA) model, implemented using the MATLAB 2015a Machine Learning and Statistics Toolbox. The overall classification accuracy is based on the average of the five iterations of the MVPA process and results in a 3D matrix of all 39 ROIs at all averaged time points for each participant. The group results for each ROI were then compared with a 50% accuracy level using a two-tailed one-sample t-test. To account for multiple comparisons, we applied the Bonferroni correction to the alpha levels.

6.3 Results

6.3.1 Behavioural Results

Participants performed binary forced-choice decisions based on either the reward-related (i.e., externally-guided) information or the preference-related (i.e., internally-guided) information, following a cue signal shaped either as a dollar sign or as a heart symbol. Behavioural performance was measured in terms of accuracy (reported in percentages), which was codified based on whether participants selected the option that awarded 100 points (for reward trials) or the option that was consistent with the initial ratings (for preference trials), depending on the cue shown on that trial. Additionally, we recorded and analysed reaction times, excluding those trials where RTs were quicker than 200ms, in order to include only intentional responses. To examine whether the reward probability condition or the congruency between food item and coloured border had an effect on accuracy rates and/or reaction times, we conducted four separate 2x2 ANOVAs on JASP (version 0.18.3.0) with reward probability and congruency as factors, separately for accuracy and reaction times and for trial type (reward and preference).

In reward trials (Figure 22 (A)), accuracy rates showed the most variability across conditions. Participants were in fact most accurate in easy (80% vs 20% reward probability) congruent trials (M = 76.31%, SD = 13.40) and least accurate in hard (60% vs 40% reward probability) incongruent trials (M = 47.63%, SD = 17.70). In preference trials (Figure 22 (B)), instead, participants' mean accuracy rates were more similar to each other, with participants being slightly more accurate in easy congruent trials (M =

79.85%, *SD* = 13.33) and less accurate in easy incongruent trials (*M* = 74.76%, *SD* = 11.84).

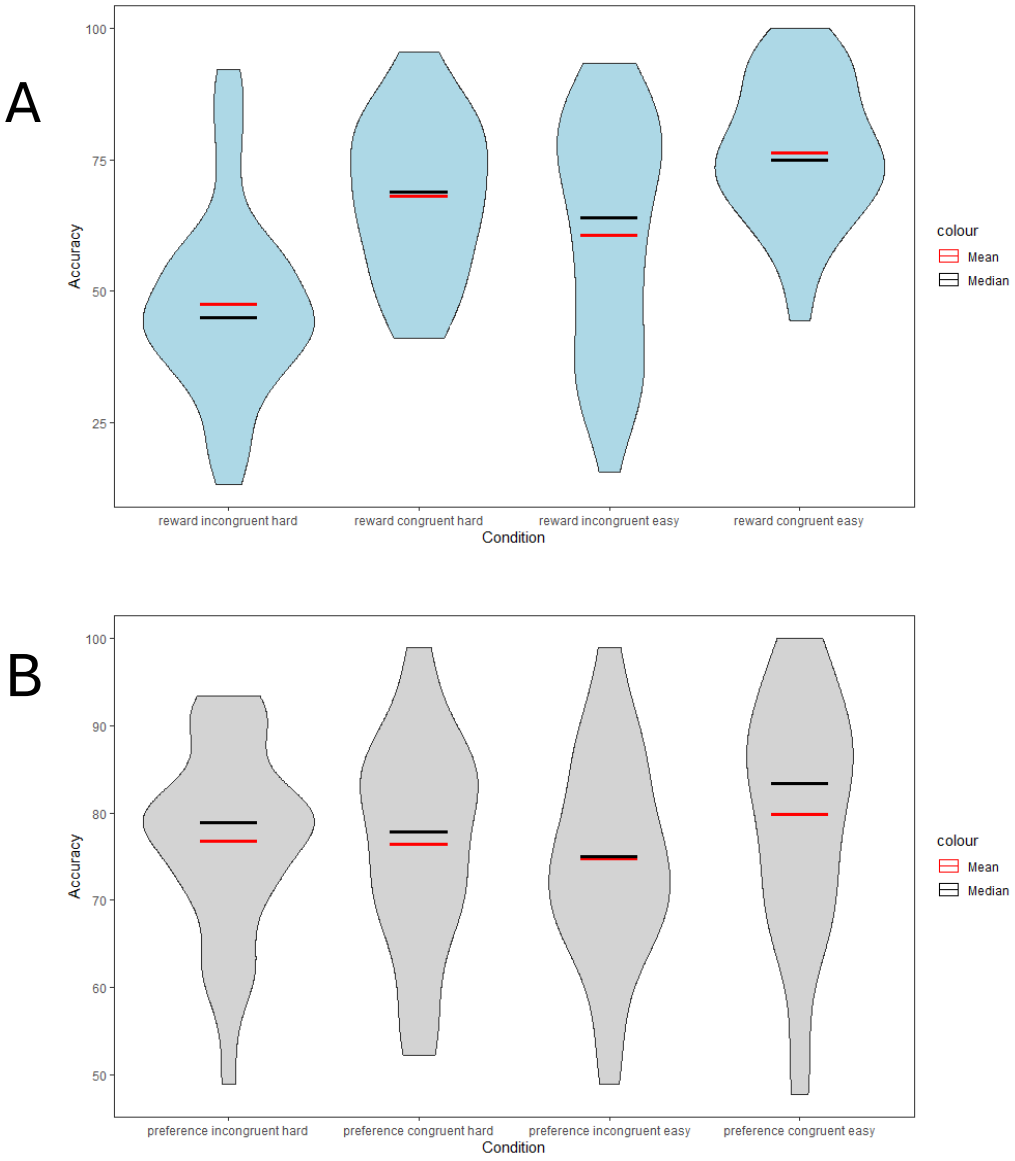


Figure 22 Violin plots depicting accuracy rates (%) across reward (A) and preference (B) trial conditions

In reward trials (Figure 23(A)), participants have shorter RTs in the congruent easy condition (*M* = 0.59 seconds, *SD* = 0.15) and slightly longer RTs in incongruent hard trials (*M* = 0.64 seconds, *SD* = 0.17). In preference trials (Figure 23(B)), we see the same pattern, with shorter RTs in the congruent easy condition (*M* = 0.58 seconds, *SD* = 0.14) and longer RTs in the incongruent hard condition (*M* = 0.62 seconds, *SD* = 0.14).

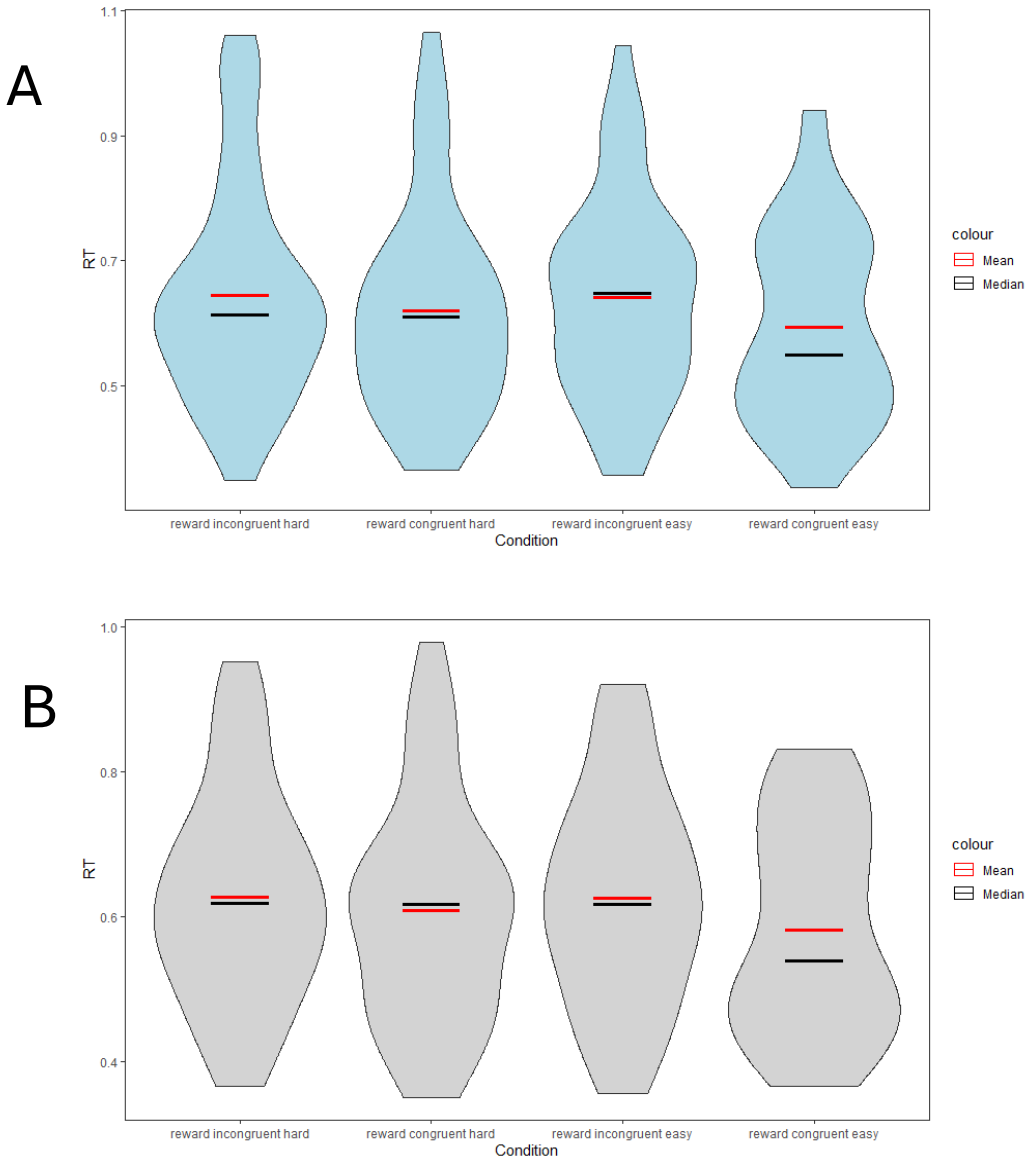


Figure 23 Violin plots depicting RTs (s) across reward (A) and preference (B) trial conditions

In reward trials, congruency significantly affects both dependent measures (accuracy: $F(1,37) = 35.016$, $p < 0.001$, $\eta_p^2 = 0.486$; RT: $F(1,37) = 9.195$, $p < 0.05$, $\eta_p^2 = 0.199$). The different reward probability conditions significantly affect accuracy rates ($F(1,37) = 24.290$, $p < 0.001$, $\eta_p^2 = 0.396$), but not reaction times. No significant interactions between congruency and reward probability were observed in either accuracy or reaction times.

In preference trials, congruency also affects both accuracy ($F(1,37) = 5.455$, $p < 0.05$, $\eta_p^2 = 0.128$) and reaction times ($F(1,37) = 7.767$, $p < 0.05$, $\eta_p^2 = 0.174$), while neither measure is affected by reward probability conditions, thus indicating that participants

were able to filter out this source of irrelevant information during preference trials. Finally, we found a significant interaction between congruency and reward probability in preference trials but only when examining accuracy rates ($F(1,37) = 6.733$, $p < 0.05$, $\eta_p^2 = 0.154$).

