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The Neurocognitive Process of Preference-Based Decisions

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Abstract

This thesis focused on three aspects of human preference-based decisions. First, integrating multiple sources of value information had an impact on behavioural performance and the underlying cognitive process. During preference-based judgments, humans combine multiple information sources into a single source of evidence, and behavioural changes are related to the quality of evidence. Second, to investigate psychophysical performance (sensitivity and bias) based on internal value and external perception information, a categorization task was conducted with value information embedded into geometric shapes. As measured by Weber ratio, attaching internal values to geometric shapes resulted in less discriminating sensitivity than perceptual judgements, and there was no difference in the response bias between the two types of decisions. Hence, these findings showed that a single computational process may underlie both value-based and perceptual decisions, and that transferring internal preference onto external perceptual input generates additional noise to the decision-making process. Third, this thesis investigated the MEG signatures of internal value-based decisions as well as their differences from perceptual decisions. Instead of geometrical shapes, internal value information embedded into spatial locations and binary choice task was conducted using the identical visual stimuli in both the internal preference and external perception context. Multivariate patten analysis on source space MEG data showed that more extended visual and frontoparietal activations are sensitive to value differences in value-based decisions. These results provide a foundation for further integrating perceptual and preference-based decision-making into a single framework. Overall, findings presented in this thesis contributes to the study of value-based decision-making by integrating novel experimental approaches, cognitive modelling, and electrophysiological investigations of the human brain.

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Chapter 1
Introduction

1.1. Background

Decision-making is defined as the cognitive process of choosing the most appropriate option between the available alternatives in order to achieve the goals or objectives of decision maker. This process involves several stages, the first of which is the integration of information from the external environment or the internal state of decision-makers themselves (e.g., individuals, groups, or organizations), followed by the accumulation of available information, the evaluation of available alternatives by considering additional factors such as uncertainty and costs, and finally choosing one of the available options (Fellows, 2004). This cognitive process is an essential component of behaviour; it spans from simple actions such as deciding whether to cross the street by judging the colour of the traffic light to complicated human judgments such as deciding which blockchain to invest money in. Therefore, decision-making research is of interest in a wide range of disciplines, including economics, neuroscience, psychology, finance, computer science, and statistics (Baron, 2000; Edwards, 1954; Gärling et al., n.d.; Rangel et al., 2008; Simon, 1966; Stirling, 2010; Trommershäuser et al., 2008).

From the economic perspective, the decision-making process is modelled by rational choice theory, which states that people's choices are motivated by the rewards and costs of their behaviour, such as benefits they expect to receive relative to the amount of time and effort they expend in decisions and resultant actions. This modelling approach is referred to as normative, and it includes different features of a decision into an algorithm that can evaluate and compare different options, with the aim of maximising reward by rationally calculating the decisions (Scott, 2000). However, during the early 1970s, scholars of the emerging discipline of behavioural economics noticed flaws in standard rational choice models, noting that conventional models are not sufficient to explain some human decisions, both in real-life conditions and in experimental studies. Subsequently, theoretical developments and convergence between economics and neuroscience led to the birth of the new field known as neuroeconomics or decision neuroscience at the turn of the last century (Bossaerts & Murawski, 2015; Gross et al., 2014; Purves et al., 2013; Rangel et al., 2008; Rustichini, 2009; D. V. Smith & Huettel, 2010).

Neuroeconomics focuses on value-based decision making, and examines the basis of value-based decisions neurobiologically and computationally (Glimcher & Fehr, 2014; Rangel et al., 2008). Value-based decision-making is normative in nature; it happens when an organism chooses among various alternatives based on subjective value. Examples involve fundamental animal activities, such as bee foraging. Value is also one of the most central concepts governing human life that plays a crucial role, because it engages almost every aspect that requires a decision. For example, deciding which career path we choose, deciding which political party we vote, choosing which consumer product we pick up, or judging whether something is aesthetically attractive, good for us, or morally right. Therefore, it is important to understand the value-based decision-making mechanism. This new field defines value-based decisions, extending the scope of decision-making from simple to complex decisions.

Generally speaking, in people's daily lives, there are two types of decisions: perceptual decisions (i.e., simple decisions), determined by objective states of the physical world; and value-based decisions based on the subjective preferences of the decision maker. The tasks in perceptual choice are simple and well-defined, requiring participants to perceive and classify sensory input. On the other hand, value-based decisions rely on the tasks whereby participants are required to make value judgments according to their own individual values and subjective preferences (Nakao et al., 2012; Christopher Summerfield & Koechlin, 2010). Typical laboratory experiments involve a series of food images to explain the internal processes underlying choices, so that subjective preferences are determined by ranking the food items from least to most valuable. However, existing experiments have not fully understood internal value decisions in order to simulate real-world decision challenges during value-based decision-making. For example, in the case of shopping scenarios, individuals make internal decisions regarding food items. Their choices are influenced not just by personal preference, but also by the location of items in the store and on the shelf, their physical packaging, and their previous experiences with this brand or food type. In light of this information, there are still unanswered questions about value-based decisions with regard to diverse internal processing factors.

1.2. The aim and the structure of thesis

The aim of this thesis is to elucidate value-based decision-making at the behavioural, cognitive modelling, and neuronal levels by extending the basis of the decision-making framework from perceptual decision-making. More specifically, this thesis focuses on how people make decisions in relation to internal values, and how internal values may affect subsequent decisions and perceptions. Throughout the thesis, I developed novel experimental paradigms to study decision-making (i.e., paradigms based on binary choice by individual preferences and external perceptions), as explained in full in the following chapters. A brief summary of each chapter is given below.

Chapter 2 gives a broad overview of theoretical and experimental explanations of research on decision-making including value-based decisions. First, I review the mathematical definitions of decision-making problems, followed by the theory behind the cognitive models that are commonly used to explain the decision-making process. Experimental observations from animal electrophysiology and human neuroimaging are then reviewed to provide an understanding of the simple decision-making process (i.e. perceptual decision-making). Finally, I present the definition of the value-based decisions along with their differences from perceptual decisions, the various concepts of value, the stages of value-based decisions, multiple value systems, current experimental paradigms and neural bases of value-based decisions as well as existing findings.

Chapter 3 considers a value-based decision-making scenario with a novel task in which participants make value-based judgments based on the combinatorial of multiple items. The study investigates the effects of the number of items on decision performance, as well as underlying cognitive processing. I used the drift-diffusion model (DDM) to identify which internal components of processing are affected by multiple sources, with the hypothesis that participants can combine multiple information sources and subjective preference into a single source of evidence in the decision-making process, thereby altering choice behaviour. The results showed that the behavioural pattern is associated with a lower drift rate, and reduced decision threshold, but increasing information sources impeded rather than improved the decision accuracy. These results suggest that humans employ a bounded combination of information sources during value-based decisions, which do not significantly alter people's choice strategies.

Chapter 4 investigates how internal values guide human behaviour during value-based decisions and their possible interaction with perceptual decisions. I developed a novel choice paradigm that allows examination of both value and perceptual decisions by using an identical stimulus (parametrically morphed geometric shapes). Participants were instructed to perform categorization task based on value and perceptual information, and I observed psychometrical performance. This study shows that assigning internal values to geometric shapes led to a lower discriminating sensitivity than for perceptual decisions, indexed by a decreased Weber ratio. There was no difference in participants' response bias between the two types of decisions. Furthermore, value-based decisions were associated with longer reaction time than perceptual decisions across stimulus levels. These findings suggest that a common computational process may underly value-based and perceptual decisions and mapping internal preference onto external perceptual information results in the incursion of additional noise in the decision-making process.

Chapter 5 presents a novel task that allows to examine decision performance in two contexts: internal preference and external perception by using identical stimuli. MEG recording was used to identify spatiotemporal signatures of value-based decisions, which were compared with perceptual decisions. This project aims to compare perceptual decision making and internal value decision-making at the behavioural, computational, and neural levels. Using MVPA, I identified stimulus-task rule associations with changes in multivariate data patterns in MEG signals. The results suggest that the brain actively maintains rule-relevant information before and throughout the decision-making process.

Chapter 6 summarizes the results and contributions presented in the thesis and discusses this work's limitations and possible directions for future research.

The results of these projects have been presented in the following conferences.

- British Association for Cognitive Neuroscience (BACN), Birmingham, 2022.
- International Symposium on Biology of Decision Making (SBDM), Online, 2021.
- The Federation of European Neuroscience Societies (FENS) Forum, Paris, 2022.
- The International Conference on Biomagnetism (BioMag), Birmingham, 2022.

Brain imaging data acquired from these projects have been also used in following methodological papers. However, they are not included in this thesis.

Tait, L., **Özkan, A**., Szul, M. J., & Zhang, J. (2021). "A systematic evaluation of source reconstruction of resting MEG of the human brain with a new high-resolution atlas: Performance, precision, and parcellation." *Human Brain Mapping*, 42(14), 4685-4707.

Karahan E, Tait L, Si R, **Özkan A**., Szul M, Zhang J. "The interindividual variability of multimodal brain connectivity maintains spatial heterogeneity and relates to tissue microstructure." *Commun Biol* 5, 1007 (2022).

Chapter 2
Literature Review

2.1. The computational principles of decision-making

2.1.1. A theoretical framework of decision-making

The decision-making process can be described as a form of statistical inference problem (Bogacz et al., 2006; Gold & Shadlen, 2007). This approach assumes that the decision variable (*DV*) integrates all available information from priors, evidence, and values while making a decision. According to signal detection theory (SDT), a DV can be defined as a ratio of two likelihoods given with the evidence (*e*) that obtained from sensory inputs and two choice options A and B in a binary decision (Bogacz et al., 2006; Gold & Shadlen, 2007), as shown below:

$$DV = \frac{P(e|A)}{P(e|B)} \tag{2.1}$$

In the equation of DV, $P(e|A)$ indicates the likelihood of obtaining an observation of *e* when A is the correct choice, and $P(e|B)$ indicates the likelihood of obtaining an observation of *e* when B is the correct choice. A decision threshold can be applied to the *DV* to make a decision. Even though this *DV* equation (2.1) can be employed for binary choices, it does not take into account the required time to make a decision.

SDT can be extended to sequential probability ratio test (SPRT) analysis that can tackle this issue. In SPRT, we assumed that the evidence from multiple observations become available for decision-making at the time step $t = 1, 2, 3, \ldots, n$. The SPRT procedure then considers a *DV* as the probability ratio of all the different pieces of evidence:

$$DV = \frac{P(e_1, e_2, e_3, \ldots e_n|A)}{P(e_1, e_2, e_3, \ldots e_n|B)} \tag{2.2}$$

Moreover, the flow of evidence $e_1, e_2, e_3, \ldots e_n$ is sampled independently over time. The SPRT considers the logarithm of the *DV,* and which can be converted to the sum of the log likelihood ratio of each piece of evidence.

$$\log DV = log\frac{P(e_1, e_2, e_3, \ldots e_n|A)}{P(e_1, e_2, e_3, \ldots e_n|B)} = \sum_{t=1}^{n} log\frac{P(e_t|A)}{P(e_t|B)} \tag{2.3}$$

The SPRT continuously accumulate the log of the DV with new pieces of evidence implements the stopping rule plays a role in continuously accumulating the logarithmic of the *DV* with new pieces of evidence, until the accumulated evidence met a satisfied a stopping rule (Bogacz et al., 2006; Gold & Shadlen, 2007). There are two choice situations that can be accounted by using SPRT. First, the log *DV* is greater than a decision threshold T_A, in which case option *A* is selected. Second, the log *DV* is less than another threshold T_B(T_B <= T_A), thus option *B* is selected. In addition to these, if T_B is less than log *DV* and greater than T_A, then there is insufficient evidence to make a determination. The decision process consequently proceeds with sampling and the accumulating of the new pieces of evidence. The decision time is equal to the number of time steps that it takes to achieve the threshold for making a decision.

2.1.2. Sequential sampling models of decision-making

The main idea behind sequential analyses such as SPRT is the accumulation of evidence samples over time to make a decision. The evidence accumulation, from a statistical point of view, decreases the noise in instantaneous evidence, and resultantly allows for making decisions more accurately. For instance, it has been demonstrated that SPRT is the most optimal test for achieving an optimal level of decision accuracy efficiency relative to the lowest amount of evidence samples (Bogacz et al., 2006; Gold & Shadlen, 2007).

This evidence accumulation approach is widely employed in studies of computational cognitive models for decision-making, known as sequential sampling models. These models propose that choice behavior is the result of a gradual accumulation of evidence for different choice alternatives until a specific criterion or threshold value is met. This concept is mathematically formalized in models such as the diffusion decision model (Ratcliff & McKoon, 1978, 2008) or the linear ballistic accumulator model (Brown & Heathcote, 2008). These models all share a common approach: modelling parameters that are hypothesized to quantify aspects of cognitive processing are estimated in order to gain insights into behaviour (Turner et al., 2017; Wilson & Collins, 2019). The parameters in cognitive models represent the underlying cognitive processes involved in decision-making and are informed by theories of decision-making. Therefore, cognitive models serve as formalized theories that objectively identify which parameters of the cognitive process influence observed behavioral differences across conditions or individuals. These models aim to explain how individuals make decisions considering factors such as values, preferences, and beliefs. On the other hand, theories of decision-making provide a comprehensive framework for understanding the psychological and social factors that influence decision-making. By incorporating theories of decision-making into cognitive models, researchers gain a better understanding of the intricate processes involved in decision-making and develop more accurate and comprehensive models of human decision-making. These models are grounded in years of psychophysics experiments, which have established statistical inferences between sensory input and behaviour (Bogacz et al., 2006; Forstmann et al., 2015; Gold & Shadlen, 2007; Ratcliff & Smith, 2004). As computational models of cognitive processes, they can convert hypotheses into numerical estimates, elucidate behavioural patterns, and account for brain responses measured through single-unit recording and brain imaging (Gold & Shadlen, 2007; Ratcliff & Smith, 2004; M. N. Shadlen & Kiani, 2013b).

Sequential sampling models are classified into two primary classes based on their stopping rules. The first group is known as random walk models. For binary decisions, these models include a single accumulator, and its activity reflects the relative accumulated evidence in favour of the option than the other (Ratcliff & Rouder, 1998; Ratcliff & Smith, 2004). The second group of sequential sampling models accumulate evidence supporting each alternative separately in multiple accumulators. Hence, each accumulator's activity reflects absolute evidence supporting each choice option. In all of these models, the general principles are the same: accumulating evidence gradually over time until a threshold is reached, and a decision is made.

The section below describes the DDM, one of the most commonly used sequential sampling models with relative evidence. Initially, this model was proposed to account for RT and accuracy measurement in memory retrieval tasks (Ratcliff, 1978, 1981; Ratcliff & Meyer, 1988; Ratdiff, 1985). It has later been applied to several tasks involving the choice reaction times, including perceptual decision-making (Gigerenzer & Gaissmaier, 2010; Ratcliff & McKoon, 2008).

2.1.3. The drift-diffusion model (DDM)

SSM models can be distinguished by their relative or absolute decision rules, use of one or two accumulator numbers, and continuous or discrete time sampling (Ratcliff et al., 2016). The DDM model is defined as continuous evidence sampling of a random walk model process and is characterized by the following equation:

$$dx(t) = \mu dt\ + \sigma dW \tag{2.4}$$

This equation is derived by extending SPRT in Equation 2.3, where dx represents the dynamics of evidence accumulation at a given t time, μ signifies the mean increase in evidence for each unit time and σdW denotes a Gaussian process with mean zero and $\sigma^2 dt$ (Bogacz et al., 2006). The DDM can be applied to a binary decision problem with two possible outcomes: correct or incorrect. From Equation 2.4, we can refer to evidence that supports the correct choice as positive evidence ($dx(t)>0$), and evidence that supports the incorrect choice as negative evidence ($dx(t)<0$). The momentary evidence information is noisy and accumulates until one of the thresholds is met. This noisy process explained with DDM by seven parameters (Ratcliff & McKoon, 2008), as shown in **Figure 2.1 and Table 1.1.**

The first is the boundary separation (a), which indicates the distance between the correct and incorrect threshold for a decision. When a is small, the decision is made more quickly but less accurately. Because of the noisy fluctuations in evidence, the incorrect decision boundary is more likely to be reached. When a is large, however, the decision is made more slowly but more accurately. The interpretation of this parameter hence entails a decisional trade-off between speed and accuracy.

The second is the starting point (z) and represents response bias toward one of the two thresholds before the accumulation process begins. If evidence accumulation process starts at $a/2$, this indicates unbiased decisions. In contrast, biased decisions can be described as an unequal distance of z toward to the thresholds, so that z is close to one of the thresholds and the subject is biased to make a decision corresponding to the closer boundary.

The third is the inter-trial variability of the z (s_z).

The fourth is the drift rate (v), which represents mean speed of evidence accumulation, and it can be interpreted as the quality of information obtained from the stimuli. The value of v is differed regarding experimental conditions such as the difficult condition has a lower drift rate than easy condition.

The fifth parameter is the inter-trial variability of the v (*eta*), which indicates the variability of the stimulus quality.

The final two parameters represent non-decisions time (T_{er}) and the inter-trial variability of the non-decisions time (s_t).

As depicted in Figure 2.1, non-decision time is defined as the overall latency time of the decision and is calculated as the sum of the encoding and motor execution duration. The information processing starts at the starting point (*z*) and proceeds accumulation until accumulated evidence reaches one of the two thresholds. The model predicts a correct response if the accumulated evidence met the upper threshold or A (upward signal). Due to the noisy fluctuations, the accumulated evidence may reach the lower threshold or B (downward signal), in which case the model predicts an incorrect response. Thus, the single-trial RT is the summation of the duration of the evidence accumulation (also known as the decision time) and the non-decision time predicted by the diffusion model.

Table 1 The seven modelling parameters of the drift diffusion model

Symbol	Modelling Parameters
a	Boundary separation
v	Drift rate
z	Starting point
T_{er}	Non-decision time
eta	Inter-trial variability of the drift rate
s_z	Inter-trial variability of the starting point
s_t	Inter-trial variability of the non-decision time

The drift diffusion model (DDM) is a valuable framework for understanding the cognitive processes involved in decision-making by linking specific model parameters to these processes. Numerous experiments have aimed to establish connections between individual model parameters and distinct cognitive mechanisms.

The decision boundary, which represents the threshold for reaching a decision in the drift diffusion model. It directly relates to the speed-accuracy trade-off (SAT) by determining the amount of evidence required before a decision is made. A larger decision boundary necessitates more evidence, resulting in slower but more accurate decisions. Conversely, a smaller boundary leads to faster but potentially more error-prone decisions. This parameter is associated with the cognitive process of adjusting decision criteria based on task difficulty or importance. Studies conducted by Bogacz et al., (2006), Forstmann et al., (2015), Hauke R.

Heekeren et al., (2008), M. N. Shadlen & Kiani, (2013a) have demonstrated that the amount of evidence accumulated over time directly influences the speed-accuracy trade-off. For example, Bogacz's study provides a comprehensive analysis of decision-making models in two-alternative forced-choice tasks, highlighting the critical role of evidence accumulation in shaping the trade-off between response time and accuracy. Furthermore, researchers have explored the neural correlates of the decision boundary by manipulating the speed-accuracy trade-off. These investigations have identified increased neural activations in specific brain regions associated with fast decision preparation compared to accurate decision preparation. Regions implicated in these findings include the premotor area, striatum, basal ganglia, thalamus, dorsolateral prefrontal cortex, and dorsal anterior cingulate cortex (Basten et al., 2010; Domenech & Dreher, 2010; Simen, 2012). These results suggest that the decision boundary parameter directly reflects the trade-off between speed and accuracy, as evidenced by neural activity in diverse brain regions.

Another parameter in the DDM is the drift rate, representing the quality of evidence accumulated over time in favor of one decision option over the other. It can be influenced by factors such as attention, stimulus salience, and memory retrieval. In a study conducted by Krajbich et al., (2010), the impact of stimulus salience on the drift rate was investigated within a simple choice task. Using eye-tracking methods, the researchers examined participants' visual fixations and decision-making processes. The findings revealed that the salience of visual stimuli influenced the drift rate, with more salient stimuli leading to higher drift rates. The authors suggested that increased stimulus salience attracts more attention, resulting in faster and more confident evidence accumulation in favor of the salient option. This study provides empirical evidence for the influence of stimulus salience on the drift rate, highlighting the role of attention and visual processing in shaping the rate of evidence accumulation during decision-making. Ratcliff and Starns, (2013) conducted another interesting investigation on the association between memory retrieval processes and the drift rate in recognition memory tasks. They proposed that the quality and efficiency of memory retrieval can impact the drift rate. When memory retrieval is more efficient and accurate, resulting in faster and more reliable access to relevant information, it leads to higher drift rates. Conversely, when memory retrieval is less efficient or uncertain, it can decrease the drift rate, slowing down the accumulation of evidence for decision-making. By integrating empirical data and computational modeling, this study provides insights into how memory retrieval processes can influence the drift rate within the framework of decision-making tasks involving recognition memory. Overall, these studies have contributed to our understanding of how the drift rate parameter in decision-making reflects changes in cognitive processes.

The non-decision time in the drift diffusion model (DDM) encompasses factors that are independent of the actual decision-making process, including motor response time and sensory processing delays. These factors contribute to the overall response time but are not directly involved in the decision-making itself. In a study conducted by Karahan et al., (2019) aimed at investigating the cognitive processes underlying the simple reaction time task, the researchers revealed that the non-decision time component during simple actions represents the time taken before information processing begins and the motor response is initiated.

The starting point in the DDM reflects the bias or initial inclination towards one decision option. It can be manipulated to examine how biases affect decision-making. A study by Mulder et al., (2012) focused on two key factors: prior probability and potential payoff. Prior probability refers to the likelihood of an outcome based on available information, while potential payoff relates to the expected benefits associated with each choice. These factors can introduce biases into decision-making processes. The results indicated that both prior probability and potential payoff influenced decision-making behavior. Higher prior probability led to higher drift rates, indicating faster and more confident decision-making processes. Similarly, higher potential payoff was associated with increased boundary separation, reflecting a more stringent decision criterion and a tendency to wait for stronger evidence before making a choice. These findings contribute to our understanding of the biases that influence decision-making processes and provide crucial insights into the cognitive mechanisms involved in incorporating prior knowledge and potential rewards into decision-making.

To summarize, the experiments conducted have demonstrated a clear association between the parameters of the drift diffusion model (DDM) and cognitive processing. These findings highlight the interplay between specific model parameters and the underlying cognitive mechanisms involved in decision-making.

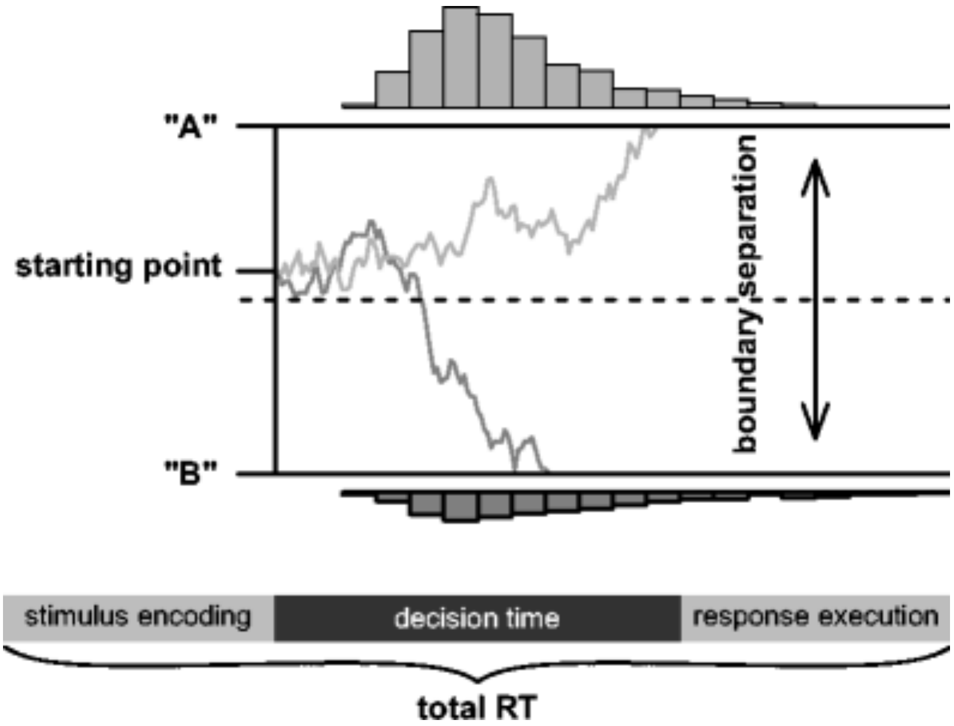

Figure 2.1 An illustration of the overview for drift diffusion model.

The two trajectories represent the accumulation of evidence from a stimulus. The upward trajectory results in a correct response, and the downward trajectory results in an incorrect response. When one of the thresholds is reached (A or B), a response is started. The histograms below and above the boundary show the response distributions that correspond to correct and incorrect responses (respectively). The total RT is computed by summing the duration of the decision component modelled by the diffusion process and the duration of a non-decision component, representing the time required for stimulus processing and response execution. Adapted from Dutilh and Rieskamp (2016).

2.2. Behavioural characteristics of perceptual decisions

A typical application of sequential sampling models is to account for the behavioural and neural processes underlying perceptual decision-making. The process of perceptual decisions relies on the integration of incoming sensory information over time using the framework of these models. This sensory input is perceived by senses (i.e., from visual, auditory, tactile, and olfactory signals) to form a decision (Newsome et al., 1989; Romo & Emilio, 2001; Tsunada et al., 2016; Uchida et al., 2006). Such decisions directly influence our behaviour; for instance, when driving in the rain and spotting a dark object approaching and deciding to stop the car to avoid an accident. Various experimental paradigms from the discipline of psychophysics have governed to investigate of perceptual decisions. Fundamental results have been obtained in perceptual decision-making studies using the psychophysical movement discrimination tasks with binary choices.

Random-dot motion discrimination (RDM) is a classical paradigm in which the task involves two types of moving dots, some of which move consistently towards one direction (i.e., the coherent motion direction), while others move randomly. Here, the coherent motion dots represent sensory signals and random dots represent noise signals. Hence, the signal-to-noise ratio is directly employed from the proportion of sensory signals to noise signals. Subjects have to decide the dominant direction of the dots (left or right) and indicate their choices by pressing a button or making a quick eye movement towards the target on the proper direction (Newsome et al., 1989). As depicted in Figure 2.2, the task difficulty can be controlled by the strength of motion coherence. This paradigm is valuable for decision-making research, because it explains the neurological underpinnings of motion perception in connection to behaviour (Gold & Shadlen, 2007; H. R. Heekeren et al., 2006; Maunsell & Newsome, 1987; Pilly & Seitz, 2009).

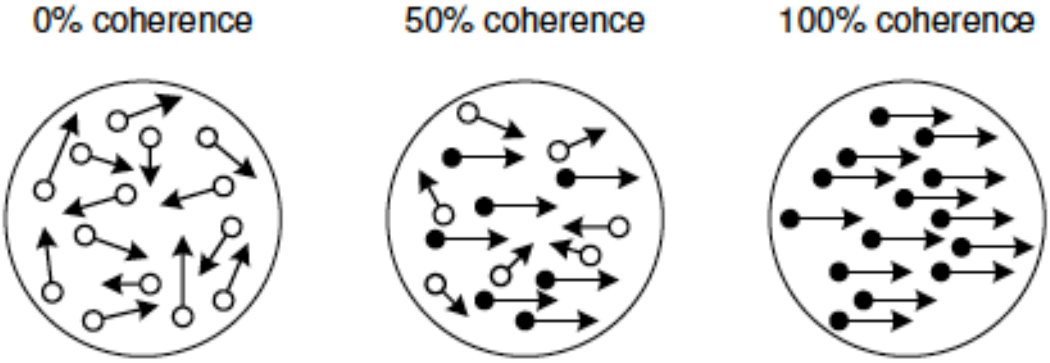

Figure 2.2 The representation of visual stimulus diagram for the RDM task.

For visual stimuli, the dots are either randomly repositioned (which is generated as noise signals) or moving to fixed direction (which is generated as sensory signals). In this diagram, the dots providing the sensory signals are depicted as solid dots, and are repositioned with respect to the right direction, which indicates the direction of coherence motion. The level of consistency across the dots is indicated by the proportion of the coherence level. The stimulus in the left panel has 0% coherence, containing only random noise (with no useful information). The stimulus in the centre panel has 50% coherence; half of the dots move to the right direction while the others move randomly. The stimulus in the right panel has 100% coherence; all dots move in the same direction (i.e., to the right in this case) and the coherence direction can be easily distinguished. Adapted from (J. Zhang, 2012).

Other experimental paradigms include performing sensory discrimination tasks across several domains. Vibrotactile frequency-discrimination tasks have employed to investigate perceptual decisions in the somatosensory area, in which subjects have to distinguish the frequency of vibration between the two tactile stimuli, and decide which stimulus has the higher frequency of oscillation (for instance, see De Lafuente & Romo, 2005; Luna et al., 2005; Romo et al., 1998; Romo & Salinas, 2003; Salinas et al., 2000). Motion discrimination studies such as RDM have widely used to examine perceptual decisions in the visual domain (Gold & Shadlen, 2007; Newsome et al., 1989; Preuschhof et al., 2006). More complicated tasks, such as home-face discrimination tasks, have also utilized, in which subjects have to categorize whether the presented image is either a house or a face by pressing a button (H. R. Heekeren et al., 2004; Christopher Summerfield et al., 2006).

Ranging from simple to complex tasks, the perceptual term refers to tasks in which the correctness of the response is indicated by an objective measure. The behavioural performance of subjects is explained by accuracy measurement and reaction times. In this context, it is also considered that these measurements provide knowledge regarding the processing of information; fast responses indicate less accumulated evidence, resulting in less accurate decisions, whereas slow responses result in more accurately decisions. This contradiction between accuracy and response times is described by the speed accuracy trade off (SAT) (Pitts', 1954; Wickelgren, 1977). The SAT is a fundamental decision-making phenomenon that has been observed in human (Wickelgren, 1977; J. Zhang & Rowe, 2014) and animal cognition (Chittka et al., 2009; Heitz & Schall, 2012) in two-choice psychophysical experiments. The DDM naturally reflects the speed-accuracy trade-off by modulating the response thresholds. When the threshold is lower, the process made rapidly so the decisions are faster. However, there is smaller amount of information, so noise has a greater influence on the process and the decisions are less accurate. In contrast, when the threshold is higher, the decisions are slower, but they are more accurate, since they are based on integration of more evidence and noise has less of an impact on the process. It has been established that the DDM provides excellent fits to behavioural data (Ratcliff & Smith, 2004; P. L. Smith & Ratcliff, 2004) while effectively accounting for variations in accuracy and response time distributions brought on by the manipulations discussed above.

Sequential sampling models, particularly the DDM stated above, have been developed to describe the cognitive processes that involved in decision making (Luce, 2008; Ratcliff, 1979). As explained previously, the neural systems in perceptual decisions were explored utilising

RDM. Recent studies on perceptual decisions have shown that certain decision-making processes are represented by distinct brain areas. In humans, for example, the prefrontal cortex and parietal cortical regions have been activated throughout the process of accumulating evidence and generating a decision variable, whereas the motor cortex has been activated during the planning and selecting motor actions (Gold & Shadlen, 2007; Hare et al., 2011; H. R. Heekeren et al., 2004; Philiastides et al., 2011). Thus, it is believed that the neural mechanism underlying perceptual decision-making has a heterarchical interaction, in which separate processing stages span several brain areas. The following section describes the brain structures and neural computations of perceptual decision-making in greater detail.

2.3. Neural mechanism of perceptual decisions

2.3.1. Neurophysiological evidence

2.3.1.1. Sensory evidence

Neurophysiological studies in monkeys have provided the first evidence for neural activity in sensory neurons. According to the sequential sampling framework, these sensory neurons accumulate noisy sensory information (Gold & Shadlen, 2001, 2007; Romo & Salinas, 2003; P. L. Smith & Ratcliff, 2004). In a number of single unit experiments with monkeys, a relationship was identified between behavioural choices and neural activity in sensory regions (Newsome et al., 1989; Salzman et al., 1992). In these studies, monkeys were trained to perform the RDM task, whereby they had to decide the direction of coherently moving dots from among randomly moving dots. The response was often given by making a saccade or pressing a button. The results showed that the activity of neurons in the middle temporal (MT/V5) area was sensitive to selective motion direction, and this neural activity provides a sufficient description of behavioural performance (K. H. Britten et al., 1992; M. N. Shadlen & Newsomet, 1996).

Similar links between behaviour and neural activity have been identified in studies using different stimuli. For example, in the vibrotactile frequency task (VTF), monkeys were trained to compare the vibration frequency between the two sequentially presented tactile stimuli and were required to choose the highest frequency stimuli. The behavioural response sensitivity was found to be similar to the sensitivity of the mean responses in the primary somatosensory cortex (S1), and fluctuations in neural responses from trial to trial were able to predict the monkeys' behavioural decisions (Romo et al., 2004; Salinas et al., 2000) These results indicate that sensory neurons are activated to encode sensory evidence, particularly neurons in the middle temporal (MT/V5) area and primary somatosensory cortex (S1).

2.3.1.2. Evidence accumulation and decision formation

Despite sensory regions such as MT and S1 encoding sensory evidence, the neural activity in these areas is not responsive to subsequent stages of decision formation. A series of monkey experiments revealed that activation of the lateral intraparietal area (LIP) is responsible for evidence accumulation processing from sensory evidence neurons (within the MT and S1) (K. H. Britten et al., 1996; Gold & Shadlen, 2007; M. N. Shadlen & Newsomet, 1996). The LIP area, which is localized a part of the intraparietal sulcus in the parietal cortex, is involved in the neural link between visual sensory information and motor action planning (Colby & Goldberg, 1999). Therefore, it is plausible to think that it is also involved in decisions utilising eye-movements to response (i.e., saccades). For a motion direction task that entailed a delay period between stimulus presentation and saccadic eye movement response, LIP neurons in monkeys increased and maintained their firing rates until a moment of decision formation and action-taking (i.e., a saccade towards a target). It is important to note that the firing rate of neurons varies between trials. In easy trials, the neuronal firing rate increases more rapidly than in more difficult trials. Moreover, the firing rate immediately dropped when the response was given (Kiani et al., 2006; M. N. Shadlen & Newsome, 2001).

Research employing an identical paradigm but with the RT condition reported that neurons accumulate evidence, but a response is only provided when a decision threshold is reached. The responses were much slower for more difficult decisions because of the response threshold was achieved late. Figure 2.3 illustrates the mean firing rate from a population of LIP neurons during the random dot motion paradigm. In these experiments, two types of targets are displayed: the one-choice target (T_{in}) is inside the response field of the LIP neurons, whereas the other target (T_{out}) and random dots stimuli are outside of the neurons' response field. After the delay period, neural activity begins to differentiate based on the subjects' preferences. It increases in trials where subjects evaluate movement towards the response field of the population and decreases if the movement is judged to be far from the response field. A similar spike of activity occurs for all coherence levels prior to the commencement of the reaction, followed by a collapse after the saccade.