6.3.2 MEG Results

We ran MVPAs on source-localised neural activity to determine whether any cortical ROIs contained task-relevant information related to the type of trial (reward vs. preference), the congruency condition (incongruent vs. congruent), and reward probability condition (hard vs. easy). The MVPA time course is aligned to the stimulus presentation and covers both stimulus and cue presentation, occurring at 0 and at 1.2 seconds, respectively (**Figure 24**(A) and **Figure 24**(B)). The whole epoch started from 200 milliseconds before the stimulus onset (which was also used for baseline correction) and ended at 2.2 seconds. The alpha level for the trial type and congruency decoding was 1.1550e-06 (i.e., 0.05/(90*481)).

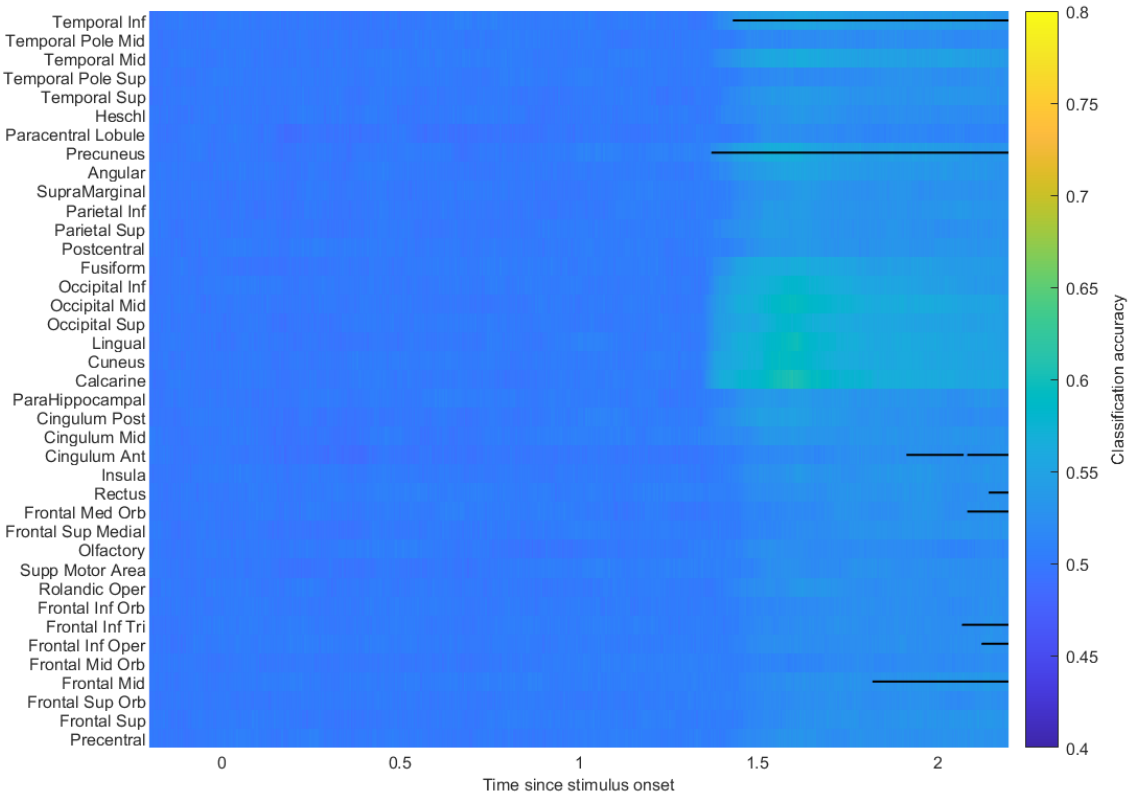
The classification results on trial type (**Figure 24**(A)) indicated that, approximately at the cue onset (1.2 seconds), it was possible to detect the different trial type (reward vs. preference). The longest activations cover around 800-1000ms and involve areas devoted to visual processing (i.e., lingual gyrus and precuneus), and to object recognition and categorisation, such as the inferior temporal cortex and the fusiform gyrus. Shorter activations, happening between 1.7 and 2.2 seconds, are related to higher cognitive functions (i.e., the gyrus rectus, frontal medio-orbital areas, and anterior cingulate cortex).

The classification results on congruency (**Figure 24**(B)) showed shorter but more widespread significant activations occurring both before and after the cue-onset. These activations ranged from approximately less than 100 to 500-600 milliseconds in duration and were found in brain areas involved in voluntary motor control (i.e., precentral and postcentral gyri), visual processing (i.e., calcarine and occipital areas as well as the lingual gyrus), object recognition and memory (i.e., multiple portions of the inferior, superior, and medial temporal lobe, alongside the parahippocampal area and

the fusiform gyrus), attentional allocation (i.e., superior parietal cortex, cuneus), and value-based decision-making (i.e., middle frontal areas and the insular cortex).

Surprisingly, no significant latencies and no significant ROIs emerged when contrasting the two different reward probability conditions (hard vs. easy). The reasons for this are explored in Section 6.4.

A



B

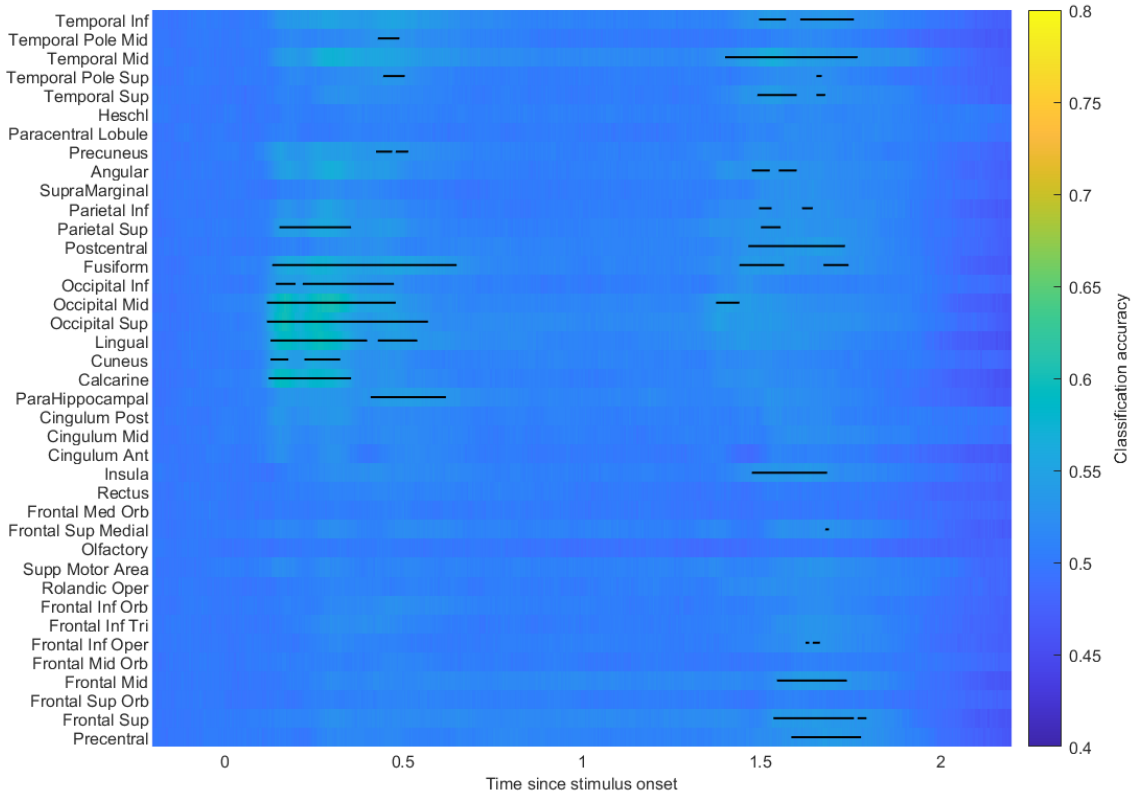


Figure 24 MVPA results of source-localised MEG data on trial type (A) and congruency condition (B). Black bars indicate significant time periods and ROIs.

6.4 Discussion

In this Chapter, we replicated and expanded the findings from Experiment 1 in Chapter 5. Our design combined both reward-related and preference-related information in the same stimulus display, followed by a cue that indicated which type of decision the participants were expected to make. The behavioural results indicate that the congruency between the two decisional domains affects accuracy and reaction times more strongly in reward trials, therefore providing further empirical support as to the robustness of this spill-over effect between decisional domains. The MVPA results from the MEG data, in turn, offer further insights into the potential neural underpinnings. Unsurprisingly, visual processing areas are heavily involved alongside motor control

areas and mid-frontal areas that have been implicated in decisional processes (Braeutigam et al., 2004). The fact that most decodable activity occurs after the onset of the cue (around 1.2 seconds) indicates that, during the stimulus presentation phase, participants are indeed naïve as to the experimental manipulations concerning trial type and congruency. However, one interesting result concerns the lack of statistically significant latencies and cortical activations when applying the MVPA classifier to the two classes of reward probability conditions (hard vs. easy). While precedents in the literature (Castegnetti et al., 2020; Doñamayor et al., 2012) tend to focus on outcome-related ERP/ERFs or decoding accuracies when investigating probabilistic decision-making, there are also studies that examine the anticipatory phase of reward processing. Therefore we might reasonably expect significant MVPA differences between the two conditions (Angus et al., 2017; Bach et al., 2017; Bijleveld et al., 2014; Bunzeck et al., 2011). On the other hand, two considerations need to be made: first of all, while the reward cue marked the need for a reward-based decision, in itself it contained no explicit information about the reward probabilities, compared to, for instance, the cues used in money incentive delay (MID) tasks (Apitz & Bunzeck, 2012). Additionally, participants were never informed of the different probabilities, only that at times either of the border colours (red vs. blue) might be more advantageous. This means that reward probabilities were implicitly learned and their encoding might have occurred at a subconscious level, thus activating a different set of brain regions perhaps at subthreshold level (Bijleveld et al., 2014). Further analysis, for instance at the sensor-level or on the oscillatory profiles of cue-locked activity, could provide additional insights.

Further evaluations will now concern the putative roles of the areas identified in the two sets of statistically significant MVPA results. Starting with the areas identified in the decoding of trial type information (Figure 24(A)), we first see that the inferotemporal region shows sustained activation for around 500 milliseconds. This area has been consistently associated with object recognition and object-based attention, with different portions of it being selectively responsive to different categories of objects, such as faces, places, animate, and inanimate objects (Baldauf & Desimone, 2014; Logothetis & Sheinberg, 1996; Rolls, 2000; Spiridon et al., 2006). Its activation in a

decision-making task that relies heavily on the visual recognition of stimuli indicates that participants were indeed attending to the cues shown on the screen. On a similar note, the activation of the precuneus, a portion of the superior parietal lobule that has been involved in visuospatial imagery, memory mechanisms, and mental representations (Cavanna & Trimble, 2006; Lundstrom et al., 2003), suggests that participants were simultaneously recollecting information related to the stimulus display shown at the start of the trial.

Two subcortical brain structures, the insula and the anterior cingulate cortex (ACC), also show significant activation when decoding trial-related information. Both have been linked to higher cognitive functions such as decision-making under uncertain conditions (Clark et al., 2014; Droutman et al., 2015; Markett et al., 2016; Uddin et al., 2017; Von Siebenthal et al., 2017), attentional processes (Egner & Hirsch, 2005; Pardo et al., 1990), and the subcortical salience network (Uddin, 2015). The ACC has also been associated with conflict and error monitoring (Bryden et al., 2011), two executive functions that allow the brain to navigate the ambiguous, uncertain, and contradicting information present in the external and internal environments. Its activation in the current MEG experiment should, therefore, come as no surprise, given that the whole design requires participants to make decisions based on, at times, incongruent information that pits external and internal demands against each other. Interestingly, however, this activation is not found in the MVPA findings regarding the congruency condition (Figure 24(B)). Nevertheless, here, we do note post-cue insular activation, a region that is still concerned with risky decision-making and attentional mechanisms. This discrepancy between the two sets of results might be explained by assuming that the conflicting information contained in the initial stimulus display might have become more salient once the trial cue was show, thus requiring an activation of the anterior cingulate cortex that can only be decoded when applying a classifier to trial-type data and not to congruency data. Finally, in Figure 24(A), we found a statistically significant activation of some inferior frontal (i.e., triangular and opercular) and mid-frontal areas. These areas have often been linked with aspects of decision conflict (Mitchell et al., 2009; Wendelken et al., 2009), stimulus valuation (Chaudhry et al., 2009; Du et al., 2020; Liu et al., 2012), and flexibility across decisional contexts (Reckless et al., 2014).

When taken together with the other areas activated in Figure 24(A), we observe a confluence of multiple functions relating to memory, attention, value processing, conflict and salience monitoring that allow decisional processes to adjust to a plethora of external and internal criteria.

Similarly, when we consider the MVPA findings reported in Figure 24(B) regarding congruence-related information, we observe a widespread brain network that is activated in two phases, i.e., before and after the presentation of the cue at 1.2 seconds. This suggests that, even if participants were never informed of the congruency manipulation, our design was effective in eliciting a cognitive conflict between external and internal value information that required the recruitment of a vast range of brain regions in order to be resolved. Indeed, we find a wider activation of temporal, occipital, parietal, insular, and frontal areas compared to Figure 24(A), some of which are active both before and after the cue presentation, while others are selectively engaged during one of the two phases.

Some of the areas active before and after cue onset include the superior parietal area, the fusiform area, and the medial occipital area. These are involved in attentional mechanisms, sensory integration, reward- and probability-related representations (Heekeren et al., 2008; P. Wang et al., 2023), as well as object recognition and general visual processing (Grill-Spector & Weiner, 2014; Weiner & Zilles, 2016). The transversality of these processes and their reactivation during the appearance of the cue suggest that participants were attending to the information being presented. We can further assume that the visual stimuli were being further elaborated based on the activation of the aforementioned areas in the occipital, temporal, and frontal lobes. The frontal areas in Figure 24(B) are of particular interest, as the MVPA detected statistically significant activity not only in medial frontal areas, which are associated with value-based decision-making, but also in superior and precentral frontal areas, which are instead associated with action planning and motor outputs. Since reaction times for both reward and preference trials indicate that participants respond within 500 and 700 milliseconds following the onset of the cue, the activation of motor and premotor areas around 300 and 500 milliseconds is in line with the behavioural findings. Intriguingly,

these areas have been detected only when considering congruency-related information and not when classifying brain activity according to the type of trial. This can be explained by considering the role of motor and premotor regions in evidence accumulation and integration, as well as in goal selection in choice contexts with multiple and conflicting sources of information (Cisek, 2007). In fact, neurophysiological evidence in humans and non-human primates supports the hypothesis that motor and premotor areas can hold parallel representations of movement goals associated with different options, enhancing the signal associated with the selected action plan whilst suppressing the others (Cisek & Kalaska, 2005; Klaes et al., 2011). The evidence pointing towards an integration between motor selection and cognitive conflict in the context of the present experiment highlights how tightly interwoven these two facets of decisional processes are (Cui & Andersen, 2011). Even though the present dissertation is focused on the initial stages of the decisional pipeline, the neural correlates underlying the congruency effect we investigated in this Chapter line up with the existing literature that suggests an interplay between multiple brain areas that together allow the individual to consider different sources of information in a parallel fashion (Gallivan et al., 2018; Kaufman et al., 2015; Song & Nakayama, 2009).

To conclude, this Chapter provides further support to the spill-over effects found in Chapter 5 and uncovers the spatiotemporal unfolding of this process at the neural level. We found a widespread network that comprises anterior and posterior, cortical and subcortical areas, with different regions coding for the type of decision and for the congruency of task-relevant and task-irrelevant information, highlighting the parallel, flexible, and integrative nature of decisional processes in conflicting scenarios.

7 The spatial distribution of multi-attribute internally-guided choice: an fMRI experiment

7.1 Introduction

We have established in this thesis that decision-making processes often require the integration of multidimensional information coming from multiple attributes or sources that characterise both the available options and the decisional context in which the individual operates (Busemeyer et al., 2019; Kahnt et al., 2011). This multidimensionality has received considerable attention in the behavioural, computational and neuroimaging literature of decision-making. Nevertheless, there is, still a need to ascertain how these behavioural and neural dynamics unfold when multiple attributes change on a trial-by-trial basis, such as the number of options available and the congruency of the information presented with internal valuation processes. The latter is a source of information that has been investigated in Chapters 5and 6, and here it will be re-examined in the context of choice sets that include more than one option each.

Our understanding of multi-attribute decision-making has been informed by a range of research avenues. Some of the evidence comes from multi-attribute computational models (Bhatia, 2013; Busemeyer et al., 2019; Jung et al., 2019; Noguchi & Stewart, 2018), while other sources are found in the neuroimaging literature. This evidence is not exclusively restricted to investigations of value-based decision-making either, as important insights can be gleaned from the study of perceptual decisions as well (Summerfield & Tsetsos, 2012). However, here we focus specifically on value-based decisions in order to bring our dissection of their behavioural and neural dynamics to a conclusion, by exploring the mechanisms that drive multi-attribute decisions, after devoting most of our attention mainly to choice scenarios where participants had to choose between single options. As explained in Section 1.2, the overarching aim is to provide an encompassing and well-rounded understanding of value-based decision processes of increasing complexity. To that end, here we reprise

concepts that are already familiar to the reader but explored in the context of decisions with multiple attributes.

As evidenced in Chapter 2, when stripped to its core, the decision-making process is often conceptualised as the sampling and accumulation of evidence until a decision threshold is reached, thus prompting a response of some kind (Busemeyer et al., 2019; Forstmann et al., 2016; Ratcliff et al., 2016). This is the basis on which most computational models of decision-making operate. However, as the aforementioned multidimensionality of decision-making (e.g., the presence of context effects, different stimulus attributes, and biases in the evidence sampling phase) is progressively addressed and taken into account in the literature, the computational models have been adapted to reflect these more complex aspects (Krajbich & Rangel, 2011; Molloy et al., 2018; Roe et al., 2001; Tsetsos et al., 2012; Usher & McClelland, 2001). Much work has been done on the assessment and comparison of these higher-level models (Turner et al., 2016, 2018), and some of it has been integrated with neuroscientific evidence (Turner et al., 2016), to provide a biologically informed framework of multi-attribute decisions. Efforts have often been focused on the localisation of the areas involved in value-based decisions (Bartra et al., 2013; Farrar et al., 2018; White et al., 2014), and our investigation into the neural correlates of multi-attribute decisions via fMRI will allow us to examine whether our findings are consistent with the extant literature.

Indeed, previous research into the neurobiological substrates of decision-making has shed light on the roles of several cortical and subcortical regions in processes such as value accumulation and integration and choice context effects (Basten et al., 2010; Gluth et al., 2013; Hunt et al., 2012), starting with the ventromedial prefrontal cortex and orbitofrontal area, which are seen as playing a central role in value representation and integration (Clithero & Rangel, 2014; Kahnt et al., 2011; Levy & Glimcher, 2012; McGinty et al., 2016; Rosenberg Katz et al., 2012; Wunderlich et al., 2009). Other cortical areas of interest include the dorsolateral (dlPFC) and dorsomedial prefrontal cortices (dmPFC), as hubs of value comparison and evidence sampling (Chau et al., 2014; Dixon & Christoff, 2014; Pisauro et al., 2017; Polanía et al., 2014); the

supplementary motor area (SMA) and pre-SMA, which are involved in motor planning and in the implementation of value-related signals (Aquino et al., 2023; Wunderlich et al., 2009); the parietal areas are, similarly to the dlPFC and dmPFC, involved in evidence accumulation (Hanks et al., 2015; Summerfield & Koechlin, 2010) as well as in coding reward-based signals, such as the amount and probability of obtaining a reward (Huettel et al., 2005; Matsui et al., 2022; Wang et al., 2023). The subcortical areas often highlighted in the literature include the basal ganglia, which are involved in action selection (Doll & Frank, 2009), the computation of reward-related signals such as the reward prediction error (Doya & Kimura, 2009; Schultz, 2016) as well as in coding both flexible and stable values that help guide behaviour (Hikosaka et al., 2014); these are followed by the anterior cingulate cortex, involved in computing choice difficulty (Shenhav et al., 2016), in weighing risks and benefits of a decision (J. W. Brown & Alexander, 2017; Fatahi et al., 2018) as well as in strategy switching (Economides et al., 2014; Kolling et al., 2016) and finally, the insula, which is sensitive to decision uncertainty (Berntson et al., 2011; Huettel et al., 2005; Rosenbloom et al., 2012). This widespread activation supports the conceptualisation of decision-making as a complex, integrative, adaptive, and flexible process and further points towards the need to use multi-attribute stimuli and tasks in the exploration and characterisation of the spatial distribution of decision-making.

The current experiment hypothesizes that, on a behavioural level, increasing the number of stimuli will result in lower accuracy rates and longer reaction times and that the introduction of incongruent information will similarly affect both accuracy and RTs. At the neural level, we opted for an exploratory approach without determining any a priori expectations in terms of increases in the BOLD response in specific regions. While it might be argued that the extant body of literature could provide enough information to constrain our search, we counter that our specific paradigm (explained in Section 7.2.2) is novel enough to warrant a data-driven approach.

7.2 Methods

7.2.1 Participants

We recruited 54 healthy participants (F = 37, M = 17; M_{age} = 22.15, SD_{age} = 3.85) through the EMS System (Sona Systems), the CUBRIC Research Digest, and word of mouth. Participants' ages ranged from 18 to 35 years old, and they had no history of neurological or psychiatric disorders, with normal or corrected-to-normal vision. Out of the whole sample, 39 individuals completed the protocol, consisting of a behavioural practice session and an fMRI session, while 15 stopped after the behavioural practice session. Our predetermined final sample size was around 30 viable participants (i.e., participants that completed the protocol and provided good quality data), which is in line with prior conventions in the neuroimaging literature (Desmond & Glover, 2002). After MRI quality control (see 7.2.4.1), our final sample consisted of 32 participants. Participants provided their informed consent at the start of both experimental sessions, and they received either monetary compensation or course credits to take part in the experiment. This applied to all participants, regardless of whether they completed the protocol or not.

The study was approved by the Ethics Committee of the School of Psychology at Cardiff University.