On the basis of these findings, and taking into account DDM, it has been suggested that in motion direction tasks requiring a saccadic response, sensory evidence is encoded in neurons located within the visual field MT, while neurons in the LIP area integrate sensory evidence until a threshold is achieved to render a decision.

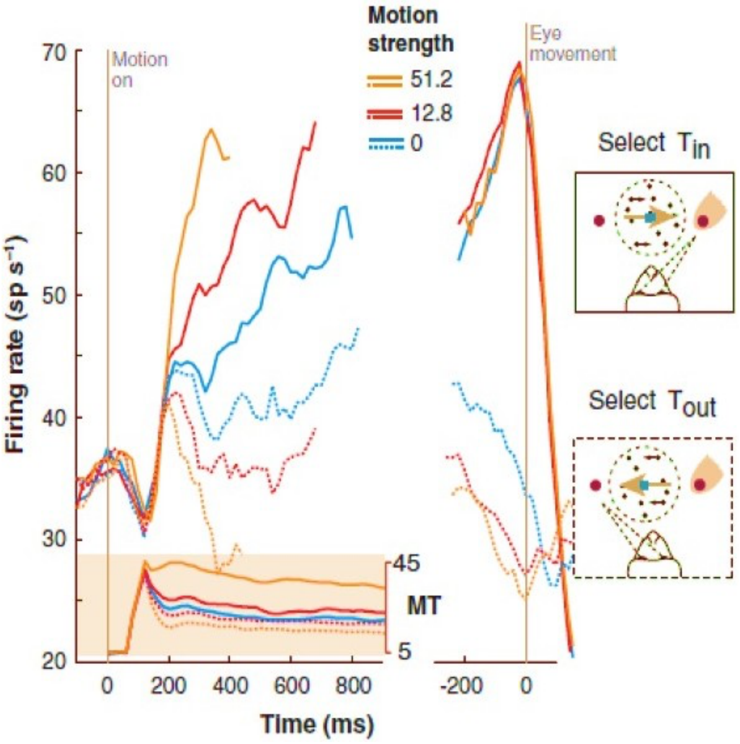

Figure 2.3 Accumulation of evidence in LIP during random dot motion task.

During the RDM experiment, one target is exhibited inside the neurons' response field while the other targets are shown outside the neurons' response field. Each line in the graphic represents the mean firing rate of the population in the LIP neurons at different levels of coherence. The left figure depicts the aligned firing rate at stimulus onset, whereas the right figure depicts the saccade on time. The solid and dashed lines indicate trials in which the subject judges the motion towards or away from the response field, respectively. Adapted from Gold and Shadlen (2007).

Studies using electrical microstimulation offered causal pathway for a close relationship between neural activity and decision behaviour in both the somatosensory and the visual domains (Hanks et al., 2006; M. N. Shadlen & Newsome, 2001). For instance, when the vibrotactile stimuli were substituted with analogous direct electrical microstimulation of primary somatosensory cortex neurons, the monkeys displayed a decision-making pattern that was remarkably similar to what was seen under normal experimental conditions (Romo et al., 1998). In a similar pattern, the visual area MT plays a causal function in the coding of sensory evidence when the RDM task is being performed. When motion-specific MT neurons were activated, monkeys demonstrated a bias toward responding in favour of the preferred direction of the stimulated neurons (Salzman et al., 1990, 1992). Microstimulation of these neurons not only accelerates the choice-making process in favour of the chosen way, but also slowed down the decision-making process in the opposing direction (Ditterich et al., 2003). Therefore, in both the visual and the somatosensory domains, microstimulation has provided direct causal evidence for a tight link between the representation of sensory evidence in sensory regions, an activity-related threshold mechanism, and perceptual decisions. In conclusion, the findings of neurophysiological studies in monkeys provide support for the fundamental idea that decision-making in the brain involves the accumulation of evidence up to a certain threshold.

In addition to the LIP-neurons, it has been discovered that neurons in the frontal eye fields (FEF) and the dorsolateral prefrontal cortex (DLPFC) are also involved in the process of evidence accumulation in visual perceptual tasks (Gold & Shadlen, 2000; Kim & Shadlen, 1999). These areas play a role in the process of selecting and preparing oculomotor execution. The process revealed here for visual perceptual decision making is applicable to research including vibrotactile stimuli. It involves regions such as the second somatosensory cortex (Romo et al., 2002) and the ventral premotor cortex (Romo et al., 2004).

The results of single-unit recordings in monkeys led to the conclusion that evidence is initially obtained in lower-level sensory regions, and subsequently accumulated in motor planning regions. These activations support the fundamental assumptions of models with sequential sampling. The activations observed in the accumulator neurons also suggest that both the decision and maintenance of the decision until the response cue occurrence is performed by the same neurons, as reported in a study employing a delayed response paradigm, in which neurons in the LIP region reached a threshold earlier for easier decisions and continued firing until a response could be given (M. N. Shadlen & Newsome, 2001).

2.4. Neuroimaging evidence from human decision-making

From the knowledge of neurophysiological studies and DDM assumptions, recent research has investigated the neural mechanism of the human brain to ascertain similarities and differences with the findings of monkey studies, including the findings explained above. Due to the invasive (and inhibitory) nature of single-unit recordings, non-invasive brain imaging techniques such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG), and magnetoencephalography (MEG) have been widely used in human studies. fMRI detects neuronal activity by measuring the blood oxygenation level dependent (BOLD) response, and provides high spatial resolution to localize which brain areas involved in decision-making processing. EEG and MEG record electrical and magnetic activity in the brain with high temporal resolution, allowing neuronal activity to be detected in milliseconds (Gold & Heekeren, 2014; Hauke R. Heekeren et al., 2008; Kelly & O'Connell, 2015).

2.4.1.1. Sensory evidence

Neuroimaging studies reveal that the human brain encodes sensory evidence in a similar way to that observed from neuropsychological findings in monkeys. The first neuroimaging studies to investigate the representation of sensory evidence in the visual domain for the human brain utilized a categorization task during simple perceptual decisions. Participants were asked to perform house-face discrimination tasks, in which they instructed to decide whether a presented visual stimulus was a house or a face. The degree of ease or difficulty of detections was adjusted by adding varying degrees of noise to the stimuli images, and neural activity was measured by fMRI. Heekeren and his colleagues found that the activity in left posterior DLFC shows evidence for comparison between face and house signals. Similar to research in monkeys, both the fusiform face area (FFA) and the parahippocampal location area (PPA) exhibit characteristics of sensory evidence encoding, with FFA and PPA activating more when detecting faces and houses, respectively. Additionally, FFA activation was stronger for easy-face trials than for difficult-face trials. The same effect was observed for houses located within the PPA (H. R. Heekeren et al., 2004, 2006). These findings support the notion that the responsible areas for the house-face selection correspond to visual sensory evidence for face and house stimuli, which is consistent with the initial results.

A recent EEG study utilized single-trial analysis to evaluate the cortical correlates of decision making during a face–car discrimination task, which is similar to the previously described face–house task. The earliest ERP component, N170, was shown to have a link with facial perception, and hence appears to provide sensory evidence. Overall, the findings in the visual domain give strong support for the assumption that sensory evidence representation in the decision-making processing (Philiastides & Sajda, 2006).

Recent fMRI investigations have provided the representation of somatosensory evidence in the human brain by utilising vibrotactile frequency discrimination tasks. The primary somatosensory cortex showed increased activity during the encoding phase of the sensory evidence of tactile decision making, consistent with neurophysiological studies from monkeys (Preuschhof et al., 2006). In a similar vein, using a somatosensory discriminating task, Pleger and colleagues found that tactile stimuli produced spontaneous activity in the somatosensory cortex, among other areas (Pleger et al., 2006).

2.4.1.2. Evidence accumulation and decision formation

Single-unit simian recordings indicate that decision-marking neuronal activity is increased gradually to an elevated level, which is subsequently sustained pending the issuance of a response. Notably, easier trials elicit a more rapid upsurge in neural activity. Downstream cortical regions, including the DLPFC and LIP, can formulate decisions based on comparison of outputs from sensory neurons that have been specifically tuned related to a certain decision threshold, and the results can consequently be correlated with actions. Heekeren and his collegues (2006) sought to ascertain the validity of these fundamental principles arising from neurophysiological studies for humans. Human subjects were asked to choose (using their eye movement to binary visual targets) to judge the direction-of-motion in response to dynamic random-dot-motion stimuli. The researchers identified local oculomotor network regions for each subject, specifically the FEF and a space related to eye movement in the intraparietal sulcus (IPS), which is assumed to be analogous to the simian LIP (Sereno et al., 2001). The decision formation period (after visual motion and response cues), a significant correlation was observed between the strength of signal motion stimuli and the BOLD percent signal change in both the FEF and the IPS (H. R. Heekeren et al., 2006). These findings affirm the single-unit murine studies described previously, which demonstrated that FEF and LIP contribute to perceptual decision-making.

The extent to which human motor actions might arise from the transformation of such decisions in the brain (aside from conventions motor plan and execution activity) was also explored by (H. R. Heekeren et al., 2006). Subjects undertook discrimination tasks (based on direction-of-motion) by saccadic eye movement or button-pressing. More abstract decision variable areas were assumed to elicit a stronger response with high coherence (i.e., be easier tasks) relative to trials with lower coherence (i.e., more difficult tasks), without impacts from the decision-expressing motor system. They identified four instrumental areas: the left fusiform / parahippocampal gyrus, the left IPS, the left posterior cingulate cortex, and the left posterior DLPFC. Significantly, these regions exhibited increased BOLD activity independent of the motor system deployed in decision expression (H. R. Heekeren et al., 2006).

fMRI outcomes corroborated the earlier results of (Kim & Shadlen, 1999), who found that simian neural activity is proportional to stimulus motion signal strength. However, (H. R. Heekeren et al., 2006) human results indicated that the posterior DLPFC is likely to be a significant network component accumulating sensory evidence for decision computation up to the decision boundary, and that this is independently translated into action independent from response modality.

Simian neurophysiological investigations have not detected such neuronal activity (conducive to independent decisions from response modality). (Rorie & Newsome, 2005). Conversely, studies have demonstrated that human cortex regions respond independently to motor effectors deployed. (Hebart et al., 2012) multivariate fMRI analysis of motion discrimination tasks with decoupled response modalities indicated independent encoding of perceptual decisions in parietal and visual brain regions. Furthermore, human cerebral general signals for decision variable domains were identified by (O'Connell et al., 2012), based on subjects viewing a continuously presented annulus, with the contrast dropped at random intervals. EEG results showed that centro-parietal positivity (CPP) signals represent decision variables and manifest the characteristics of decision variables (in being modality-independent and tracking decision formation independently of overt motor responses).

Additionally, neuroimaging research shows that IPS decision-related activity integrates evidence from the visual motion area MT+ (Kayser, Buchsbaum, et al., 2010), and this is affected by key factors including attention (Kayser, Erickson, et al., 2010). Causal evidence also supports the emerging evidence integration framework. The TMS of the DLPFC (a region formerly presumed to integrate evidence accumulated for choice alternatives for decision variable computation, without being instrumental in the decision threshold), combined with diffusion modelling, actually plays a detrimental role in the evidence accumulation process (Philiastides et al., 2011).

In conclusion, neurophysiological and neuroimaging results support the assumption that evidence accumulation models capture important aspects of latent information processing supporting simple perceptual decision making.

2.5. Value-based decision-making

As previously stated in Chapter 1, decision-making is a pervasive cognitive process that occurs across all domains of daily life, and which involves behavioural outputs ranging from simple decisions, such as perceptual choices based on sensory input, to complicated decisions, such as value-based choices based on subjective value. These two categories of choices have been studied by separate examinations conducted within different paradigms and fields. Perceptual decisions have been typically subjected in experimental psychology and neuroscience by measuring accuracy measurement and reaction times in simple psychophysical experiments, in which participants are required to classify perceived sensory evidence (Kenneth H. Britten et al., 1993; Hanks & Summerfield, 2017; Hauser & Salinas, 2014; Purves et al., 2013; P. L. Smith & Ratcliff, 2004; C. Summerfield & Blangero, 2017).

On the other hand, value-based decisions are based on the individual value assigned by decision-makers' preferences. These decisions first began to be studied in the early 1970s with the emergence of a new field called neuroeconomics or decision neuroscience, which was born with the integration of concepts from economics and neuroscience (Glimcher & Fehr, 2014; Rangel et al., 2008; Sanfey, 2007; D. V. Smith & Huettel, 2010). The new discipline of neuroeconomics addresses the subjective valuation process, how the brain computes these values, and what is the neural basis underlying valuation and decision-making. By expanding the scope of decision-making from simpler situations, this field seeks to develop a neurobiologically valid theory of how humans make complex decisions that can be employed in the social sciences. For example, successful performance in a random dot motion task requires executive functions but does not involve personal value judgments in the same way as choosing a food item from the menu in a restaurant.

As pointed out above, in terms of paradigms and disciplines, perceptual and value-based judgements are distinct from one another. Furthermore, the primary distinction between these two decisions is that the quality of the response is determined by different criteria. The tasks in the perceptual decisions are simple and straightforward, and participants' responses can be objectively evaluated as correct or incorrect. In such tasks, the optimality in decisions is defined by statistical inference based on SPRT benchmark, which minimises the response time for a given level of accuracy. Perceptual decision-making studies have a longstanding history, having originally been established in behavioural psychophysics research, and extensive physiological evidence suggests that the process behind perceptual decisions can be estimated using the SPRT test, offering statistical optimality. Signal detection theory is increasingly being applied to investigate the process of making this type of decision (Bogacz, 2007, 2009; Forstmann et al., 2015; Gold & Shadlen, 2007; Ratcliff et al., 2016; M. N. Shadlen & Kiani, 2013b).

On the other hand, value-based decisions, more specifically preference-based judgments, are based on subjective value judgments, whereby each choice option is evaluated by examining its outcomes in relation to internal goods, motivations, or actions. Therefore, unlike perceptual situations, preference-based choices involve subjective criteria, which means that there are no objective factors that determine which response is correct. The theoretical framework for these judgments is provided by the expected utility theory, which is a cornerstone of mainstream economic analyses (von Neumann & Morgenstern, 2007). In all research inquiries concerning these theories and paradigms, the study objectives require perceptual tasks that aim to maximise correct responses, whereas subjective value-based tasks are more concerned with individual's preferences. Despite its relative novelty, the discipline of value-based decisions has been studied from various interesting aspects, from economics to neuroscience, this diversity makes it difficult to identify the value and summarise the current findings. In the chapter that follows, I first give a brief overview of the definition of the value-based decision-making, the various concepts of value, and the general framework of value-based decisions, then finally focus on the neural underpinnings of value-based decisions as well as the relationship between theory and models.

Value-based decision-making is defined as a process in which different options are associated with internal or subjective values, such as choosing food items according to individuals' preferences; or in which different choice options are related to external values, such as the choice alternatives are associated with monetary gain or loss in the gambling task. Aside from the difference on the option context, the decision-making process follows the same principle: first defining the available value options, then evaluating those values, and finally making a decision based on purpose given by external context or individual preference (Gold & Shadlen, 2007). In this process, the term "value" does not refer to a property that is constant in nature, but rather to a property that has flexible and relative characteristic, and therefore is affected by external and internal conditions. Due to the changing nature of internal and external states, value-based decision-making has noisy processes, accumulating evidence stochastically, and fluctuating over time (Fellows, 2004; Gold & Shadlen, 2007).

When such noise is external in origin, it can be interpreted as stimulus-related characteristics such as uncertainty and ambiguity, which determine the task difficulty levels of the decision. For example, in the gambling task, the experimenter may externally adjust the probability of gaining or losing and the magnitude of the reward by an association with the stimuli. On the other hand, when the source of the noise is internal, this cannot be controlled by the experimenter; instead, it is linked to the individual states of the participants, such as motivation, attention, and thoughts (Fellows, 2004).

The discussion thus far has focused on the definition of value-based decision-making. Before explaining the general theoretical framework, it is necessary to explain different value approaches. The study of value concepts has been addressed from different aspects, and the meaning of the term "value" has been debated within a variety of disciplines, ranging from economics to psychology (Kahnt & Tobler, 2017; O'Doherty, 2014; O'Doherty et al., 2016). Value can be referred to as a function of, which is a function used to identify an individual's preferences regarding a group of different value options (Glimcher & Rustichini, 2004). For example, if a person prefers option one more than option two, this suggests that option one has higher utility (and thus value) for than option two (for that person).

In experimental studies, subjective preference can be evaluated from participants' ratings of choice options, assuming that the participants' internal states remain stable and consistent over the experimental period (O'Doherty, 2014). An alternative definition of value, commonly used in behavioural neuroscience, conceptualise value as a reinforcer, which indicates the amount of effort that an organism is willing to invest (Shizgal, 1997).

Apart from the differences across these definitions, it is expected that these concepts would share common predictions about whether a given stimulus may or may not be considered valuable, as well as similar prediction in the neural substrates of the value. However, this generalisation may result in differing estimations in certain instances, such as decisions based on habit. Animals may select options based on higher reward actions that might not accurately reflect their preferences. As a result, the animal does not consume the good that obtained by habitual behaviour. (Berridge, 1996) study suggested that the terms "wanting" and "liking" can be differentiated both behaviourally and neurally. Similarly, the term "value" can be decomposed into different forms, such as "wanting", "liking", and "being rewarded". These aspects of value are ambiguous, making it challenging to operationalise them, and they may require different computations and neuronal underpinnings.

Since multiple forms have been used to describe value terms, it is essential to build a common lexicon and provide a common framework in order to avoid confusion between different disciplines (Rangel et al., 2008). To begin, the process of making decisions can be divided into three stages using a simplified model that is originated from classical decision theory: (1) possible options are identified; (2) they are then evaluated according to their associated value; and (3) the choice is made on the basis of its value (Baron, 2000; Lipshitz et al., 2001).