7.2.2 Design

The aim of the study was to investigate the behavioural and neural components of multi-attribute internally-guided (i.e., preference-based) binary choices in a 2x2 factorial design. The first factor was the number of items shown on the screen (2 versus 4), the second factor was the congruency condition (non-swapped/congruent versus swapped/incongruent). The congruency condition refers to whether two food items from the positive and negative rating category were swapped with each other in the trial. These factors delineated the attributes of the IDM choices that the participants were instructed to make and created 4 choice categories of varying difficulty.

The main task consisted of 320 trials, with 80 trials for each of the four conditions, i.e.:

1. Two items with no swapping (easy and congruent)
2. Two items with swapping (easy and incongruent)
3. Four items with no swapping (difficult and congruent)
4. Four items with swapping (difficult and incongruent)

7.2.3 Procedure

7.2.3.1 Behavioural Session

Before attending the behavioural session, participants received and filled in the CUBRIC MRI Screening Form, to ensure that they were suitable for the fMRI session. If the screening was successful, i.e., there were no concerns regarding the participant's suitability, participants were then invited to the first session. Here, they sat in front of a computer at a distance of approximately 60cm and were instructed to first rate 150 food items in two consecutive rounds of rating.

The food pictures were selected from the Foodpics_extended database (Blechert et al., 2019) according to the following criteria (which are the same ones used in Chapters 4 and 5):

1. A single item had to be present in the picture
2. No plates or other indicators of portion size could be present
3. Each picture displayed a unique item (no duplicates or similar items)

The rating task was programmed using Psychtoolbox on MATLAB 2015a and it was presented via a desktop computer with a screen resolution of 1920x1080 pixels. On each trial, one picture was presented in the centre of the screen on a gray background. Under it, the categorical rating scale was displayed as a black line with three ticks, labelled from left to right "Dislike", "Neutral", "Like", respectively. Participants had to press either the left arrow key, the down arrow key, or the right arrow key to indicate their rating. There was no time limit to their response. After they pressed one of the keys, there was a 1s pause before the next item was displayed on the screen (see Figure 25).

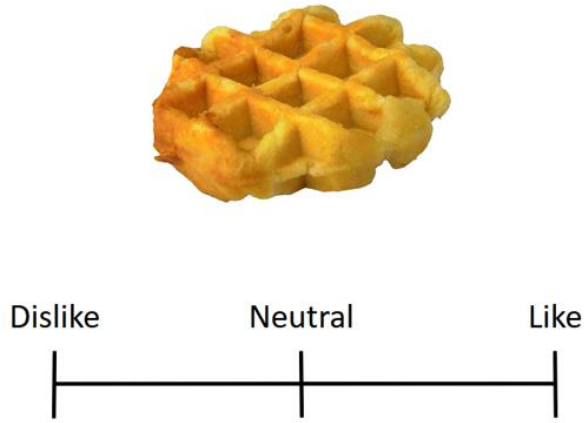


Figure 25 An example of a rating trial. Participants had to press either the left, the down, or the right arrow key to indicate their preference. The three keys corresponded to "Dislike", "Neutral", or "Like", respectively.

In order to proceed to the practice session of the main task, participants had to satisfy two criteria: they needed to have a consistency index of 85%, which was calculated based on the proportion of items that received the same rating across the two ratings. Secondly, the positive and the negative rating categories needed to include a minimum of 20 items each. This was set to ensure that we had a minimum number of pictures at our disposal to allow for a high enough number of unique combinations. Participants were instructed to be consistent and were told to distribute their ratings but were not informed of this specific threshold.

If participants fulfilled both requirements for the rating task, they then proceeded to the practice session of the main task. Here, only the pictures included in the positive and negative rating categories were used, while the ones in the neutral category were discarded. As mentioned in Section 7.2.2, the full task comprised 320 trials, while the practice only 160 trials. In each trial, multiple pictures (either two or four pictures per side) were shown on a gray background on the two sides of a centrally presented black fixation cross (see Figure 26 Figure 27). The participants were instructed to press either the left or the right arrow key to indicate which set of options they preferred. They had a maximum of 3.5s to make their response, otherwise the trial would be counted as null, and the experiment would proceed to the next one after a jittered ITI ranging between 3 and 6s.

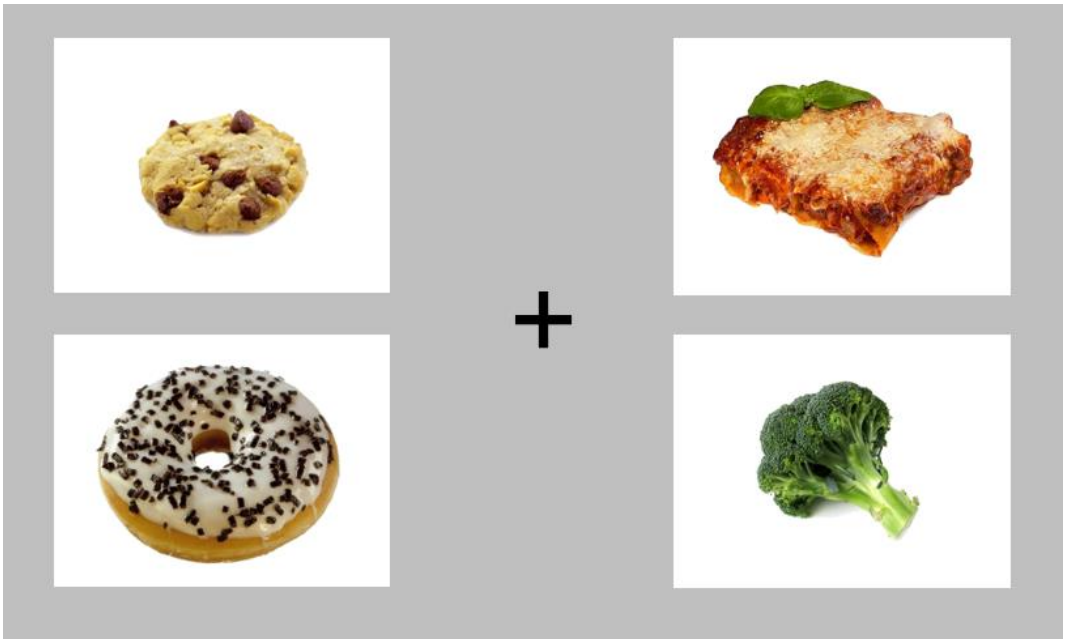


Figure 26 An example of a trial with two items per column

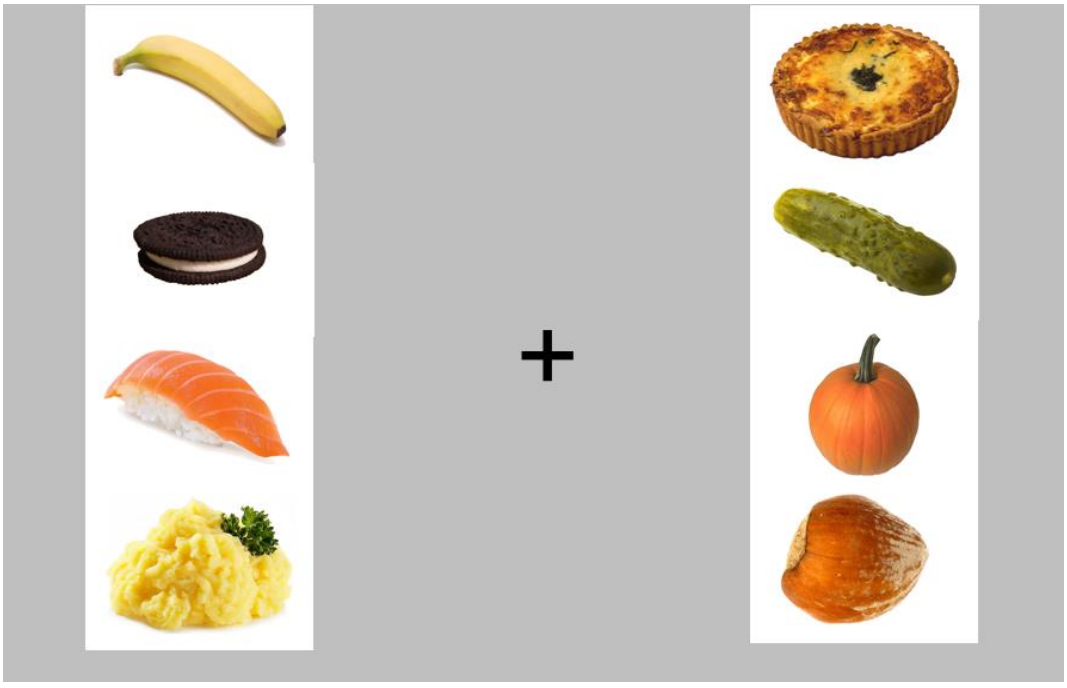


Figure 27 An example of a trial with four items per column

Once the practice task was completed, participants were scheduled for the fMRI session.

7.2.3.2 fMRI Session & Data Acquisition

Brain images were collected using a 3T MRI Scanner (Siemens PRISMA, Siemens, Erlangen, Germany). Head motion was minimised by positioning additional foam paddings around the participant's head and they were provided with earplugs to insulate them from the noise of the machine. Functional images (at least 900 volumes for each scanning session) sensitive to blood oxygen level-dependent (BOLD) contrasts were acquired by a multiband echo-planar imaging (EPI) sequence (TR = 2.01s, TE = 30ms, flip angle = 78°, acquisition matrix = 64x64, number of slices per volume = 33, voxel size = 3 mm^3). During the functional image acquisition, participants completed the full version of the task, i.e., the one comprised of 320 trials, lasting approximately 35-40 minutes with a 30 second break after the 160th trial. The experimental task with a 1920x1080 resolution was projected by a PROPixx DLP LED projector on a matched MR-compatible screen. Participants were given a handheld response box and were instructed to press either the second or the third button with their right index or middle finger to indicate whether they preferred the set of options on the left or right side of the screen, respectively.

Once the functional scans were acquired, we collected structural scans for all participants with an MPRAGE sequence (TR = 2.1s, TE = 3.24ms, flip angle = 8°, acquisition matrix = 256x256, voxel size = 1 mm^3).

7.2.4 fMRI Data Analysis Pipeline

7.2.4.1 Quality Control

We assessed the quality of the functional and structural images using the MRIQC toolbox (Esteban et al., 2017), which allows to evaluate image-quality metrics (IQMs) extracted from the MRI scans. For the functional images, we focused on the millimetres of frame-wise displacement (FD) and excluded those participants that had a FD above 0.2mm. Out of the 39 participants that completed the protocol, 7 of them were excluded after this step both for the fMRI and behavioural analysis. We also assessed the group-level SNR and TSNR, which have median values of 6.62 and 41.81, respectively.

7.2.4.2 fMRI Preprocessing

The fMRI data were pre-processed with a custom-made pipeline on SPM12 (http://www.fil.ion.ucl.ac.uk/spm/) that included the following steps: (1) realignment (estimate and re-slice) with quality = 0.9, separation = 4mm, FWHM of the Gaussian smoothing kernel = 5 mm; (2) slice timing carried out in descending order on 33 slices with TR = 2 and TA = 1.939; (3) co-registration (estimate & re-slice) that used the mean image from step (1) as the reference image and the subjects first T1w NIfTI volume as the source image, with separation between sampled points = [4 2], and histogram smoothing = [7 7]; (4) segmentation using the co-registered images as volumes, with light bias regularisation (0.001) and a cutoff value of the bias FWHM = 60mm; (5) normalisation with forward deformation and 3x3x3mm voxel size; (6) spatial smoothing with a FWHM kernel = 8 mm.