This model is used as a starting point for further exploration of decision-making component processes. However, it is unable to precisely describe the differences between the three stages, since it contains somewhat arbitrary and insufficiently informational aspects, such as the stopping criterion for difficult decisions during the option identification stage is not clearly defined (Fellows, 2004). Later, (Rangel et al., 2008) developed a revised model with five stages to describe the value-based decision-making process more systematically (Figure 2.4). The following section explains these stages and provides a brief description of our understanding of the underlying neurobiology. Finally, I address how the research presented in this thesis contributes to the existing body of knowledge.

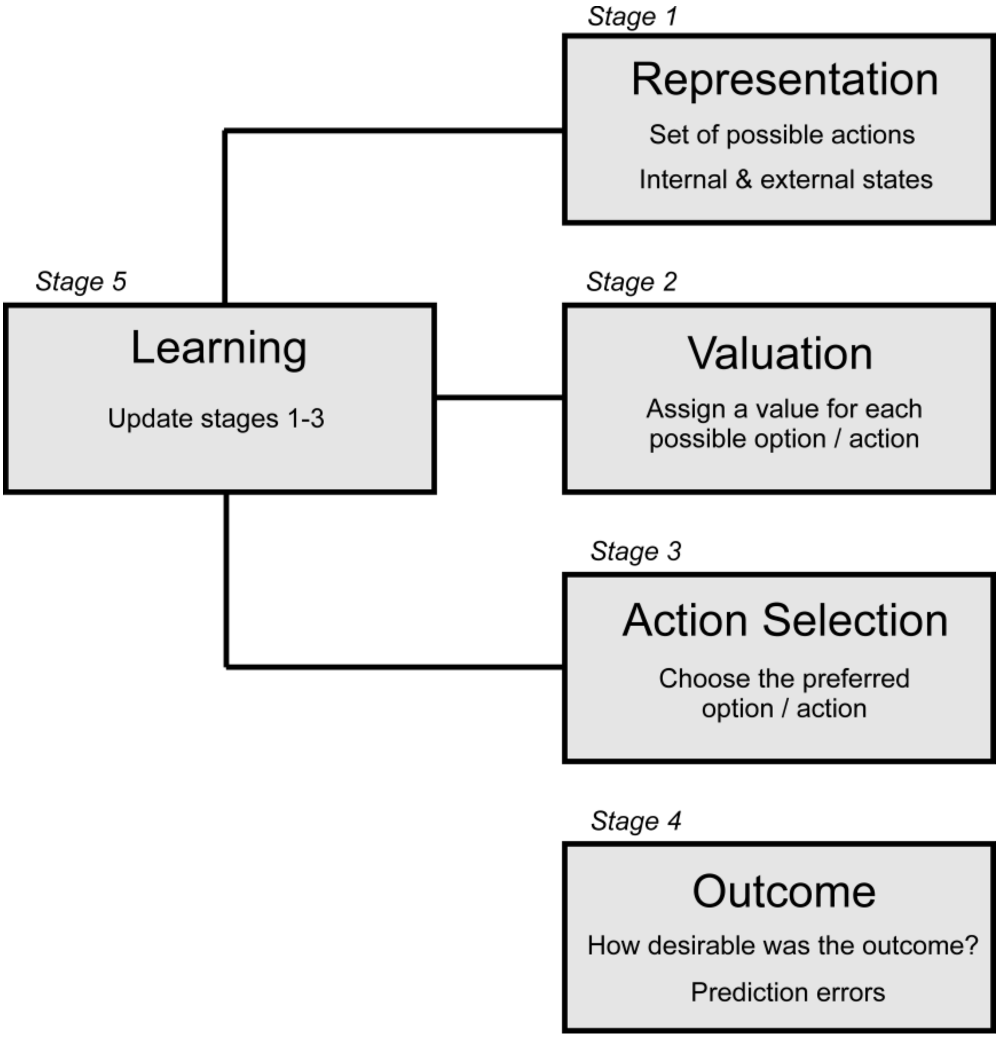

Figure 2.4 Computations involved in decision-making.

In order to initiate a decision, an agent must first identify and represent their internal state, the external state of the world, and the possible set of actions available. Next, a value must be assigned to each of these actions, which are compared in order to select the action with the highest expected utility. Once the chosen action is executed, the agent can then assess the desirability of the outcome. Any discrepancy between the expected and received outcome is used to inform future choice through learning. Adapted from (Rangel et al., 2008b).

2.5.1. The stages of value-based decision-making

According to (Rangel et al., 2008) framework, value-based decision-making process has been described according to the following five computational stages:

i. Representation: This initial stage entails presenting the decision problem by evaluating internal variables derived from subjects' internal states and external conditions derived from the external environment, as well as possibly viable courses of action.

ii. Valuation: At this stage, each of the detected choices is assigned a value based on the present state of internal and external variables.

iii. Action selection: Based on a comparison of the values generated in the preceding phase, an action is chosen to acquire the highest-valued choice.

iv. Outcome evaluation: comparing the actual outcome to the anticipated outcome of the decision.

v. Learning: Based on the findings of the outcome evaluation stage, internal representations of available alternatives are updated, along with their value and the activities required to attain these options.

The results of this stage impact the preceding stages of representation, evaluation, and action selection. The above paradigm is ambiguous on the timing of the comparative process; do we compare values as they are computed during the valuation stage, after this stage is complete, or in light of their associated actions during the action-selection stage? While (Rangel et al., 2008) allowed some flexibility in this regard, (Padoa-Schioppa & Cai, 2011) proposed a similar, albeit more detailed, framework which included an ‘integration’ stage, in which external and internal variables are integrated with option characteristics to generate abstract values, which are then compared. Based on the outcome of this comparison, an action plan is generated in order to obtain the chosen option. It is implicit in this framework that these stages are (i) discrete, (ii) serial, and (iii) implemented in separate brain regions.

While these stages may indeed describe how the brain transforms sensory information into a choice, this does not necessarily imply any of the above three characteristics. Some or all of the stages of this process might overlap in time or in brain tissue. Cognitive models of value-based decision-making have, in fact, often proposed that the evaluation and comparison stages occur in parallel (Busemeyer et al., 2019; Noguchi & Stewart, 2018; Sugrue et al., 2005). However, most neuronal circuit models of value-based decision-making have focused solely on the comparison stage, implying that evaluation occurs somewhere upstream of the modelled circuit (Chau et al., 2014; Rustichini & Padoa-Schioppa, 2015; Soltani & Wang, 2006; X. J. Wang, 2008), and mostly remaining silent on the question of when the action plan is determined (Yim et al., 2019).

2.5.2. Multiple value systems

Multi-valuation systems during valuation are an important part of the framework. Based on the outcomes from a large number of animal and human behavioural studies, three different types of valuation system have been suggested: Pavlovian, habitual, and goal-directed (Bray et al., 2008; Clark et al., 2012; Matzel, 2002; O'Doherty et al., 2016; Raab & Hartley, 2018; Van Der Meer et al., 2012).

- According to Pavlovian systems, only a small group is assigned a prepared behavioural group value, and it therefore has limited behaviours. However, they may be the driving force behind behaviours that cause significant economic outcomes (e.g., over-eating). Consumption behaviours such as approaching a sign that predicts food or consuming existing foods can be given as examples of this system.
- Habitual valuation systems learn to value stimulus-response relationships based on the trial-and-error process in their previous experience. For example, a smoker wants to smoke at certain times of the day or after certain other behaviours, which is habitual smoking behaviour.
- Goal-directed systems value actions by computing action-result relationships and then evaluating the rewards related to different results. The decision during food choice in a new restaurant can be given an example for this type of system.

Habitual and goal-directed systems differ in their reactions to changes in the environment; the former only learn to change value assignment as a result of repeated experiences, while the latter change the value of action immediately after the value changes (Rangel et al., 2008). In addition to this valuation system, (J. Peters & Büchel, 2010) proposed that the concept of value can be classified differently in relation to the value-measurement relationship. Accordingly, the subjective value of an option can be divided into different subtypes as outcome value, goal value, decision value, and action value. This classification mainly relies on the differences in computational aspects, suggesting that a decision is driven by the integration of costs, efforts, and risks. The outcome value (OV) is explained by the value of a reinforcer on consumption, rather than involving rewards with risks, costs, and effort such as experiments with using simple ratings to understand consumer behaviour. Similarly, the goal value (GV) does not involve costs. It refers to an abstract term to define the value is associated with consumption and rewards such as experiments based on willingness to pay strategy.

Unlike GV and OV, the decision value (DV) incorporates costs and indicates the total value of a certain option, which can be affected by both internal states of an agent or external variability of the environment, such as experiments with monetary rewards based on temporal delaying. Lastly, the action value (AV) can be defined as a complicated term in which it refers to the value of the action that can lead to the highest value in the pre-choice period. Depending on the complexity of the decision context, these values may be based on OV, GV or DV. Thus, action values reflect a particular action's matching to a particular value, which can be OV, GV, or DV. For example, in (Rangel et al., 2008) multi-class value system, the Pavlovian system and the goal-directed system have utilised action value as an outcome value.

In relation to the above discussion on definitions of value concepts and frameworks, another theory has been proposed to unify value frameworks through linking value classification and value systems. This notion is crucial in the study of decision neuroscience and neuroeconomics for the value comparison stage. The idea behind that theory refers to the process of translating different values of multiple options into a single common scale for value comparison (Chib et al., 2009; Glimcher & Rustichini, 2004; Levy & Glimcher, 2011, 2012; Sugrue et al., 2005). For instance, when participants are deciding between different food options such as apples and oranges, the value of each option is translated into a single unit (single common currency).

Although this concept is not directly addressed in (Rangel et al., 2008) framework, their research admits that option values need to be compared and combined in order to convert them into a single action, which precisely defines the term of common currency. Since this common unit provides value comparisons into different features of items, this theory is also employed in multi-attribute decisions in which each choice option is characterised by multiple attributes or elements. Accordingly, different attributes of each option are taken into account (for example, the flavour, calorie count, health status, and cost of the food options), after which the value of each of the attributes is evaluated, and all these attributes are combined into single coherent value representation, which enables comparison with any other possible option (Busemeyer et al., 2019; Levy & Glimcher, 2012). At the conclusion of this chapter, I will consider a number of value-based decision-making scenarios in which individuals make decisions based on combinatorial of multiple items.

2.5.3. Existing paradigms in value-based decision-making

This subsection presents a brief overview of existing paradigms commonly used in experimental studies of value-based decisions. According to (Nakao et al., 2012), value-based decisions can be largely categorised into externally guided decisions (i.e., external or extrinsic value judgments) and internally guided decisions (i.e., internal or intrinsic value judgments). External value judgments are based on scenarios where there is an objectively correct answer that depends on external conditions, such as when there is uncertainty and only one less predictable correct response exists.

In contrast to externally guided judgments, internal value decisions refer to the process of making decisions based on one's own personal values and beliefs, rather than external factors such as financial gain. These decisions are often driven by individuals' moral judgments and personal preferences, rendering them subjective. Since the outcome is determined by the subject's internal values rather than by external criteria, there is no correct answer relying on external conditions for the subject. Ultimately, the goal of internal value decision-making is to make choices that are true to oneself and align with one's personal values and beliefs.

This thesis mainly considers the investigations of internal value judgments; more specifically it examines scenarios in the context of preference judgment. Several tasks can be utilised to measure subjective values during internal value judgments. The following section describes the most common types of tasks used to study internal value judgments: rating, willingness-to-pay, temporal discounting, and binary choice preference tasks.

2.5.4. Internal value judgement paradigms

2.5.4.1. Temporal discounting task

The first one is the temporal discounting paradigm, which is widely used in psychology and neuroscience research to study decision-making. These tasks typically involve making a choice between two possible options, one of which offers a small reward immediately and the other of which provides a larger reward later. Hence, temporal discounting reflects the tendency of individuals to evaluate rewards according to what they receive sooner or later. The decision that an individual makes between the two alternatives is then utilised to draw conclusions about the individual's level of temporal discounting (Green & Myerson, 2004; Samuelson, 1937; Schultz, 2010). Recent study indicates that, in general, participants prefer the immediate reward and that the rate at which rewards are discounted varies considerably amongst individuals (Berns et al., 2007; Jan Peters & Büchel, 2011).

2.5.4.2. Willingness to pay tasks

Willingness to pay (WTP) is a concept most commonly used in economics and financial decisions and refers to the maximum amount of money that an individual is willing to pay for a good or things (Plassmann et al., 2007). In most cases, these tasks are typically based on the Becker-DeGroot-Marschak (BDM) auction paradigm (Becker et al., 1964), which is a method for determining the WTP of individuals within the context of a group setting. In the study design, an item is shown, and participants are asked to bid (i.e., offer) a certain amount of money by selecting one of the available options. The individual’s willingness to spend more money on an item indicates that this item is more valuable to the participant than others. As a consequence, the amount of money they are willing to spend acts as a direct indicator of preference (Fiedler, 2010; Harris et al., 2011; Motoki et al., 2019; Schoen et al., 2018).

2.5.4.3. Rating tasks

Rating tasks rely on the concept of internal value, whereby participants are instructed to rate a certain item, object, or situation on a scale by stating how much they would be pleased to receive the item (Lebreton et al., 2009). Based on the task presentation, individuals’ responses may indicate a range of various aspects. Some examples of these aspects include wanting (i.e., desiring), liking, being familiar with, or finding the experience pleasant (Goto et al., 2017). In the majority of experimental research, such tasks are performed in combination with others, such as binary choice preference tasks (Brus et al., 2021; Milosavljevic et al., 2010; Philiastides & Ratcliff, 2013). Nonetheless, there are situations in which these tasks serve as the principal focus of experimental studies in their own right (Qiu et al., 2020; Sun et al., 2020; Tashiro et al., 2019).

2.5.4.4. Forced-choice preference tasks

This task involves preference-based decisions in which participants were asked to choose their preferred item or items from a set of two or more options. Typically, making a decision is based on picking one of the two alternatives (i.e., binary choices such as responding with yes or no or, responding with whether or not one wants to consume). The effort tasks may also be utilised as a kind of forced-choice preference task where participants were required to decide how much effort they would like to exert in order to achieve a reward (Cléry-Melin et al., 2011; Harris & Lim, 2016a; Pessiglione et al., 2007).

All these internal value judgement paradigms provide approaches to making judgements that are based on an individual's subjective values. In these paradigms, decisions are made by assigning values to different options and choosing the one that aligns most closely with the individual's personal values. In my investigations, I will combine different versions of rating tasks and forced-choice preference tasks in order to evaluate various scenarios involving value-based decision-making across novel tasks.

Chapter 3

Multiple Information Sources' Impact on Value-Based Decisions

3.1. Background

From ordinary and even unconscious decisions made in everyday life to complex international political policies, decisions are made as a result of evaluating many diverse pieces of information concerning pertinent factors. Rational decision-making depends on evaluating different attributes simultaneously in order to assay the highest expected overall value relative to the expected and potential costs inherent in decisions. Making an optimal choice requires an integration process in which the reward estimates of all attributes should be integrated into a combined value. Previous research has examined how people integrate different sources of information in various experimental paradigms (Noguchi & Stewart, 2018; Trueblood et al., 2013; Tsetsos et al., 2010; Usher & McClelland, 2004).

Accordingly, the evidence supporting each alternative is integrated over time, until sufficient evidence in support of one alternative reaches a response threshold. This integration process can provide an optimal strategy for fast and accurate decisions by reducing the noise in the accumulated information. The cognitive process during decision-making has been successfully explained by this general framework, commonly referred to as sequential sampling models (Bogacz et al., 2006). For perceptual decisions, although a few studies have examined how multiple pieces of information can influence behaviour (James, 2000; Krzemí & Zhang, 2021; Palmer, 1995; Shaw, 1982), choices on the basis of a single source are commonly used to examine the process of evidence accumulation (Gold & Shadlen, 2007). For value-based, more specifically preference-based decisions, most related research focused on multi-attribute choices, in which different types of information need to be combined to guide choices (Slovic, 1995). For example, when renting a home, one need to consider the combination of room size, price, and location. This raises the issue of how multiple sources of information can be integrated during decision-making. The traditional approach suggested that multi-attribute choices entail that attributes are optimally weighted and combined in a way that reaches maximum utility (Dawes & Corrigan, 1974; Doyle, 1997; M. D. Lee & Cummins, 2004). More recent perspectives propose alternative heuristic models, such as the take-the-best model, assuming that only a few attributes are taken into account by a decision-making while others are ignored (Gigerenzer & Gaissmaier, 2010; Gigerenzer & Goldstein, 2011; Gigezenger & Goldstain, 1999).

The current study focused on the relatively neglected decision paradigm of value-based decision-making (VBDM), which posits that choices are made based on multiple sources of information of the same type. For example, when buying a chocolate assortment box, the nature of each item within the box may have similar values. Here, to make an optimal choice among multiple boxes, one needs to integrate their preferences towards individual items (i.e., select the box with the highest expected value). In such cases, how multiple information sources affects behavioural performance remains unclear.

The standard accumulation model assumes that evidence for decision-making is accumulated over time. However, little research has been conducted to understand whether humans can effectively combine evidence from spatially distributed or dispersed sources. The DDM model relies on the assumption that evidence comes from a single source continuously over time. It is unknown, however, how people will behave when information is distributed from multiple sources.

The present study aims to investigate the integration of information from multiple sources in decision-making and its implications for human cognitive processes. Although previous research supports the proposition that humans do indeed combine multiple sources of information during VBDM (Krajbich et al., 2010, 2012), such processes are inevitably constrained by limited attentional capacity. As a result, selective attention may direct the decision process to a subset of information sources, leading to biased choice behaviour. Two critical questions have yet to be addressed in this field:

- How is VBDM affected by the number of information sources?
- Is a decision-maker sensitive to the presence of incongruent information between multiple sources?