7.2.4.3 fMRI Analyses

We estimated brain activity for the pre-processed functional time series using an event-related general linear model (GLM) implemented in SPM12. The four conditions of the 2x2 design were used as predictors, while the head motion data were used as regressors. These were then convoluted with a haemodynamic response function (HRF) to generate the main model regressors. We also added temporal derivatives for each predictor to account for slice-timing variability in the HRF delay across regions.

We used trial onsets with RTs as duration corresponding to the occurrences of each of the four conditions to capture the entire time-course of the neural activity. The ITIs were used as baseline periods, as both perceptual and cognitive demands in between trials were minimal except for a change in colour of the fixation cross, which turned from black to white after the participant pressed a button.

7.2.4.4 Region of Interest (ROI) Analyses

By comparing the whole brain activation map of all the conditions' onsets with the baseline period, we extracted 7 statistically significant clusters that were used to construct the regions of interest (ROI). These roughly corresponded to both cortical and

subcortical regions that included the bilateral superior parietal cortices, the right pre-SMA, the bilateral insular areas, and the bilateral ventral visual pathways.

The ROIs were created using the MarsBaR toolbox on SPM12 (Brett et al., n.d.) and based on the MNI coordinates of the peaks. Each of the ROIs was defined based on a sphere with an 8-mm radius and with the MNI peak coordinates as its centre. We then extracted the activation data from the 7 clusters for each of the four conditions across all participants and conducted a repeated-measures ANOVA with 2x2x7 factors (2 conditions for the number of items, 2 congruency conditions, 7 ROIs) in JASP (version 0.18.3.0).

Additionally, we extracted a number of significant clusters from other contrasts of interest that showed suprathreshold activation. Specifically, we extracted 3 significant clusters from the difference in activations between the "2 items per side" condition and the "4 items per side" condition (i.e., 2 items – 4 items); 7 clusters were extracted for the reverse contrast (i.e., 4 items – 2 items); finally, 2 significant clusters were extracted from the difference between the incongruent and congruent conditions (i.e., swapped – not swapped).

7.3 Results

7.3.1 Behavioural Results

Participants performed binary forced-choice preference decisions between sets of options with two or four items each, and with congruent or incongruent information (swapped or non-swapped items). Behavioural performace was measured in terms of accuracy, defined as their consistency with the initial ratings, and reaction times. To test whether the number of items and the swapping condition had an impact on either the accuracy rates and/or the reaction times, we conducted two separate 2x2 repeated-measures ANOVAs using JASP (version 0.18.3.0). In the first one, accuracy was the dependent variable, while reaction times were the dependent variable in the second ANOVA.

Preference-based decisions with two items and congruent information had much higher accuracy (M = 87.049, SD = 8.171) (Figure 28(A)) and faster RTs (M = 1.222, SD = 0.236) (Figure 28(B)) than decisions between two items with incongruent (swapped) information (Accuracy: M = 48.676, SD = 6.303; RT: M = 1.342, SD = 0.271). Accuracy rates for choices with four items and congruent information were comparable to that for two items with congruent information (M = 90.794, SD = 7.057), but RTs were longer (M = 1.415, SD = 0.308). The fourth, and most cognitively demanding, condition with four items and incongruent information resulted in lower accuracy rates compared to four and two items with congruent information (M = 78.763, SD = 7.592) and the longest RTs out of all conditions (M = 1.467, SD = 0.345).

As we expected, there was a significant main effect of the number of items (i.e., the visual load) on accuracy ($F(1, 31) = 525.016$, $p < 0.001$, $\eta_p^2 = 0.944$) and RT ($F(1,31) = 57.484$, $p < 0.001$, $\eta_p^2 = 0.650$). Additionally, we find a main effect of information congruency (i.e., swapping, which here is used as a measure of cognitive load) on both accuracy ($F(1,31) = 670.616$, $p < 0.001$, $\eta_p^2 = 0.956$) and RT ($F(1,31) = 32.631$, $p < 0.001$, $\eta_p^2 = 0.513$), where the introduction of swapped items leads to a decrease in accuracy and an increase in reaction times. Finally, there are significant positive interactions between the main effects on both accuracy ($F(1,31) = 230.827$, $p < 0.001$, $\eta_p^2 = 0.882$) and RT ($F(1,31) = 18.194$, $p < 0.001$, $\eta_p^2 = 0.370$) (Figure 29). Here we can see that the introduction of incongruent information, especially when only two items per side are presented, is the driving effect behind the decrease in accuracy. When participants had to choose between sets of options with two items each and incongruent information, that created a highly ambiguous scenario where the two choices were fundamentally equivalent.

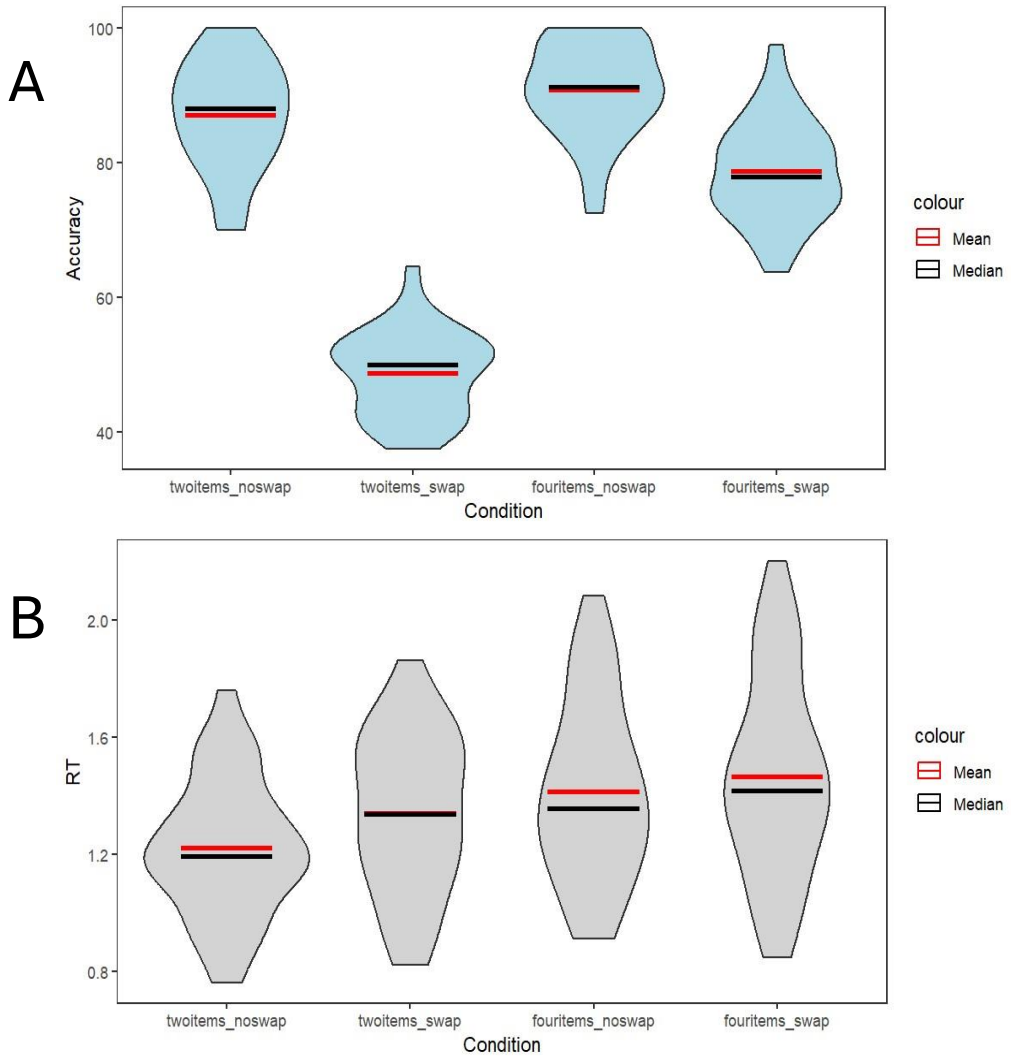
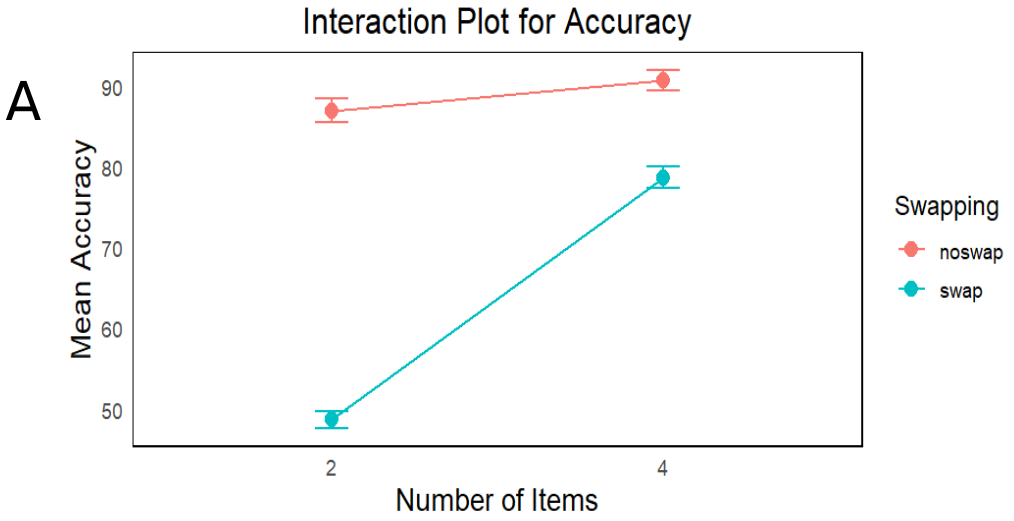


Figure 28 Violin plots showing accuracy rates (%) (A) and RTs (ms) across conditions (B)



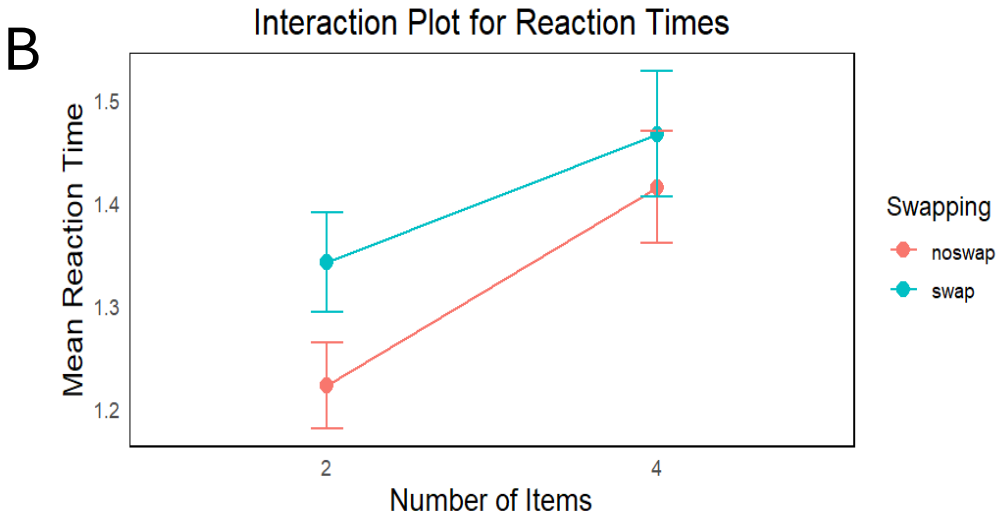


Figure 29 Interaction plots for accuracy (A) and RTs (B)

7.3.2 Functional Magnetic Resonance Imaging Results

7.3.2.1 Whole-brain Analysis

We found that several cortical and subcortical areas showed an increased BOLD response compared to the baseline period (all conditions – baseline) (FWE correction at $p < 0.01$, cluster-corrected) (Figure 30). These include extrastriate areas, the superior parietal cortices, the pre-SMA, inferotemporal areas, as well as insular ones, thus suggesting a widespread activation of regions involved in visuo-attentional processing, memory mechanisms and stimulus evaluation. Table 6 shows the MNI coordinates of these significant clusters.