These questions were addressed with regard to VBDM in two internet-based experiments, in which human participants were instructed to make binary forced choices based on their preferences, whereby each choice option consisted of multiple food items (Figure 3.1).

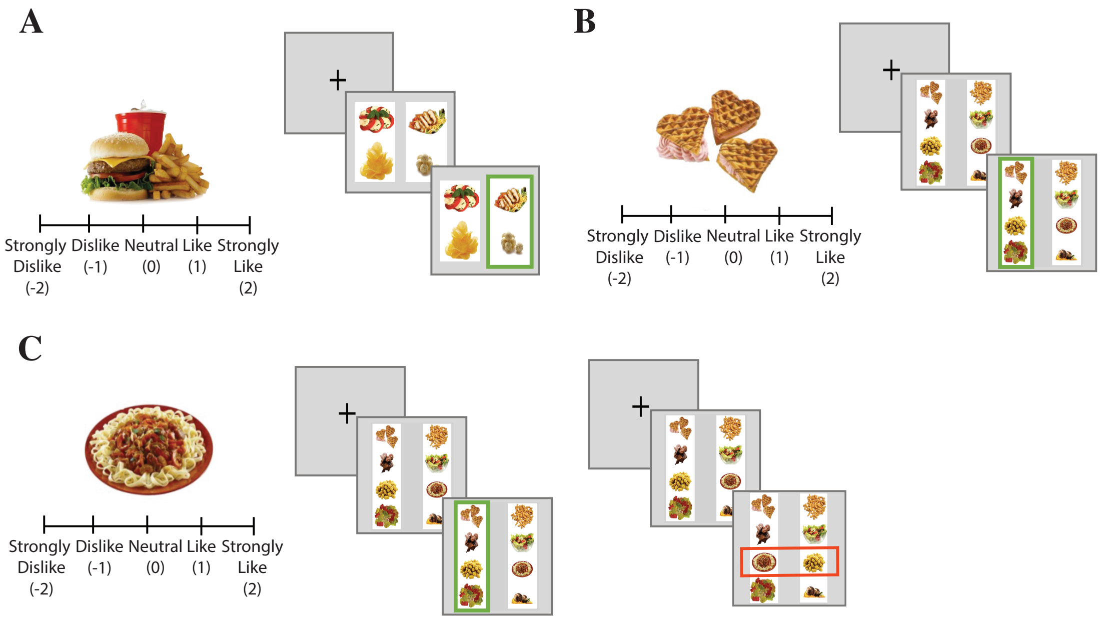

Figure 3.1 Experimental paradigms for both two-items task and four-items task.

A. Two-items task experimental paradigm. Participants were asked to rate food items before making a binary choice between two alternatives, each of which contained two food items. **B.** Four-items task experimental paradigm. After completing a rating task, participants were instructed to choose between two options, each of which contained four food items. **C.** Four-items task experimental paradigm containing congruent and incongruent information. Participants completed a rating task followed by a binary choice task between two alternatives, each of which contained four food items

Experiment 1 investigated the effect of the number of food items on behavioural performance. In one session, participants chose between two options, with each containing two food items. In another session, each option included four food items. Importantly, all food items assembled in each choice option were at the same level of preference rating. We hypothesized that such within-option consistency would promote one of two possible types of behaviour. First, as the number of food items per option increases, participants may evaluate additional items, which leads to prolonged reaction time (RT). Alternatively, participants may ignore the additional information because it is redundant, and hence show no behavioural change. By manipulating the number of food items per choice option, we examined how the number of information sources affects choice behaviour and RT. Furthermore, the decision task was presented in four difficulty levels, according to the extent of value difference between the preference ratings of food items.

Experiment 2 aimed to replicate and extend the findings from Experiment 1 with the addition of incongruent information. Participants performed a binary choice task between two options, each of which contained four food items. Two trial types were presented, depending on whether the food items in each choice option contained congruent or incongruent preference information. In congruent trials, all food items in each option had the same level of preference rating as in Experiment 1. In incongruent trials, one incongruent pair was created by swapping the locations of two food items in the two choice options. We expected that the presence of incongruent pairs would lead to one of two possible types of behaviour. First, if the participants made decisions by integrating multiple information sources, incongruent pairs had a negative impact on behavioural performance, leading to a lower accuracy and longer RT. Alternatively, participants could disregard the additional (incongruent) information and hence the manipulation of information congruency would not impact on behavioural performance.

In both experiments, we fitted a cognitive model, the drift-diffusion model (DDM) (Ratcliff & McKoon, 2008), to the behavioural data and inferred the effects of information sources, information congruency, and task difficulty on the underlying decision-making process. The outcomes are reported in more depth below.

Overall, the primary objective of this research is to investigate the integration of information from multiple sources in value-based decision-making in terms of behavioural performance and cognitive processes. The first experiment aims to examine behavioural patterns when the number of information sources increases. The second experiment focuses on understanding how people respond when information from multiple sources becomes incongruent. If individuals can successfully combine the information even when they are incongruent, it suggests that the combinations or the combined evidence may be diminished, leading to changes in behaviour.

To explore participants' ability to evaluate multiple sources of information per alternative, we manipulated the preference level on a single source. As a straightforward manipulation, when individuals solely focus on a single pair of information, we do not anticipate observing any significant effects on their behaviour when the information becomes incongruent or when the number of information sources increases.

By conducting this research, our aim is to contribute to our understanding of human cognitive processes by shedding light on the complexity of decision-making in real-world contexts.

3.2. Experiment 1: Two Items vs. Four Items Study

3.2.1. Participants

A total of 52 participants were recruited from an online recruitment portal Prolific (prolific.co) and took part in the experiment online. Participants' age ranged from 19–56 years, with a median age of 24, and 16 were females). Table 2 shows demographic information about the participants. Prolific users are aware that they participate in research studies and are compensated for their participation based on minimum payment rates (Palan & Schitter, 2018). All participants received monetary payments for their participation. Consent was obtained from all participants. The study was approved by the Cardiff University School of Psychology Research Ethics Committee.

Table 2 Demographic information about the participants. STD - standard deviation

Category	Value
gender	female (16), male (36)
age (years)	mean: 26.2, median: 24, STD: 7.4
nationality	United Kingdom (12), Poland (12), Portugal (6), Italy (3), United States (6), Greece (4), China (1), Spain (2), Canada (1), Hungary (1), Finland (1), South Africa (1), Spain (1), Czech Republic (1)

3.2.2. Apparatus

The experiment was carried out online. Experimental scripts for stimulus presentation and response collection are written in HTML with a JavaScript library jsPsych 6.1.0 (de Leeuw, 2015). The online experiment was run on the Pavlovia web server (pavlovia.org), and participants used web browsers on their computers to complete the experiment. It has been shown that online studies using modern web browsers can be employed as an efficient tool to accurately measure behavioural responses and reaction times (Anwyl-Irvine et al., 2020; de Leeuw & Motz, 2016; Semmelmann & Weigelt, 2017).

3.2.3. Experimental Design

All participants completed two experimental sessions. In each session, choice options were comprised of either two or four food items. Half of the participants completed the session with two-item options first, whereas the other half completed the four-item session first. Each session included a rating part and a decision-making part. In the rating part, participants were asked to give preference ratings (i.e., how much they would like to consume the food item) to each food item chosen. A total of 100 food pictures were chosen from an online food database (Blechert et al., 2019). Participants were informed that they needed to rate the food items as evenly spread as possible. If their rating responses were severely biased, the session was terminated prior to the decision part, and their data was discarded without further analyses.

The Likert-type rating scale contained five discrete values from -2 to 2, representing five preference levels: “strongly dislike” (-2), “dislike” (-1), “neutral” (0), “like” (1) and “strongly like” (2). In the decision-making part, participants were asked to make a binary choice between two options containing the combination of food items. The instruction is to decide which group of food items is more preferred. In each trial, two groups of food stimuli were presented on the left and right sides of the screen (two-item session in Figure 3.1A and four-item session in Figure 3.1B). In both two-item and four-item sessions, each option contained food items with the same level of preference rating (i.e., from -2 to 2).

In both sessions, there were four different difficulty levels, depending on the relative value difference between two options: *hard*, *middle*, *easy*, and *easiest*. On a hard trial, two groups with one rating point difference appeared on the left and right of the screen (e.g., 0 vs. 1, 0 vs. -1, 2 vs. 1, -1 vs. -2). On a middle trial, the two groups which the graded difference is two appeared on the left and right sides of the screen (e.g., 0 vs. 2, 0 vs. -2, -1 vs. 1). On an easy trial, the rating difference between the groups is three and these groups appeared on the left and right sides (e.g., 2 vs. -1, -2 vs. 1). On an easiest trial, the rating difference which the highest grade is four. Similar to other trials, the two groups appeared on the left and right sides (e.g., -2 vs. 2).

3.2.4. Procedure

Each experimental session comprised 450 trials, which were divided into 15 blocks of 30 trials. Participants took short breaks between blocks. Each block contained 12 hard trials (3 trials from 0 vs. 1, 3 trials from 0 vs. -1, 3 trials from 2 vs. 1, and 3 trials from -1 vs. -2), 9 middle trials (3 trials from 0 vs. 2, 3 trials from 0 vs. -2, and 3 trials from -1 vs. 1), 6 easy trials (3 trials from 2 vs. -1 and 3 trials from -2 vs. 1), and 3 easiest trials (3 trials from -2 vs. 2). The order of the four difficulty levels was randomized across trials in a block.

Each trial began with the presentation of a fixation point at the centre of the screen, with a uniformly distributed latency between 250 and 1500 ms. After the fixation, two choice options (each with two or four food items) appeared on the left and right side of the screen. Each trial was presented for a maximum of 3000 ms, during which time participants were instructed to click on one option using a mouse. Immediately after each choice action, the colour of the rectangular border of the chosen option changed colour to indicate the registration of a response, and the choice stimulus disappeared after the response. If participants did not respond within 3000 ms, a warning message was given, and the next trial began.

3.2.5. Data Analysis

We quantified the response time (RT) of each trial as the time between the onset of the food stimulus and the time of the behavioural response. Response accuracy was quantified as the proportion of trials in which the option with a higher preference rating was chosen. Trials with RTs faster than 300 ms were removed, to exclude fast guesses (i.e., inaccurate results). The trials that were discarded accounted for 0.08% of all trials. To make group inferences on mean decision accuracy and RT, we used Bayesian ANOVA, with the difficulty level and the number of information sources as within-subject factors. We used JASP (jasp-stats.org) to perform post-hoc comparisons and Bayes Factors (BFincl, BF10) to characterise the strength of evidence (Wagenmakers et al., 2018).

3.2.6. Cognitive Modelling of Behavioural Data

We used the hierarchical drift-diffusion model (HDDM) toolbox (Wiecki et al., 2013) to fit the DDM to each participant’s response time distribution and accuracy. HDDM is a hierarchical extension of DDM. It assumes that model parameters for individual participants are random examples drawn from group-level distributions and uses the Bayesian approach to estimate the posterior distributions of all model parameters at both individual and group levels (Wiecki et al., 2013). DDM assumes that a binary choice is made by a noisy process that accumulates information over time from a starting point until the accumulated information reaches one of two decision boundaries, corresponding to the two choice options (Ratcliff & McKoon, 2008). When one of the boundaries is reached, a motor response is executed. The model decomposes behavioural data into four components:

- The drift rate (v) refers to the average rate of information accumulation.
- The decision threshold (a) refers to the distance between two response boundaries.
- The non-decision time (T_{er}) refers to the latencies of stimulus encoding and the response execution.
- The starting point (z) refers to a priory bias toward one of the two options.

Furthermore, the DDM can be extended to involve trial-by-trial variability in drift rate *sv* and non-decision time *st* in order to improve model fitting (Ratcliff & McKoon, 2008). The model predicts RTs as the sum of the time period of accumulation process and non-decision time, the latter accounts for sensory encoding and motor execution delays (Karahan et al., 2019).

In our study, the starting point was fixed at 0.5. Unlike previous studies like (Leite & Ratcliff, 2011; Mulder et al., 2012; Simen et al., 2009), which explicitly manipulated the outcome of each option, our study took a different approach. We presented the position of the correct option (either left or right) randomly across trials without explicit manipulation. This randomization ensured that participants did not develop biases or preferences towards a specific position. To keep the model reasonably simple, by presenting the correct option randomly, we aimed to create a neutral decision-making environment where participants based their choices solely on the task requirements, rather than any preconceived biases towards one side. This approach allowed us to investigate the underlying cognitive processes involved in decision-making without the confounding influence of prior preferences or expectations.

To accommodate changes in behavioural performance, one or more model parameters need to vary between conditions. We evaluated a total of 26 variants of the DDM model with different parameter constraints. In all but one model, the three main parameters (a, v, and T_{er}) were allowed to vary between conditions and/or sessions.

For each model, we generated 20,000 samples from the joint posterior distribution of all model parameters by using Markov chain Monte Carlo sampling. The initial 2000 samples were discarded as burn-in to provide the stability of posterior estimates (Wiecki et al., 2013).

Model fits were evaluated by comparing each model's deviance information criterion (DIC) value (Spiegelhalter et al., 2002), where lower values indicate a better model fit. We used Bayesian hypothesis testing (Gelman et al., 2013) to make inferences between conditions from the posterior parameter distributions for the best fitting model variant. To clarify our statistical report, we used p to refer to frequentist p-values and Pp|D to refer to the proportion of posteriors supporting the testing hypothesis at the group level from Bayesian hypothesis testing.

3.2.7. Behavioural Results

Participants performed binary preference-based choices between options incorporating two or four items in different sessions. Behavioural performance was quantified by accuracy (proportion of correct responses) and RT.

Participants performed with a higher accuracy and faster reaction time in the two-item task (mean accuracy = 89.46%, mean reaction time:1231.56 ms) than in the four-item one (mean accuracy = 85.62%, mean reaction time:1342.19 ms). A repeated measures ANOVA revealed that there was significant main effect of task differences on participants' behavioural performance (accuracy: $F(1,50) = 8.041$, $p = 0.007$, $\eta p^2 = 0.139$, $BF\text{incl} = 47918.650$; RT: $F(1,50) = 22.450$, $p < 0.001$, $\eta p^2 = 0.310$, $BF\text{incl} = 51280.966$) (Figure 3.2A and Figure 3.2B).

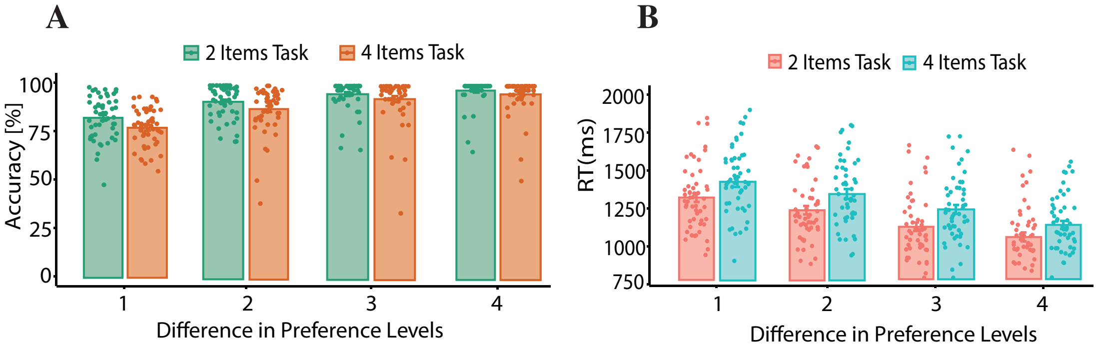

Figure 3.2 Behavioural results.

A. The accuracy measurement (ratio of correct responses) between the two items decision-making task (green) and four items decision-making task (orange) across all conditions. **B.** The average of RTs between the two items decision-making task (red) and four items decision-making task (blue) across all conditions

The ANOVA also revealed that behavioural performance differed significantly between difficulty levels in both two-item and four-item trials (accuracy: $F(3,150) = 214.647$, $p < 0.001$, $\eta p^2 = 0.303$, $BF\text{incl} = 3.129\text{e}+59$, RT: $F(3,150) = 162.900$, $p < 0.001$, $\eta p^2 = 0.765$, $BF\text{incl} = 3.375\text{e}+58$). In other words, as the preference rating of two options became more closer (i.e., more difficult), participants had lower accuracy and longer RT. Furthermore, there was a significant interaction between the number of sources and task difficulty (accuracy: $F(3,150)$

$= 3.201$, $p = 0.025$, $\eta p^2 = 0.003$, $BF\text{incl} = 0.131$, RT: $F(3,150) = 3.006$, $p = 0.032$, $\eta p^2 = 0.057$, $BF\text{incl} = 0.126$), indicating that the behavioural effects of the number of information sources vary between task difficulty levels.

To explore whether choosing between options including preferred items differed from choosing with non-preferred items, we conducted pairwise comparisons between trials at the same difficulty level but including positive vs. negative rated items. Making choices involving positively rated items was faster across all difficulty levels: 0/1 versus 0/-1 ($F\,(1, 51) = 20.924$, $p<0.001$, $\eta p^2 = 0.291$), 0/2 versus 0/-2 ($F\,(1, 51) = 5.764$, $p<0.001$, $\eta p^2 = 0.102$) and 2/1 versus -2/-1 ($F\,(1, 51) = 0.030$, $p<0.001$, $\eta p^2 =$ 5.939e-4). However, no difference was observed in decision accuracy: 0/1 versus 0/-1 ($F\,(1, 51) = 1.128$, $p = 0.293$, $\eta p^2 = 0.022$), 0/2 versus 0/- 2 ($F\,(1, 51) = 0.011$, $p = 0.917$, $\eta p^2 =$ 2.175e-4), and 2/1 versus -2/-1 ($F\,(1, 51) = 0.030$, $p = 0.862$, $\eta p^2 =$ 5.939e-4).

3.2.8. Cognitive Modelling Results

We used a hierarchical Bayesian version (Cavanagh et al., 2011; Vandekerckhove et al., 2011) of the DDM (Bogacz et al., 2006; Ratcliff & Tuerlinckx, 2002) to decompose individual participants' behavioural data into model parameters to infer their latent cognitive processes. We allowed three model parameters (i.e., the drift-rate v, the non-decision time T_{er}, and the decision threshold a) to be fixed or vary between difficulty conditions, sessions (i.e., two-item vs. four-item options) or both. For each model variant, we ran 5 MCMCs, each having 20.000 samples, with the first 5.000 samples disregarded due to burn-ins. Model convergence was assessed using the Gelman-Rubin statistic, with values lower than 1.1 indicating successful model convergence. The maximum value of the statistic from all parameters was R = 1.00085, which is less than the convergence criterion of 1.1(Gelman & Rubin, 1992), supposing that all parameter estimates converged after 20,000 steps.

The model variant that described the data best (i.e., the one with the lowest DIC value) allows all three parameters (v, T_{er}, and a) to vary between sessions with two or four food items per option, and v and T_{er} to further vary between the difficulty levels (Figure 3.3B). To assess the model's fit, we simulated the model with its posterior parameter estimates. In all conditions, the observed data and model simulations were in good agreement (Figure 3.3A).

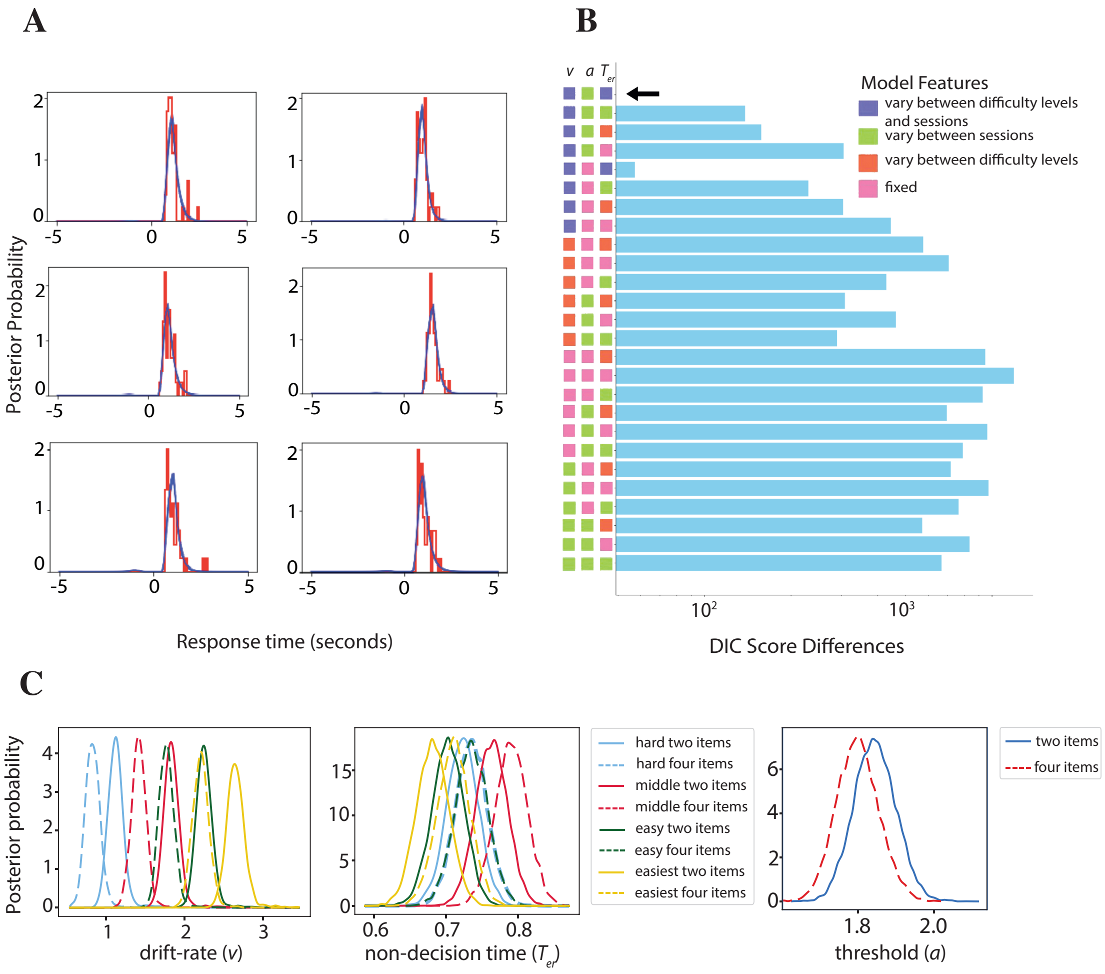

Figure 3.3 Drift-diffusion model (DDM) fitting results.

A. Showing model simulations on best fitting model from different participants. The red line depicts participant RT distribution data and blue line indicates model fit with varying model parameters. **B.** The deviance information criterion (DIC) score of 26 DDM model variants. The DIC score differences between all models and best fitting model are shown against corresponding model dependencies which were depicted on the left side of the graph. A purple-filled square indicates that corresponding parameter can vary between the difficulty levels on preference and two items/four items options. An orange or green-filled square indicates that corresponding parameter can vary between difficulty levels on preference or two items/four items options, respectively. Pink-filled square indicates that the parameter is fixed between conditions. The best fitting model had a 0 DIC score difference and was indicated by a black arrow. **C.** Group-level DDM model parameters of the best fitting model, which is the first model variant in Panel **B**. Each posterior distribution was obtained from 20,000 MCMC samples. Blue, red, green, and yellow lines represent different preference levels on the parameter of v and T_{er}. Solid and dashed lines represent different numbers of information sources on the parameter of v, T_{er}, and a

We used Bayesian statistics to quantify the proportion of non-overlaps between the posterior distributions of parameters (Gelman et al., 2013; Kruschke, 2010). For the drift rate, there was strong evidence to support differences between all conditions between difficulty levels. The drift rate was also higher in choosing options with two items than those with four (Pp|D = 0.003, across four conditions). The mean posterior value across four conditions from two items was 1.568, whereas the mean posterior value across four conditions from four items was 1.968. Furthermore, choosing between two-item options led to a small increase in the decision threshold than four-item options (Pp|D = 0.728). We did not observe strong evidence supporting a difference in the non-decision time between conditions (Figure 3.3C and Table 3).

Table 3 Posterior comparisons of the model parameters (v and T_{er})

		v		T_{er}	
		Two items	Four items	Two items	Four items
Difference in preference level = 1	x = Middle; y = Hard	1.000	1.000	0.907	0.962
	x = Easy; y = Middle	0.999	0.997	0.026	0.045
	x = Easiest; y = Easy	0.997	0.999	0.246	0.217
Difference in preference level = 2	x = Easy; y = Hard	1.000	1.000	0.256	0.501
	x = Easiest; y = Middle	1.000	1.000	0.005	0.006
Difference in preference level = 3	x = Easiest; y = Hard	1.000	1.000	0.093	0.218

The table displays the proportion of non-overlap between posterior parameter estimates x and y, which equates to a Bayesian test of the hypothesis $P_{p|D}(x > y)$. Experimental conditions are hard, middle, easy, easiest refer to different preference levels and the DDM parameters are v drift-rate and T_{er} non-decision time.

3.3. Experiment 2: Swapping vs. Non-Swapping Study

3.3.1. Participants

Prolific online recruitment portal (prolific.co) was used to recruit 52 participants in the online experiment. Their ages ranged from 19 to 56 years, with a median age of 23.5 years, and 17 participants were female. Table 4 summaries demographic information about the participants.

Informed consent was obtained from all participants. The study was approved by the Cardiff University School of Psychology Research Ethics Committee.

Table 4 Demographic information about the participants. STD - standard deviation

Category	Value
gender	female (17), male (35)
age (years)	mean: 25.8, median: 23.5, STD: 6.8
nationality	Mexico (9), Portugal (8), Poland (7), Spain (4), United Kingdom (3), Italy (3), United States (3), Greece (2), Hungary (2), Austria (1), Colombia (1), Switzerland (1), Malaysia (1), Netherlands (1), France (1), Norway (1), Canada (1), India (1), South Africa (1), Zimbabwe (1)

3.3.2. Apparatus

Experimental scripts for stimulus display and response collection are written in HTML with a JavaScript library jsPsych 6.1.0 (de Leeuw, 2015a), as in Experiment 1.

3.3.3. Experimental Design

Similar to Experiment 1, Experiment 2 comprised two parts: an initial rating part and a main decision-making part. The rating part was the same as in Experiment 1. Each participant rated 100 food items according to their subjective preference on a five-point Likert-type scale: “strongly dislike” (-2), “dislike” (-1), “neutral” (0), “like” (1) and “strongly like” (2). In the decision-making part, two groups of food items presented on the left and right sides of the screen in each trial. Each group consisted of four food items, from which participants were instructed to choose their preferred group of food items (Figure 3.1C).

Half of the decision-making trials followed the similar design as in Experiment 1: all food items in a group had the same level of preference rating (hereinafter referred to as “non-swapping trials”). There were three difficulty levels based on the value difference between the two food item groups: *hard*, *middle*, and *easy*. The difference in preference ratings between the two groups was only one on the hard level (e.g., 0 vs. 1, 0 vs. -1, 2 vs. 1, -1 vs. -2). A two-point preference rating gap existed between the two groups on the middle level (e.g., 0 vs. 2, 0 vs. -

2, -1 vs. 1). The difference in rating value between the groups was three on the easy level (e.g., 2 vs. -1, -2 vs. 1).

In the other half of trials, we first generated two groups of food items in the same way as the non-swapping trial. We then swapped the position of food items in a random row, hereinafter referred to as "swapping trials". As a result, the swapped row contains incongruent value information compared with the other rows.

3.3.4. Procedure

The decision-making part comprised 576 trials, including 288 non-swapping and 288 swapping trials. The decision accuracy (proportion of correct responses) was provided on the screen as feedback after every 48 trials. Self-paced breaks were given after every 64 trials. Each trial began with the presentation of a fixation point at the centre of the screen with a uniformly distributed latency between 250 and 1500 ms. After the fixation, two food items groups appeared on the left and right sides of the screen until a response was received.

3.3.5. Data Analysis and Cognitive Modelling

As in Experiment 1, Statistical analyses were performed to quantify RT and accuracy. The response time (RT) of each trial was calculated as the time between the onset of the food stimulus and the time of the behavioural response. In the congruent conditions, response accuracy was measured as the proportion of trials in which the option with a higher preference rating was chosen, while in the incongruent conditions, response accuracy was measured as the proportion of trials in which the option with the higher preference rating was selected despite the presence of incongruent pairs. Specifically, incongruent conditions involved the manipulation of information congruency by swapping the locations of two food items. In these trials, the locations of two food items within the two choice options were swapped, resulting in incongruency between the preference ratings of the items and their actual positions. The correct responses were determined based on the overall preference ratings of the food items rather than the specific locations of the foods. Following the statistical analysis, we then evaluated the fit of 26 DDM with different parameter constraints to the behavioural data. please edit in academic language.

3.3.6. Behavioural Results

Participants made binary value-based choices between two groups of food items. In half of the trials, incongruent information was introduced by swapping a pair of food items between the two groups (i.e., swapping trials). Repeated measures ANOVA showed that, compared with non-swapping trials, swapping trials had lower accuracy and slower RT (accuracy: $F(1,51) = 372.668$, $p < 0.001$, $\eta \mathrm{p}^2 = 0.880$, $BF\mathrm{incl} = 3.191\mathrm{e}{+}60$; RT: $F(1,51) = 99.727$, $p < 0.001$, $\eta p^2 = 0.662$, $BF\mathrm{incl} = 8.544\mathrm{e}{+}22$) , (Figure 3.4A and Figure 3.4B) indicating that the presence of incongruent information hinders behavioural performance. We further replicated the effect of value difference observed in Experiment 1. Across swapping and non-swapping trials, larger value difference was associated with faster RT ($F(1,51) = 99.727$, $p < 0.001$, $\eta p^2 = 0.662$, $BF\mathrm{incl} = 8.544\mathrm{e}{+}22$) and higher decision accuracy ($F(1,51) = 372.668$, $p < 0.001$, $\eta \mathrm{p}^2 = 0.880$, $BF\mathrm{incl} = 3.191\mathrm{e}{+}60$). There was significant interactions between swapping conditions and task difficulty in RT ($F(2,102) = 111.702$, $p < 0.001$, $\eta p^2 = 0.687$, $BF\mathrm{incl} = 1.182\mathrm{e}{+}38$) and accuracy ($F(2,102) = 286.372$, $p < 0.001$, $\eta p^2 = 0.849$, $BF\mathrm{incl} = 1.056\mathrm{e}{+}61$). These results suggested that the effect of information congruency from multiple sources is dependent on the average value difference between options.

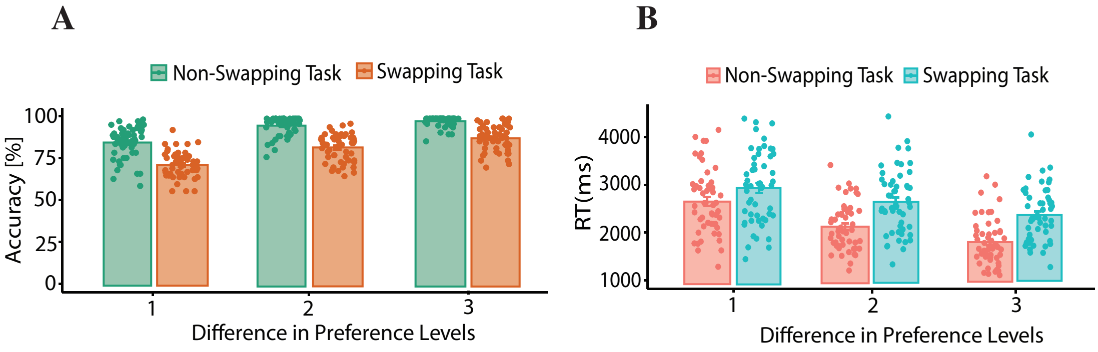

Figure 3.4 Behavioural results.

A. The accuracy measurement (ratio of correct responses) between the non-swapping task (green) and swapping task (orange) across all conditions. **B.** The average of RTs between the non-swapping task (red) and swapping task (blue) across all conditions

Furthermore, we compared the behavioural performance between trials at the same value difference but with positive or negative rated items (versus the group of neutral items). Across swapping and non-swapping conditions, making choices involving positively rated items were faster in all difficulty levels: 0/1 versus 0/-1 ($F(1, 51) = 13.871$, $p<0.001$, $\eta p^2 = 0.214$), 0/2 versus 0/-2 (F (1, 51) = 7.074, p = 0.010, $\eta p^2 =$ 0.122) and 2/1 versus -2/-1 (F (1, 51) = 10.138, p = 0.002, $\eta p^2 =$ 0.166). However, no difference was observed in decision accuracy: 0/1 versus 0/-1 (F (1, 51) = 0.768, p = 0.385, $\eta p^2 =$ 0.015), 0/2 versus 0/- 2 (F (1, 51) = 0.010, p = 0.920, $\eta p^2 =$ 1.993e-4), and 2/1 versus -2/-1 (F (1, 51) = 5.738e-4, p = 0.981, $\eta p^2 =$ 1.125e-5). Therefore, we replicated the facilitation effect in choices with positive options observed in Experiment 1.

3.3.7. Cognitive Modelling Results

Similar to Experiment 1, the HDDM model was used to decompose each participants' behavioural data into internal components of cognitive processing (Wiecki et al., 2013). We allowed three model parameters (i.e., the drift-rate v, the non-decision time T_{er}, the decision threshold a) to be fixed or vary between difficulty conditions, task type (i.e., swapping or non-swapping options) or both. For each model variant, we ran 5 MCMCs, with each one having 20.000 samples, with the first 2.000 samples disregarded due to burn-ins. Model convergence was assessed using the Gelman-Rubin statistic, with values lower than 1.1 indicating successful model convergence. The maximum value of the statistic from all parameters was R = 1.00083 (Gelman & Rubin, 1992), supposing that all parameter estimates converged after 20,000 steps.

The best-fitting model version (i.e., the one with the lowest DIC value) allows all three parameters (v, T_{er}, and a) to vary between swapping and non-swapping conditions, and v to further vary between the difficulty levels (Figure 3.5B). The observed data and model simulations were in good agreement for all conditions (Figure 3.5A).