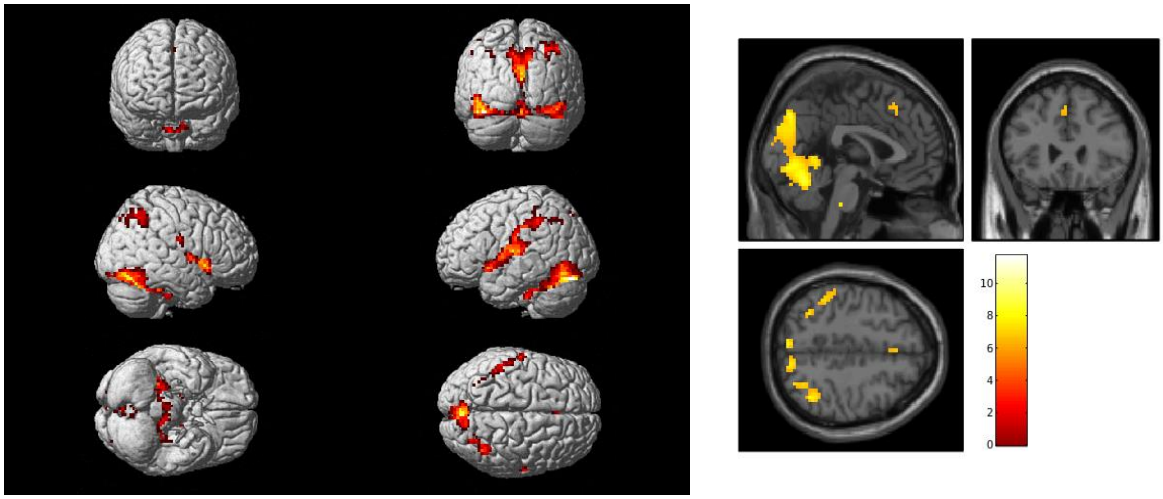


Figure 30 All conditions - Baseline Contrast. SPM12 single subject T1 template depicts medial view of preSMA activation.

ROI	X	Y	Z	T value
Insula (L)	-42	-7	5	10.70
Insula (R)	42	-4	5	9.71
Inferotemporal cortex (L)	-33	-37	-22	11.69
Inferotemporal cortex (R)	36	-37	-22	11.43
Superior parietal cortex (L)	-33	-55	41	7.48
Superior parietal cortex (R)	42	-55	44	7.95
Pre-SMA (L)	0	26	47	6.63

Table 6 MNI Coordinates and T-values of significant ROIs in all conditions - baseline contrast.

The 7x2x2 RM-ANOVA on the cluster activation levels indicates that the clusters, the number of items, and the swapping conditions are all statistically significant main effects on the mean activation levels (Greenhouse-Geisser correction, clusters: $F(6, 186) = 14.212$, $p < 0.001$, $\eta^2_p = 0.314$; number of items: $F(1, 31) = 179.346$, $p < 0.001$, $\eta^2_p = 0.853$; swapping: $F(1, 31) = 160.815$, $p < 0.001$, $\eta^2_p = 0.838$). However, by breaking these effects down for each condition, we see that (Figure 31), that the most cognitively demanding condition, with four items per side and incongruent (i.e., swapped) information, is the one that results in the highest levels of BOLD response across all clusters and that drives the significant ANOVA effects, while the other conditions show very similar levels of BOLD activation. Additionally, the two-way and three-way interactions between main effects are also statistically significant (Greenhouse-Geisser correction, clusters x number of items: $F(6, 186) = 15.826$, $p < 0.001$, $\eta^2_p = 0.338$; clusters x swapping condition: $F(6, 186) = 13.063$, $p < 0.001$, $\eta^2_p = 0.296$; number of items x swapping = 189.340, $p < 0.001$, $\eta^2_p = 0.859$; clusters x number of items x swapping condition: $F(6, 186)$, $p < 0.001$, $\eta^2_p = 0.333$).

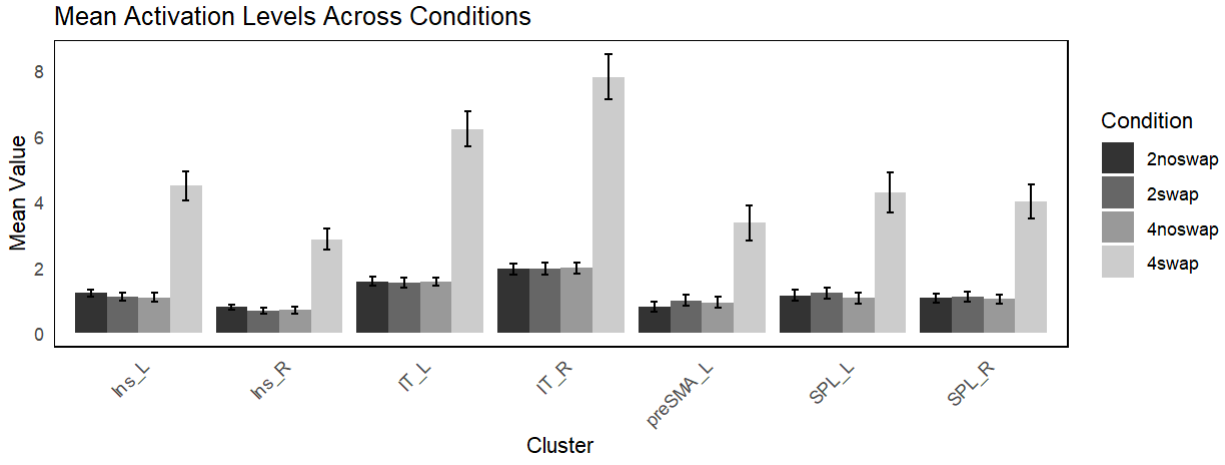


Figure 31 Mean activation levels across clusters and conditions

To gain additional insights into the three-way interaction found in the 7x2x2 RM-ANOVA, specifically which ROIs were sensitive to the different number of items and swapping conditions, we ran 2x2 post-hoc RM-ANOVAs on each of the seven clusters (Table 7).

Cluster	F (n. items)	*p*	F (swapping)	*p*
Insula (L)	80.411	<0.001	91.153	<0.001
Insula (R)	61.834	<0.001	66.110	<0.001
Inferotemporal (L)	152.340	<0.001	112.297	<0.001
Inferotemporal (R)	130.651	<0.001	109.799	<0.001
Pre-SMA (L)	35.262	<0.001	32.560	<0.001
Superior parietal (L)	44.316	<0.001	48.987	<0.001
Superior parietal (R)	49.723	<0.001	50.250	<0.001

Table 7 Results of the post-hoc RM-ANOVA on 7 ROIs to assess the effects of the number of items and swapping conditions.

7.3.2.2 Exploratory Brain Analyses

We also compared BOLD responses between the number of items and between the congruency conditions. We display the rendering and T1w single-subject brain sections relating to the following contrasts: 2 items – 4 items; 4 items – 2 items; incongruent (swapped) – congruent; 4 items congruent (not swapped) – 2 items congruent. All the contrasts were cluster FDR-corrected, $p < 0.05$.

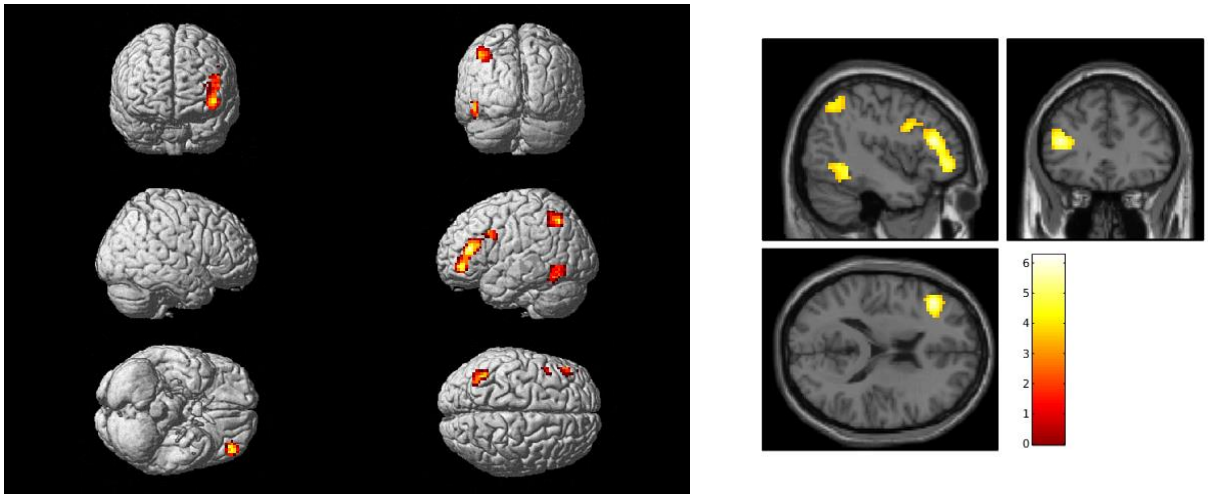


Figure 32 Whole brain comparison of 2 items – 4 items contrast

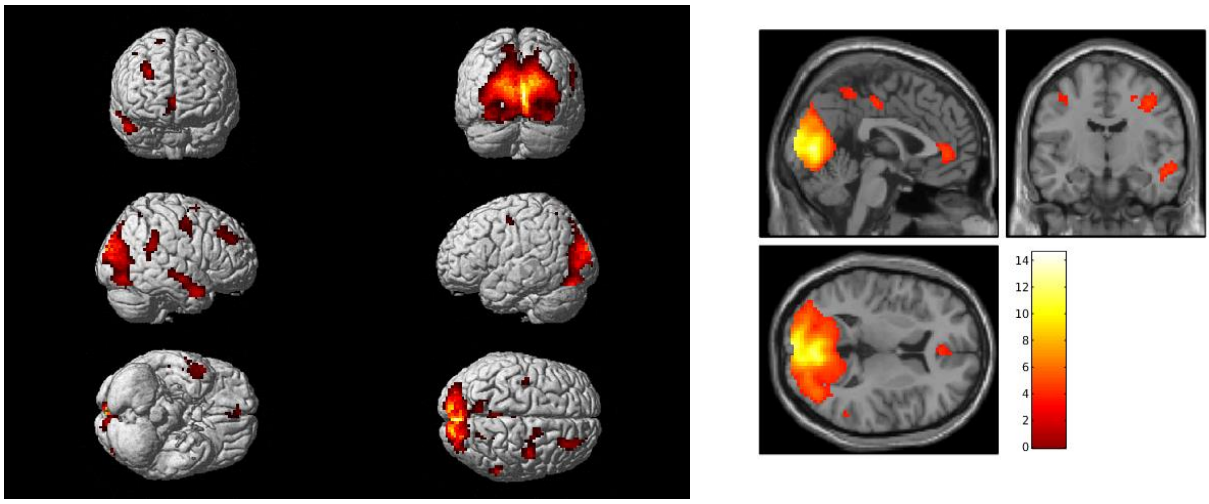


Figure 33 Whole brain comparison of 4 items – 2 items contrast

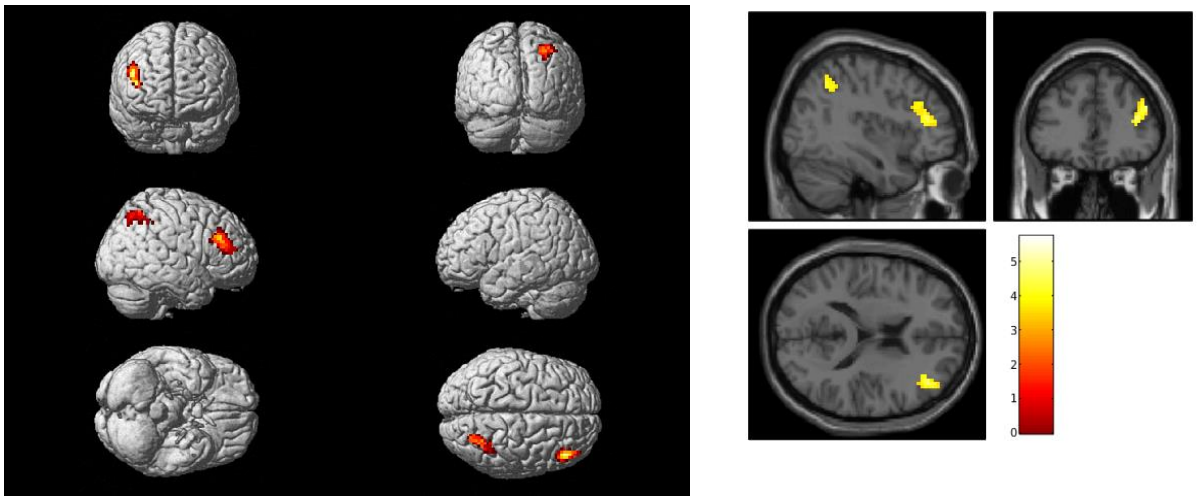


Figure 34 Whole brain comparison of swapped – not swapped contrast

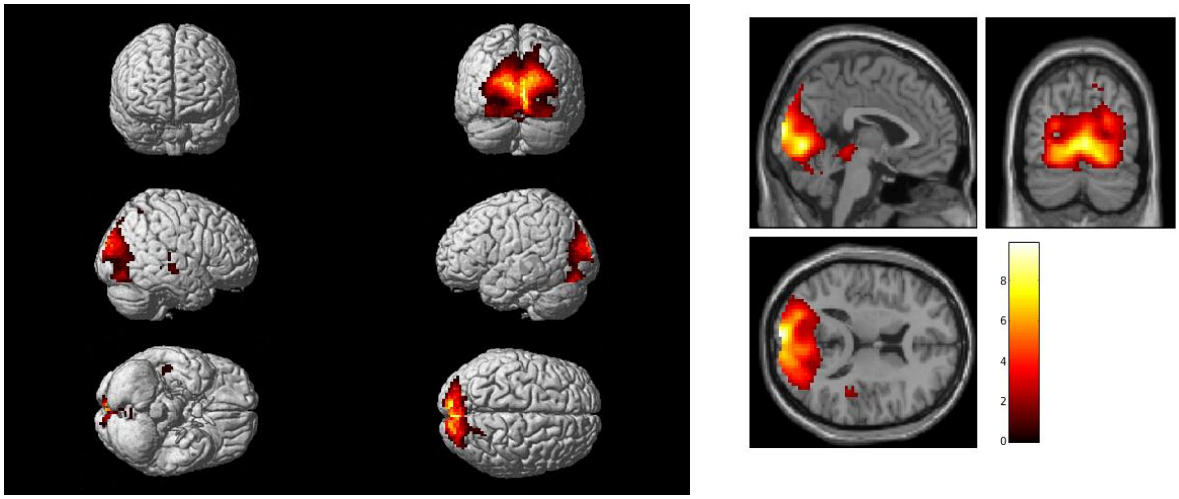


Figure 35 Whole brain comparison of 4 items not swapped - 2 items not swapped contrast

One of the most notable findings of this exploratory analysis concerns Figure 33 and Figure 35, where we see an increased BOLD response in striate and extrastriate areas when computing the differences in brain activations between 4 items and 2 items. This is consistent with the increased visual load presented on those trials.

7.4 Discussion

The current experiment aimed to examine the behavioural and neural correlates of multi-attribute choice sets that differed on a trial-by-trial basis in the number of items presented on the screen (two or four per side) and in the introduction of incongruent information, with the swapping of food items between the positively and negatively rated sets of options.

Our behavioural findings show that, as the number of items increases, participants become slower in their choices and that this effect is further accentuated by the presence of incongruent information, i.e., the swapped items, which also greatly affects accuracy rates (i.e., the consistency with their initial ratings). This suggests that participants were actively engaged in the task and that increasing the difficulty of the choice sets can negatively affect performance. Such results are in line with the extant literature on choice difficulty and complexity (Kahnt et al., 2011), adding to a growing body of information on human behaviour in complex decision-making scenarios (Cho et al., 2013; Greifeneder et al., 2010; Haynes, 2009). In particular, the lower accuracy and

longer reaction times for the most difficult condition (i.e., four items with swapping) seems to suggest that decision-makers' attention might be biased by the presence of incongruent information (e.g., a negatively rated item in the positively rated set of items), leading to choices that are inconsistent with their initial ratings. Attentional allocation has, indeed, been at the forefront of multiple psychological, computational, and neuroscientific inquiries on decision-making and has been described as having an amplifying effect on choice behaviour (Fisher, 2021; McGinty et al., 2016; Yang & Krajbich, 2023). In the present work, it is however difficult to ascertain the effects of attentional processes as no eye-tracking data was collected. A further reiteration of this experiment could consider collecting eye-tracking and pupillometry data to complete the picture.

Nevertheless, the fMRI data can provide important insights into the biological workings of multi-attribute choice. Our key contrast consisted of a comparison of all conditions against baseline activation and the BOLD response significantly increased in seven regions of interest. These ROIs mostly reflect the activity of the so-called "multi-demands network" (Camilleri et al., 2018; Crittenden et al., 2016; Duncan, 2010), which has been identified as having a crucial role in executive functioning. These ROIs include the posterior medial frontal cortex, i.e., the pre-SMA, the superior parietal lobule, and the insula. We also found strong activations of the occipito-temporal cortex, corresponding with ventral visual stream, which is consistent with the primary function of this pathway, i.e., object recognition.

Findings on the connectivity of the "multi-demands network" also indicate a partial dependence with the "salience network" (Seeley, 2019), in particular in the activation of the pre-SMA. Both of these networks are associated with behavioural coordination, working memory, and attention (Camilleri et al., 2018). Our data also indicates a partial activation of the "fronto-parietal attentional network" (Parlatini et al., 2017), as shown by the bilateral activation of superior frontal and superior parietal cortices. This network acts as an integration hub between the dorsal attention system, which acts in a top-down manner on incoming sensory information, and the hippocampal-cortical network, which is involved in the formation of declarative

memories (Vincent et al., 2008). Parlatini et al. (2017) found further overlap between the fronto-parietal and the multi-demand network in areas such as the SMA, the inferior frontal sulcus, the frontal operculum, and the intraparietal sulcus, some of which are also present in our findings. All these networks seem to share a feature, i.e., they are involved in the production of flexible and adaptive behaviour, which is crucial for successful interactions with the external environment and its demands.

Overall, the present work further highlights, both on a behavioural and neurobiological level, the complex mechanisms involved in decisional processes and provides insights into the multifaceted brain responses that underlie the behavioural patterns elicited by complex decisional scenarios. Finally, our findings replicate previous research and reflect the need for continued investigations into multi-attribute decision-making from a cross-methodological perspective.

8 Summary

The present dissertation focuses on the interplay between different domains of decision-making, specifically between value-based and perceptual decisions and within the value-based domain, where we contrast internal (i.e., preference-based) with external value information, following the operationalisation proposed by Nakao et al. (2012). This chapter summarises the key findings of each chapter and highlights their contributions to the existing literature in Section 8.1. Limitations and future directions of the present work will be discussed in Section 8.2.

8.1 Contributions

In Chapter 2, we outlined the rationale for the whole dissertation, by highlighting the need for clear and operationalizable constructs to study decision-making processes at the behavioural and cognitive level. We discussed the major theories in value-based decision-making and exposed the sprawling array of definitions, classifications, models, and frameworks present in the literature, which complicate the conceptualisation of a unifying framework. The division proposed by Nakao et al. (2012), whereby decision-making is categorised as either externally-guided (i.e., where an objective external criterion is present) or internally-guided (i.e., where there is no objective external criterion) is, in our opinion, an elegant solution that provides a simple yet effective way to study decision-making.

In Chapter 3, we used the division in EDM and IDM to categorise 100 papers extracted from the PubMed and PMC databases to provide a comprehensive view of the value-based decision-making paradigms used in MEG and EEG studies. The reason we chose to focus on these two methodologies was to address a gap in the literature, where such systematic reviews are scarce, compared to fMRI metanalyses and reviews (Acikalin et al., 2017; Bartra et al., 2013; Clithero & Rangel, 2014; Flannery et al., 2020; Keuken et al., 2014; Krain et al., 2006). Therefore, information on the localisation of decisional mechanisms is abundant while a systematic understanding of the temporal unfolding of these same mechanisms was lacking. In our systematic review, we provide a thorough classification of value-based paradigms used in the M/EEG literature,

alongside information on the most consistently reported time windows and activated sensors as well as information on the brain areas reported in those studies that conducted source-level analyses. While it may be argued that we provide only qualitative data in this chapter, we do emphasise in Section 3.4 that the lack of standardised protocols across MEG and EEG studies concerning the systems used, the number of sensors, and the approaches used to define time windows of interests, poses important challenges to the implementation of more rigorous and quantitative summaries of the extant data. Nevertheless, Chapter 3 provides a comprehensive overview of experimental paradigms, sensor-level and time-domain data that will undoubtedly be useful to the study of value-based decision-making processes.