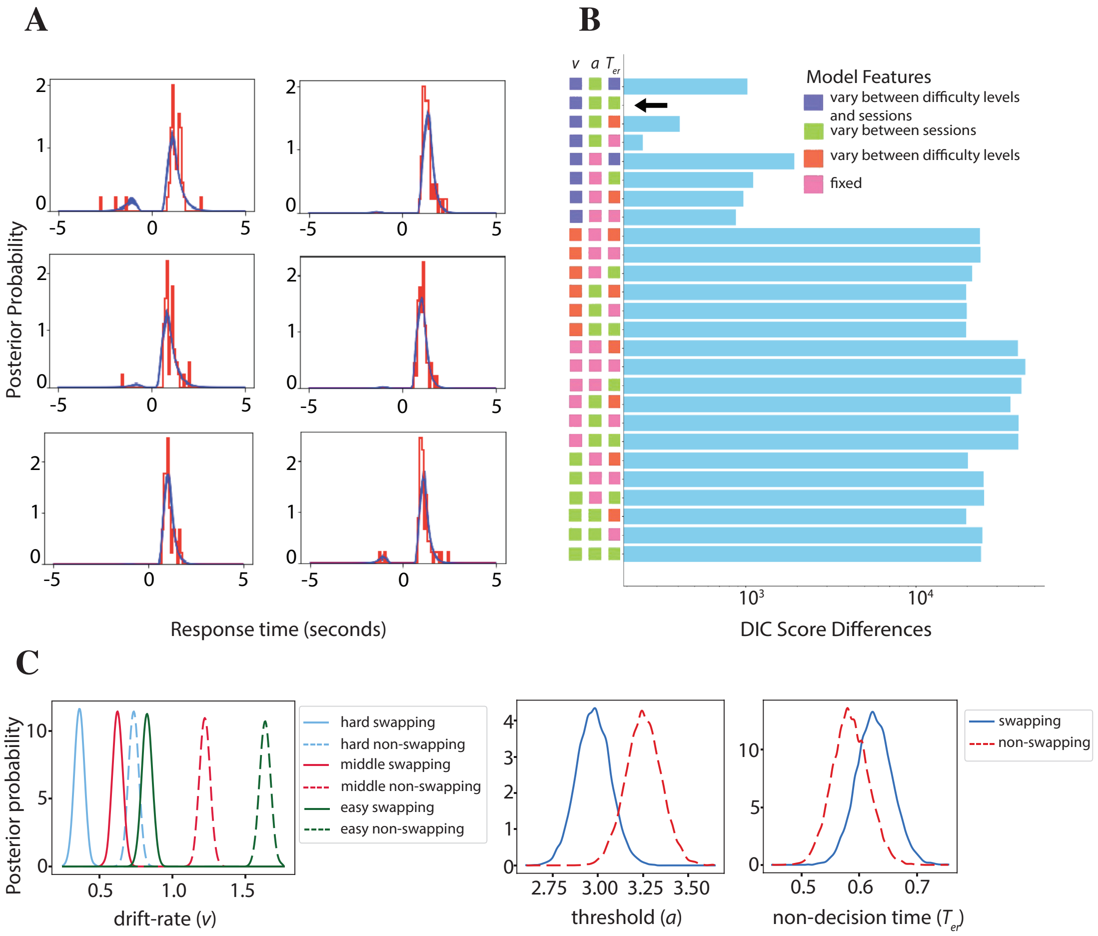

Figure 3.5 Cognitive modelling results.

A. Model simulations on the best fitting model are shown on six participants. The red line represents data from participants' RT distributions, whereas the blue line represents model fit with varying parameters. **B.** The DIC score of the 26 DDM model variants. The DIC score differences between all models and the best-fitting model are shown against the model dependencies depicted on the graph's left side. A square filled with purple indicates that the corresponding parameter can vary between the preference levels and congruent/incongruent options. A square filled with orange or green indicates that the corresponding parameter can vary based on preference levels or congruent/incongruent pairs options, respectively. The square filled with pink indicates that the corresponding parameter is constant between conditions. A black arrow pointed to the best-fitting model, which had a DIC score difference of 0 and was denoted by a score of 0. **C.** Group-level DDM model parameters for the best fitting model, which corresponds to second model variant in Panel **B**. Each posterior distribution was derived from 20,000 MCMC samples. Blue, red, and green lines reflect varying levels of preference for the parameter of *v*. On the parameter of *v*, T_{er}, and *a,* incongruent and congruent information sources are represented by solid and dashed lines, respectively.

We used Bayesian statistics (Gelman et al., 2013; Kruschke, 2010) to quantify the proportion of non-overlaps between the posterior distributions of parameters. For the drift rate, we found strong evidence supporting differences in difficulty levels between task types. Furthermore, choosing between four-item options with congruent conditions led to a small increase in the decision threshold than that of four-item options with incongruent conditions (Pp|D = 0.982) (Figure 3.5C).

3.4. Discussion

VBDM involves complex cognitive processes, because choices often depend on subjective motivations or preferences. During the decision process, each alternative needs to be associated with possible outcomes (Bogacz, 2007). To understand these decisions, several cognitive models have been developed. More recently, sequential sampling models have been used to examine the cognitive process underlying VBDM. Those models explain the accumulation process in the form of shifting of attention. Accordingly, a stochastic approach assumes that attention shifts between the attributes from moment to moment. The shifting comparisons are integrated over time into an evolving preference state to guide behaviour (Busemeyer et al., 2019).

In two independent experiments, we investigated how the existence of multiple information sources impacts preference-based decisions in terms of behavioural performance and its underlying cognitive mechanism. Experiment 1 investigated the impact of the number of information sources on decision-making. When the number of items in each choice option increased, human participants made slower and less accurate choices. Experiment 2 replicated and extended the main results of the first experiment. Consequently, when the number of items remains the same, incongruent information among each option lead to less accurate and slower decisions. Furthermore, in both experiments, decisions were slower and less accurate in more difficult conditions, in which preference ratings between options were closer.

Our experimental design and procedure are similar to those used by Philiastides and Ratcliff, 2013, who sought to identify how branding bias affects behavioural and decision processes, and specifically which internal components of processing are affected by the presence of branding. When making preference-based decisions between options associated with single items, they reported that behavioural performance varied according to the difference in the preference ratings of items. The current study did not consider the effect of branding, as all stimuli were presented without brands; instead, both experiments replicated the main finding of Philiastides and Ratcliff (2013), with the extension to options associated with two and four items. Taken together, these results suggest that the value difference influences both the speed and accuracy of preference-based decisions, which calls for the need of computational modelling to combine both behavioural measures.

One noteworthy addition is that our research was carried out in an online setting, suggesting the validity and reproducibility of online experiments to investigate the integration of subjective value during decision-making. When compared with trials with negatively rated items, the presence of positively rated items with the same value difference facilitates RT, but not decision accuracy. These results are akin to the effect of reward magnitude, which also demonstrates a facilitating effect on RT in probabilistic reward tasks (X. J. Chen & Kwak, 2017; Schurman & Belcher, 2013).

As highlighted above, in Experiment 1, the number of items per option affected behavioural performance. Since choices with four-item options consist of more pieces of information than those with two-item options, the prolonged RT associated with four-item options was expected, because of the additional time required to evaluate additional information sources. However, more items per option also led to less accurate decisions. This may appear to be counterintuitive, as all items within an option had the same level of subjective value (i.e., preference rating). The negative impact of multiple information sources on accuracy is more prominent in difficult trials. Preference or value judgement is generally a noisy process (Bogacz et al., 2007). Hence, the integration of the values from more items are susceptible to the fluctuations of value samples.

Experiment 2 revealed that participants do not make preference-based decisions based on only a single item. In the incongruent condition, one pair of items had their value difference opposite to the rest of item pairs, but the magnitude of their value difference was the same as the rest pairs. If participants only evaluated one item pair, one would expect no change in the RT between congruent and incongruent conditions, which was not supported by our results. Instead, the inferior behavioural performance in the incongruent condition implied that information from multiple sources (i.e., multiple pairs) was combined during decision-making.

Previous studies support the proposition of the integration of multiple information sources during food choices (Krajbich et al., 2010; Krajbich & Rangel, 2011). Similarly, information from different domains, such as price and preference, can jointly guide decision-making (Krajbich et al., 2012). Indeed, small attentional variations during the decision process, measured by visual fixation, impact the final choice, suggesting that people tend to consider all items when making a choice. This hypothesis is also closely linked to theoretical models of multi-attribute choice: preference formation is driven by attention switching between different attributes, as suggested by the decision field theory (Roe et al., 2001), and the value-based LCA model (Usher & McClelland, 2004).

Using a Bayesian hierarchical implementation of the DDM, our findings confirm that sequential sampling models provide a good fit to response accuracy and RT data in preference-based decisions. Although sequential sampling models have been used to describe a wide range of multi-alternative, multi-attribute decision tasks (Bhatia, 2013; Krajbich & Rangel, 2011; Noguchi & Stewart, 2018; Trueblood et al., 2014; Tsetsos et al., 2010, 2012), to the best of our knowledge, this is the first attempt to use the DDM to investigate the effect of multiple information sources. It is worth noting that, unlike previous studies that explicitly manipulate the outcome of each option (Leite, 2011; Mulder et al., 2012; Simen et al., 2009), the current study presented the position of the correct option (i.e., left or right) randomly across trials. Therefore, we did not model response bias during parameter fitting. Bayesian inferences from the best-fitted model support that the number of information sources and task difficulty affect selective model parameters.

First, our cognitive modelling has shown that increasing the amount of information affects the drift rate of the value integration process. In Experiment 1, the four-item task yielded a lower drift rate than the two-item task across all difficulty levels, and this change is accompanied by a moderate decrease in the decision threshold. In other words, as the number of information sources arises, participants accumulate value-based information of much lower quality (i.e., low signal-to-noise ratio), and make decisions based on less accumulated evidence. The magnitude of the drift rate has been associated with the allocation of attention (Schmiedek et al., 2007). It is possible that there is an additional cost in relation to selective attention on more information sources (Palmer, 1995; Reynolds & Chelazzi, 2004), which in turn leads to lowered drift rate.

Second, in Experiment 2, the drift rate differs between choices with congruent and incongruent information. The incongruent condition had a lower drift rate than the congruent condition at all difficulty levels, and this change was accompanied by a reduction in the decision threshold. In the incongruent condition, the four items contained conflicting information. In addition to decreasing the total value score, this conflict of information may have a distracting effect on attention. Thereby the evidence accumulation was adversely affected.

This would be in accordance with the findings of Fisher's 2014 multi-attribute study, which investigated how differential attention to positive and negative features of a product affects purchasing decisions with a choice between appetitive and aversive food alternatives. It was found that consumers give more weight to negative features than positive features in their choices, and attention is paid to negative features for a longer period of time during the choice process. In our case, the incongruent condition involved one non-preferred item in each choice option; hence, there may be an additional attentional cost associated with the incongruent pair during the integration of values (Fisher, 2014).

Third, in both experiments, the drift rates vary with the difference in the preference level between options (i.e., task difficulty). The easiest task (with the highest difference in preference ratings) had the highest drift rate, and the drift rate decreased as task difficulty increased. These results are in line with the mathematical definition of the drift rate, which represents the difference in the average evidence in favour of two choice alternatives. Critically, when taking into consideration the number of free parameters, more complex models with a varying threshold between difficulty levels did not yield good fits. Therefore, value differences between choice options did not elicit changes in participants' decision strategy or speed-accuracy trade-off.

Fourth, non-decision time is considered as the delay period during the decision process (Ratcliff & McKoon, 2008). Brain imaging studies suggested that the non-decision time estimated from accumulation models represents the latencies of early sensory processing (Nunez et al., 2017) and motor preparation (Karahan et al., 2019). In this research, the model allowing non-decision time to vary produced a better fit. However, there was no strong evidence to support that non-decision time changes between task difficulty levels or different information sources. Hence, our experimental manipulation did not have an effect on visual encoding and motor preparation latencies during preference-based decisions.

This study only presented behavioural results from a heterogeneous sample and an internet-based experiment, and consequently could not infer underlying neural processes during VBDM. Neurological investigations could provide more insight in this regard. A large brain network has been shown to encode the subjective value and ins integration, including the prefrontal cortex, the striatum, and the hippocampus (Kenning & Plassmann, 2008; McClure et al., 2004; Plassmann et al., 2007; Schaefer, 2009; Schaefer & Rotte, 2010). More specifically, the ventromedial prefrontal cortex has been shown to encode the subjective value in multi-attribute decisions (Hunt et al., 2012; Strait et al., 2014). Future research could explore the neural representation of multiple information sources as examined in the current study.

As a limitation, in this chapter, post ratings were not conducted, which means that participant preferences may have shifted slightly for certain items. However, in the following chapter (Chapter 4), pre and post-rating data were collected using food pictures from the same database. This data provides evidence that participant preferences are relatively stable, particularly towards individual food pictures from the same database. The strong correlation observed before and after the rating process suggests that participant preferences remained consistent. This stability in participant preferences towards the food pictures from the database has important implications for the current results. Firstly, using the same database across multiple chapters allows for a direct comparison and highlights the consistency of preferences. Secondly, similar procedures and methodologies have been employed in previous studies (Philiastides & Ratcliff, 2013). Even if there are minor changes in individual preferences within the experimental session, these fluctuations are likely to have a minimal impact on the overall results. The high correlation observed between pre and post-ratings indicates that any potential shifts in preferences are unlikely to significantly influence the final outcomes. Considering these factors, it can be concluded that the stability of participant preferences, as demonstrated by the strong correlation between pre and post-ratings, suggests that any minor changes in preferences during the experimental session are unlikely to have a substantial impact on the final results.

In summary, when deciding between options comprised of multiple items, both the number of information sources and the averaged value difference influence choice behaviour. Such behavioural change relates to the quality of evidence required for rational and speeded actions, but not to the latency of sensorimotor encoding.

Chapter 4

Preference Context Varies Perceptual Sensitivity During Decision-Making

4.1. Introduction

Everyday decisions often require consideration of several alternatives and rapidly choosing one of several options. As highlighted in Chapter 2, perceptual decisions are based on the physical properties of items, while value-based decisions rely on preferences or decision makers' subjective goals. Research into the neural and computational underpinnings of decision making has progressed in two parallel but distinct streams. Perceptual decision making arose from the field of classical psychophysics, and is based on the processing of perceived information from external states. Perceptual tasks are straightforward in terms of designing, manipulating, and measuring with an objective approach, leading to only one correct answer. In this regard, studies can examine how humans choose particular actions during simple tasks, such as detection, discrimination, or categorization of sensory information.

On the other hand, value-based (or preference-based) decisions are built on internal values and situations that have no correct answer *per se*, as the decision outcomes rely on a subjective evaluation. Such decisions investigate how humans choose options by assigning an individual value to distinct goods and actions, and in this approach, it is not easy to measure in a reliable manner (Gold & Shadlen, 2007; Hauke R. Heekeren et al., 2008; Kable & Glimcher, 2009; Rangel & Hare, 2010; Rushworth et al., 2011).

Apart from these critical differences, both decision types share a common mechanism, in that they entail considering and processing information in order to make a final decision. Although a large number of existing studies in the literature have examined these two types of decisions on their similarities and differences by focusing on computational models and behavioural responses, the question of the ways in which they potentially interact, and to what extent, remains largely unanswered.

A relatively recent study by Summerfield and Tsetsos (2012) argued that almost all decision-making problems share a common structure, including both aspects of the decisions: the subjects need to determine one or more stimuli in a given sensory modality (i.e., answering to themselves *what is that?*), and then choose a response that will attempt to maximize the possibility of positive feedback or reward (i.e., *what is the value of that?*). The authors suggested that preferential decisions are affected by external states, since they require a perceptual or extrinsic evaluation of the options on offer. Similarly, all perceptual decisions are associated with value options, mainly because they support the existence of reward value or loss aversion. Our study specifically focuses on internal value and its impact on cognitive processing. The aim of the research is to investigate how our preferential choices impact on perceptual decisions, based on the interaction between the two decision types.

Our choices and actions are navigated through the values which reflect internal intentions, habits, or external incentives. Although value-based decisions often rely on internal value (i.e., intrinsic motivations and internal intentions), most research to date has focused on external value (i.e., extrinsic motivations and external incentives), whereby decision options have objective characteristics; this means that the value of the options is defined externally by the experimenter, and so the objective response exists.

Value-based decisions with external value are examined by reward-based tasks, where the value of available choice options is determined by reward magnitude and reward probability. Reward tasks often entail a probabilistic aspect, whereby the task structure includes risk factors in order to gain or lose rewards (e.g., points or money). For instance, in a gambling task, the choice options are associated with different prospective rewards and different reward magnitudes, and participants need to decide the value of the option with the outcome as monetary gain or monetary loss (Gluth et al., 2013; Trimber & Luhmann, 2017; Zajkowski et al., 2021; X. Zhang et al., 2017).

Another group of tasks uses the learning strategy regarding the probability of rewards, such as probabilistic reversal (Boehme et al., 2017; Chase et al., 2011; Cools et al., 2002), stimulus response (Bland & Schaefer, 2011), and instrumental reward learning tasks (Bach et al., 2017). Various types of stimuli, such as visual abstract patterns (Chase et al., 2011; Cools et al., 2002), geometric symbols (Bach et al., 2017), and geometric shapes (Bland & Schaefer, 2011; Boehme et al., 2017) can be used, and participants need to learn these stimuli in association with rewards, which differ in terms of magnitudes and variability.

Another group of tasks focuses on how reward learning is influenced by value-based attentional capture (Itthipuripat et al., 2015; Jahfari & Theeuwes, 2016). For example, tthipuripat et al., (2015) used a novel probabilistic binary choice paradigm in which participants were asked to choose one target stimulus among three choice options (which included two target stimuli and one decoy or distractor stimulus). The critical point here was that the two target stimuli were assigned with high and low values by means of three different colours. However, colours were randomly changed among the three choice options. Thus, by using decoy stimuli with a highly-rewarded colour, this research showed how value-based learning might alter behavioural performance due to value-driven attentional bias. In all these tasks, the reward motivated individuals to engage in behaviours that maximize overall gain, hence demonstrating that human behaviours are induced by the enticements of rewards. Since the reward mechanism has an impact on behaviour, it also should affect the perceptual and cognitive processes that are crucial for the generation of behavioural response. Moreover, reward and attention are highly interactive during value-based decisions, such that they jointly influence behavioural outcomes (Anderson, 2016b; Sugrue et al., 2005).