In Chapters 4 and 5, we focus on the potential interactions between task relevant and task irrelevant information across and within decisional domains. In Chapter 4, we describe two online behavioural experiments where we show that, with regards to surface size, a perceptual component that has received less attention in the literature on decision-making, there is a double dissociation between the value-based and the perceptual decision-making domain. This means that manipulating surface size had no effect on the preference judgments, and that preference information had no effect on size judgments. To investigate the effects of value-based and size-related variables, we used mixed linear models, which allow for more robust and precise estimates of repeated measurements within the same subjects. In Chapter 5, instead, we assessed whether there is an interference of task relevant and task irrelevant information within the value-based decisional domain, by contrasting externally-guided and internally-guided sources of information within the same trials. The paradigm we created is, to our knowledge, novel in the extant literature, as most value-based decision-making studies tend to focus on either EDM or IDM tasks, as found in Chapter 3. We conducted three online experiments with three separate samples of participants, where we varied the position of the trial cue (i.e., whether participants had to make an EDM or an IDM decision) by putting it at the start of the trial (Experiment 2), and by adding a 1.5 second delay (Experiment 3). The findings indicate a replicable “spillover” effect between EDM and IDM domains, namely, the preference-related information negatively affects accuracy rates and reaction times. In Experiment 2, surprisingly, the

effect went in both directions, with reward information also affecting preference trials. The reasons behind this empirical discrepancy between Chapters 4 and 5 could reside in the 'distance' between the decisional domains we tapped into. While the perceptual and value-based decisional domains have some shared characteristics (see Section 2.2.1), they also have significant differences, especially in how they are studied in the literature, as perceptual paradigms tend to differ in complexity compared to value-based decisions (Klein, 2001; Newsome et al., 1989; Strasburger, 2001). Instead, in Chapter 5, we are focusing on decisions that share a much closer ontological relationship and often overlap in terms of neural substrates. Another factor that might drive this difference, as briefly mentioned in Section 4.4, concerns the temporal constraints within which participants were asked to respond (i.e., 5000ms for the trials in Chapter 4 and 2500ms in Chapter 5). This methodological difference, alongside the distance between decisional domains, could partially drive these interference effects or lack thereof, thus emphasising the importance of contextual demands on decision-making and its susceptibility to the presence irrelevant information. To conclude, depending on the type of decision, the available sources of information, and external demands, decisions might be differentially affected.

In Chapters 6 and 0, instead, we investigate the temporal (Chapter 6) and the spatial (Chapter 0) distribution of value-based decisions in an MEG experiment and an fMRI one, respectively. The MEG experiment replicates and expands the findings of Experiment 1 in Chapter 5. Even though we did not apply a mixed linear model to the behavioural data, but a standard repeated measures ANOVA, we still find significant differences in the variables of interest, such as the congruency between reward- and preference-related information, thus supporting the robustness of the previous behavioural results. The fMRI experiment added another degree of complexity to the study of preferential decisions by contrasting complex option sets with 4 or 8 items in total and by swapping one negatively rated item with a positively rated one on a portion of the trials. Both experiments explicitly investigate differences between task contexts, as well as building upon the interference effects derived from irrelevant and relevant task information previously discussed. This sets them apart from other examples found in the literature, that instead focus on the implementational details of single decision-

making tasks (Basten et al., 2010; Domenech et al., 2018; Larsen & O'Doherty, 2014; Payzan-LeNestour et al., 2013; Wunderlich et al., 2012). Moreover, the two experiments, while using different methods with different strengths and weaknesses (see Sections 2.1.2.3.1and 2.1.2.3.2), share overlaps in the brain areas activated during the decisional process. For instance, we see shared activations of superior parietal, frontal, occipital, and insular cortices. This is not surprising, as these regions are robustly found in relation to decisional processes (Aquino et al., 2023; Bach et al., 2017; Bartra et al., 2013; Camilleri et al., 2018; Chouiter et al., 2014; Magrabi et al., 2022; Parlatini et al., 2017), but it does point towards a common neural system that encodes and evaluates evidence and choice outcomes in both single tasks and in tasks focused on the differences between decisional processes. In particular, the involvement of superior parietal cortices in both experiments when contrasting congruency or swapping conditions is of great interest, as this area is thought to play a role in attentional allocation (Alahmadi, 2021; Corbetta et al., 1995; Corbetta & Shulman, 2002; Domenech et al., 2018), therefore it is appropriate for it to be involved when participants are presented with mismatched sources of value-based information. Overall, we see that across methodologies we were able to capture similar dynamics and to provide complementary data on the spatial and temporal distribution of decisional mechanisms that fits with the existing literature.

In addition to considering the contributions of the single chapters included in the present work, it is worth to dwell on some of its wider implications as well. First, we consistently use a specific theoretical framework, based on the division between internally guided vs externally guided decisions (Nakao et al., 2012), that in our opinion would allow for a significant advancement towards a unifying view of decisional processes across multiple fields. The clear categorisation offered by this approach would also allow for more precise and operationalizable comparisons across different studies, in turn permitting researchers to disentangle more complex decisional mechanisms. While it could be argued that this could lead to an oversimplification of a process as varied and adaptable as that of decision-making, we believe that working towards a shared nomenclature and classification of the different types of decisions based on objective parameters (i.e., the presence or absence of an external criterion)

would contribute greatly to the continued development of this area of scientific inquiry. Indeed, one of the issues highlighted in the present dissertation is the lack of agreement amongst researchers in the field, which has in turn engendered a multitude of models, frameworks, theories, and approaches, often with few common features. The first contribution of this thesis is, therefore, to provide clear guidelines that apply to both theoretical development and robust empirical findings.

A second contribution concerns the wide array of behavioural and neuroimaging data that we collected in our pursuit to better understand and capture the dynamics of externally-guided and internally-guided value-based decisions. By including this range of empirical data, we addressed two key gaps in the extant literature: first, we started to address the lack of further behavioural and neuroimaging studies that applied the EDM vs IDM framework by using this operationalisation in a consistent manner throughout most of the present thesis. Secondly, the inclusion of electrophysiological data, whether directly collected as in Chapter 6 or collated from secondary sources like in Chapter 3, provides us with deeper insights into the temporal correlates of value-based decision-making, thus supplementing the localisation-based information obtained from fMRI studies, which comprise the majority of experiments on the subject (Acikalin et al., 2017; Bartra et al., 2013; Bobadilla-Suarez et al., 2020; Crittenden et al., 2016; Economides et al., 2014; Farrar et al., 2018; Foo et al., 2014; Fouragnan et al., 2017; Frömer et al., 2019; Lim et al., 2011). In essence, this dissertation shows that following a multimodal approach yields more robust findings as well as more comprehensive insights into the different levels of a biopsychological phenomenon.

Finally, the data presented here paints an intriguing picture of the behavioural and the spatiotemporal unfolding of value-based decision-making, whereby this process is highly reflective of the context in which the decision occurs. Specifically, depending on this context, decisions can be more or less sensitive to the introduction of irrelevant or incongruent information. Based on our findings in Chapters 4, 5, and 6, it seems that the distance between decisional domains is one of the key factors influencing whether individuals are more or less susceptible to task-irrelevant information. For instance, in Chapter 4, we contrasted value-based and perceptual decisions, which did not yield

significant results concerning a potential spill-over effect. On the other hand, when we contrasted externally-guided and internally-guided value information within the same tasks in Chapters 5 and 6, we found robust spill-over effects that persisted across different decisional contexts. The interference effect found emphasises a view of decisional processes as one that incorporates parallel and potentially competing streams of information, which aligns with and expands the current literature (Diao et al., 2021; Fellows, 2011; Glöckner et al., 2014; Hikosaka et al., 2014; Kałamała et al., 2020; Krebs et al., 2013; Rushworth et al., 2012) by applying the EDM vs IDM framework to the question of whether decisional parameters are processed simultaneously or sequentially. Moreover, the finding that preference-related information consistently affects reward-based decisions could have important ramifications for the study of cognitive control, attention, and economic decisions. To conclude, the present work provides novel and original findings on a previously unexplored interplay within the valuation system that could have further applications in the conceptualisation and examination of the behavioural and neural correlates of decision-making in a variety of contexts.

8.2 Limitations and Future directions

In this dissertation, we have conducted a total of five online behavioural experiments between Chapters 4 and 5. Due to the impact of the COVID-19 pandemic, many behavioural experiments were moved to online platforms such as Prolific. While this means that we potentially have access to a wider range of participants in terms of age, level of education, socio-economic status, gender, and ethnicity, as well as a reduction in cost and an increase in data collection efficiency, there are some challenges worth addressing. One of these concerns the attrition rate, i.e., the number of participants that drop out of an experiment due to technical issues or to decreasing motivation over the course of the experiment, with the latter potentially posing internal validity issues (Arechar et al., 2018; Zhou & Fishbach, 2016). Another concern revolves around data quality, which is considered to be poorer in online experiments compared to lab-based ones, as participants might misunderstand instructions or incur in technical issues. In this dissertation, we have applied rigorous checks as well as

stringent inclusion and exclusion criteria of the participants' data, which partly address the issue. Additionally, the five different experiments were conducted on five different samples, which adds to the robustness of the findings discussed in Chapters 4 and 5. As more and more experiments take place online, having clear analytical and sampling strategies will be paramount to ensure high data quality as well as internal and external validity.

Another limitation of the present work consists in the lack of any computational works, despite covering the extant literature on the topic in depth. This is due to the nature of the research questions at the basis of the thesis, as we were specifically interested in the behavioural and neural signatures of contrasting different decision-making processes. Future works could use these findings to provide insights into the computational workings of different decisional processes, for example, by applying different SSMs and examining which one provides a better fit to the empirical data.

Thirdly, future directions could expand the neuroimaging analyses conducted in Chapters 6 and 0, by including for instance psychophysiological interaction analysis (PPI) to explore changes in connectivity between conditions in the fMRI experiment, or by investigating the MEG data at the sensor-level and in the time-frequency space or even by examining the effective connectivity between the regions marked as significant in the MVPA. These suggestions could provide a richer and more comprehensive picture of the current findings, by exploring how brain areas interact with one another, instead of being considered in isolated roles.

8.3 Conclusions

To conclude, the present work describes a series of studies on human decision-making that progress from one another to explore this cognitive process in increasing depth. In Chapter 2, we covered the theoretical background of decision-making and proposed a specific framework to operationalise key constructs in value-based decisions. This prompted the work in Chapter 3, where we examined the spatial and temporal distribution of value-based decisions in 100 M/EEG experiments as well as providing a thorough classification of the existing paradigms, thus addressing a

significant gap in the literature. In Chapter 4, we investigated any potential interference effects across macro-domains in decision-making, i.e., perceptual (surface size) and value-based (preference judgments), finding a double dissociation across two online experiments. In Chapter 5, we resumed the thread started in Chapter 3 by directly contrasting two types of value-based decisions (internally-guided vs. externally guided) that had been studied separately from each other. Across three novel paradigms, we replicated a crucial finding whereby preference-based information "spills over" the reward-based domain in reward trials, affecting behavioural performance. In Chapter 6, we conducted an MEG-version of Experiment 1 in Chapter 5 and applied multivariate pattern analysis (MVPA). This allowed us to decode the spatiotemporal distribution of trial type and congruency information, providing richer insights into the neural substrate of contrasting value-based decisions. Finally in Chapter 0, we carried out a novel fMRI experiment with more complex option sets, that varied in the number of options available and in the congruency between positively and negatively rated items. Repeated measures ANOVA revealed an engagement of areas compatible with the "multi-demands network", which is consistent with the manipulations of cognitive load used in our paradigm. Taken together, these studies contribute to the behavioural and neuroscientific research on decision-making processes by providing a comprehensive synthesis of the extant literature, by using novel experimental paradigms, and by integrating multi-modal measurements of this complex and multifaceted cognitive function.

9 Bibliography

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