Previous studies pointed out that the allocation of attention is controlled by the probability of earning a reward. In particular, rewards have an effect on how attention is distributed among stimuli, and attention is biased towards reward-related objects or stimulus features. For example, neuroimaging studies on the neural underpinnings of reward processing have revealed a parallel stream of the reward and attention associations. The activation in the lateral intraparietal area (LIP), which is the brain area responsible for visual attentional processing (Bisley & Goldberg, 2010) is directly modulated by the probability of reward gains (Dorris & Glimcher, 2004; Louie et al., 2011; Sugrue et al., 2005). In a similar vein, many studies have examined the link between monetary reward and attentional performance. According to these studies, the presence of monetary incentives improves attentional performance by enhancing detection sensitivity, which could also be linked to increased cerebral perceptual sensitivity to reward-related stimuli (Engelmann et al., 2009; Luna et al., 2005; Mohanty et al., 2008). Furthermore, Berridge and Robinson (1998) proposed the incentive salience theory, which states that mesencephalic dopamine plays an effective role in perceptual responses to reward-related stimuli. The engagement of the dopaminergic reward system may result in an enhancement of the perceptual representation of stimuli associated with reward value, making these stimuli more salient and attention-grabbing (Awh et al., 2012).

Consistent with this notion, several studies demonstrated that reward has a robust effect on attentional selection of the visual characteristics, including a series of important studies led by Brian A. Anderson, using a reward association paradigm to understand value-driven attentional capture (Anderson, 2013, 2016a, 2016b; Anderson et al., 2011a, 2011b). Their tasks used the colour of stimuli to identify different visual features. Accordingly, in the learning session, the probability of gaining a high or a low reward was associated with either the green or red colour (respectively) among the different colours of the non-rewarded stimuli. In the following task, reward-related stimuli were presented as distractors. Their findings demonstrated that previously reward-related cues led to bias on visual attention, with a distracting effect on selective attention and slowed behavioural performance.

Similarly, in other study by Failing and Theeuwes (2014) associated target stimuli and rewards with colours, and it was found that non-target, but reward-associated stimuli attracted attention and had a detrimental effect on behavioural performance. Another study investigated how the visual feature of stimuli such as orientation is associated with the prospect of reward, whereby previously reward-related orientations were found to attract more attention due to increased attentional capture, and thereby led to changes in behavioural performance (Laurent et al., 2014).

Furthermore, other studies claimed that rewards have an interaction with physical salience, and that high reward facilitates processing perception of a feature by making it more attentive (Hickey et al., 2010; Qin et al., 2021; L. Wang et al., 2013). All in all, these studies showed that stimuli which are either associated with reward or were previously related with reward capture more attention than stimuli that are associated with low or no reward (Anderson, 2013; Chelazzi et al., 2013; Kiss et al., 2009; Libera & Chelazzi, 2009; Sawaki et al., 2015), and that highly-rewarded stimuli become more salient for the future decisions (Michel F. Failing & Theeuwes, 2014; Ikeda & Hikosaka, 2003; Kiss et al., 2009; Schiffer et al., 2014) thereby showing that behaviours are shaped by reward along with attention.

Most previous studies focused on how reward affects the perception of visual features in terms of behavioural performance, but some studies have examined the effect of reward on the perception of timing behaviour (Akdoğan & Balcı, 2016; Balci et al., 2009; Michel Fabian Failing & Theeuwes, 2015). For instance, Michel Fabian Failing and Theeuwes (2015) investigated the idea that prospective reward alters timing perception using temporal oddball tasks, which required participants to judge the time durations between standard stimuli and temporal oddball stimuli. Standard stimuli were presented with a fixed duration, whereas oddball stimuli were shown with varying durations and associated with high, low, or no reward. The time durations for temporal oddball stimuli were indicated as either a longer or shorter period of time compared to standard stimuli duration. The results showed that the probability of high reward made the stimulus more salient by drawing more attention, and thus led to distortion of the subjective timing perception. Therefore, stimuli with a high reward were perceived for longer than stimuli with low or no rewards due to attentional bias.

Moreover, Anderson (2016a) examined how the reward-related auditory stimuli might influence attentional capture for the subsequent visual detection task. His research indicated that auditory sounds that were associated with a reward could interfere with performance, making the visual targets more identifiable. This finding suggests that value-driven attention might be captured at a cross-model level. Pooresmaeili et al., (2014) examined reward-associated sound effect on performance in a perceptual discrimination task, and found that auditory stimuli that were previously associated with a high reward could improve the sensitivity of visual perception, and that this effect was observed even when the sounds and their reward associations were task-irrelevant. Altogether, these studies have shown that reward has a broad effect on attention. Reward-related stimuli or targets capture more attention, thereby enhancing their perceptual representation and making them more salient. This impact occurs not only in the visual domain but also in the auditory domain, and is transmitted between the domains, whereby reward information might interact across different task and shape behaviours.

These earlier studies investigated how external value affects value-based decisions in different domains, with experimenters defining reward value options, thus objective responses were obtainable. Unlike the previous studies, this research investigates how internal values guide human behaviour during preferential decisions and their possible interaction with perceptual decisions. Rather than decisions based on external values, preference-based decisions (i.e., on internal values) rely on an individual's subjective criteria that varies from person to person.

Although internal values influence behaviour as much as external values, very little is currently known about the potential effects of the former. The aim of the present research is to fill this gap by investigating internal values by preferences and their interaction with external perception. For this aim, we developed a novel choice paradigm that allows us to examine both preference-based and perceptual decisions by using an identical stimulus. We hypothesized that assigning internal values to the stimulus alters people's behaviour by changing the perception of visual sensitivity to the stimulus. Consequently, if internal value associations make the stimuli more salient, as in reward decisions, this should increase perceptual sensitivity to stimuli and change people's responses given in perceptual decisions compared to the preferential task.

4.2. Materials and Methods

4.2.1. Participants

60 participants were recruited from an online recruitment portal (Prolific, prolific.co) and took part in the online experiment (age range 19–51 years old, median age 24 years old, 27 females). Table 5 shows demographic information about the participants. Participants were informed that they could voluntarily participate in a research study and be compensated for their time. All participants received monetary payments for their participation. Informed consent was obtained from all participants. The study was approved by the Cardiff University School of Psychology Research Ethics Committee.

Table 5 Demographic information about the participants. STD - standard deviation

Category	Value
gender	female (27), male (33)
age (years)	mean: 25.6, Median: 24, Std: 7.2
nationality	Poland (9), Mexico (7), Portugal (5), South Africa (5), United States (5), Hungary (3), Spain (3), United Kingdom (3), Canada (2), Czech Republic (2), Greece (2), Finland (2), Slovenia (2), Zimbabwe (2), Australia (1), Belgium (1), Brazil (1), China (1), Ireland (1), Sweden (1), Uganda (1)

4.2.2. Apparatus

Similar to the study in Chapter 3, this experiment was carried out online. Experimental scripts for stimulus presentation and response collection are written in HTML with a JavaScript library jsPsych 6.1.0 (de Leeuw, 2015). The online experiment was run on the Pavlovia web server (pavlovia.org), and participants used web browsers on their computers to complete the experiment.

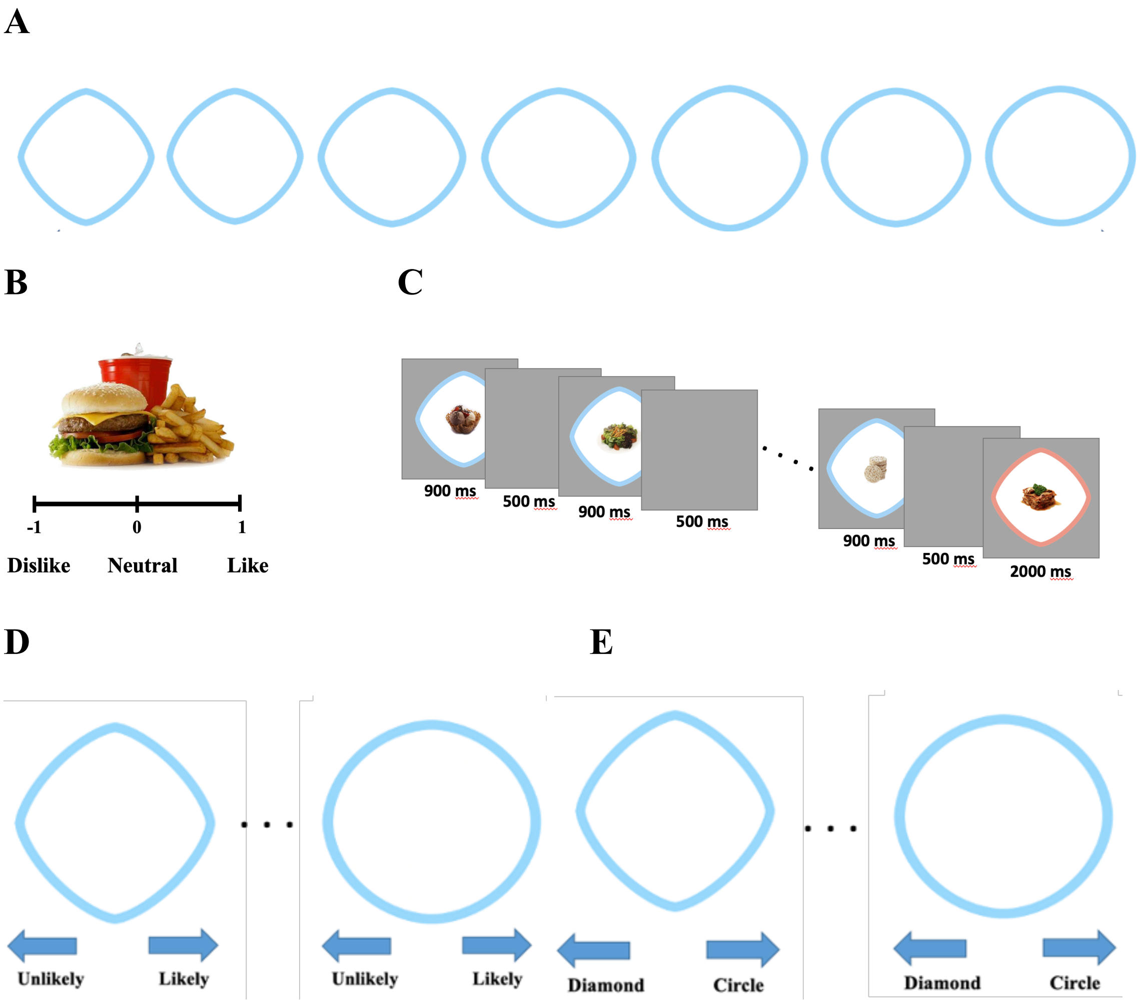

Figure 4.1 The representation of stimuli and experiment phases.

A. The shape stimuli. This figure depicts the morphology of superellipses from diamond-like to circle-like using different n values ranging from 1.45 to 1.85. **B.** Rating phase. Participants were required to rate 60 food items according to subjective preferences (how much they would like to eat the presented food item) with using a rating scale anchored with “dislike”, “neutral”, “like”. **C.** Association phase. Participants were exposed to a series of shape and food pictures while performing a cover task to detect the target shape. **D.** Value-based decision-making phase. Participants were instructed to recall the association between shapes and food items and required to judge if the given shape was likely linked with food items they preferred. **E.** Perceptual-based decision-making phase. Participants were required to make judgements based on the shape's appearance

4.2.3. Stimuli

The shape stimuli used in this study were superellipses with different shape parameters. A superellipse is a closed curve that can appear like circles, stars, and diamonds. In the 2D Cartesian coordinate system, the set of all points (*x, y*) on a superellipse satisfies the equation below:

$$\left|\frac{x}{a}\right|^n + \left|\frac{y}{b}\right|^n = 1, \tag{4.1}$$

where n, a, and b are positive numbers. a and b define the length of two axes. n controls the curvature of the shape. When n changes from 1.45 to 1.85, the resulting stimulus morphs from a diamond-like shape to a circle-like shape. For $1 \leq n \leq 2$, the superellipse defined by the equation above morphs between a clear diamond shape (n=1) and a clear circle shape (n=2). In the current study, we set a=b=200, and the appearance of superellipses changes from diamond-like to circle-like using different n values (Figure 4.1A).

4.2.4. Experimental design

All participants completed two experimental sessions, which comprised perception-based decisions and value-based decisions. Half of the participants completed the perceptual decision session first, and the other half completed the value-based decision session first.

Value-based decision-making

The value-based decision session included four parts, comprising: (1) rating, (2) association, (3) decision-making, and (4) re-rating. In the initial rating part, participants were asked to give their preference rating for each food item (i.e., the extent to which they would like to consume the food item). A total of 60 food pictures were chosen from an online food database (Blechert et al., 2019). The rating scale contains three values from -1 to 1, representing three preference levels: “dislike” (-1), “neutral” (0), and “like” (1) (Figure 4.1B). To eliminate the order effect, all 60 food items were shown together on the screen for 10 seconds at the beginning of the session. Participants performed three rating trials to familiarize themselves with the procedure, and then proceeded to rate all of the remaining food items.

In the association part, participants established associations between preference levels and abstract geometric shapes. This part included four blocks, with 22 trials in each block. In each trial, a superellipse stimulus was constantly presented in the background as a blank frame and 11 food items was presented serially at the centre of the superellipse. Only two superellipses with extreme shapes were used in this stage: a diamond-like shape (n=1.45) and a circle-like shape (n=1.85). 50% of trials were presented with a diamond shape, during which we presented 11 randomly chosen food items that were rated as “dislike” by participants. In the other 50% of trials, we presented a circle shape and 11 randomly chosen food items from the “like” category.

Participants were instructed to learn the association between the superellipse shape and the preference level of food items. To maintain participants' attention, they performed a rapid serial visual presentation task orthogonal to their preference of food items. In each trial, 10 food item were presented for 900 ms followed by a 500 ms fixed fixation interval. One food item was presented for a maximum of 2000 ms, during which the superellipse changed its border colour was changed from blue to red (i.e., the target), and participants had to respond to the target with a mouse-click response (Figure 4.1C). The position of the target stimulus within a trial was randomized across blocks. If participants failed to respond to the target within 3000 ms, a warning message was presented. A short break (1 seconds) was given after each block, and a long break (10 seconds) was given at the end of the association part.

In the value decision-making part, seven groups of superellipses were used as stimuli, ranging from diamond-like to circle-like. The mean shape parameter of superellipse stimuli ranges from diamond-like (n=1.455) to circle-like (n=1.855), with intermediate steps at 1.455, 1.555, 1.605, 1.655, 1.705, 1.755, and 1.855. Within each group, to avoid repetitions of presenting the same geometric shape, we variated the n value of superellipses between [-0.004, +0.004] around the group's mean shape parameter. The decision-making part consisted of 420 trials, including 60 trials per shape group in a randomized order. On each trial, one shape was shown without food items. Participants were instructed to recall food items associated with their shape background and decide if the presented shape was likely associated with food items they prefer, by pressing right or left arrow keys on a keyboard (Figure 4.1D). There was no time limit on responses in the decision-making part. Participants had self-paced breaks after each 60 trials, during which their performance was presented on the screen. To maintain participants' engagement with the value-based assessment, after every 70 trials, six food items were presented on the screen and participants needed to make binary decision on whether they liked or disliked the food shown.

After the decision-making part, participants again rated their preference towards individual food items. The design and procedure of the re-rating part was the same as the initial rating part.

Perceptual decision-making

In the perceptual decision-making session, there was no rating or association parts on food items. In each decision-making trial, a single superellipse was presented on the centre of the screen, and participants made binary decisions on whether the presented shape was more similar to a diamond or a circle (Figure 4.1E). Similar to the value decision-making session, the perceptual decision-making session consisted of 420 trials with 60 trials per shape group. Participants had self-paced breaks after each 60 trials, during which their performance was presented on the screen.

4.2.5. Data analysis

For decision-making tasks, the seven shape groups and two decision contexts (value-based and perceptual-based) served as independent variables. For each shape group and decision context, the dependent variables were the proportion of “likely” (in value-based sessions) or “circle” (in perceptual-based sessions) and the corresponding RT from stimulus onset. A cumulative Gauss functions were fitted to the proportion of likely/circle responses using the psignifit toolbox (Wichmann & Hill, 2001). We then derived the point of subjective equality (PSE) and Weber ratio (WR) from the psychometric curve of each task. The PSE describes the 50% response threshold from the psychometric function, which indicates the shape parameter at which the participant made a 50% likely or circle response. The WR is a normalized measure of variability, calculated as the just noticeable difference (JND) divided by the PSE. The JND was defined as half the distance between the 75% and 25% thresholds. A smaller WR indicates a steeper psychometric function slope, which is thus more sensitive to the change of stimuli.

In our study, PSE and WR were utilised because they were common measures taken from psychometric functions and there was a limited number of trials per preference level. By calculating PSE and WR, we aimed to assess participants' perceptual discriminability and sensitivity in making decisions based on shape discrimination. These measures offer valuable information about participants' ability to perceive and discriminate between different stimulus levels, providing a quantitative assessment of their decision-making performance. Instead of other models, using PSE and WR allowed us to specifically evaluate the distinguishability and sensitivity of perceptual judgments in our study, which was relevant to our research objectives.

4.3. Results

In a two-session internet-based experiment, we evaluated participants’ value-based and perceptual decisions on superellipse shapes that morphed between a diamond and a circle (Figure 4.1D and Figure 4.1E). In value-based decisions, participants decided whether a superellipse shape likely contained their preferred or non-preferred food items, with *a priori* association training whereby a diamond was associated with preferred foods and a circle with non-preferred foods. In perceptual decisions, participants were explicitly instructed to perform two-alternative shape discrimination tasks on superellipse shapes (i.e., diamond or circle). Behavioural performance was quantified by the proportion of likely/circle responses and RT at each level of stimulus groups.

Repeated-measures ANOVA showed a significant main effect between the two decision contexts for RT: ($F(1, 59) = 7.124$, p=0.01, $\eta_p^2 = 0.108$), but there was no significant main effect between the two decision contexts for choice proportion: ($F(1, 59) = 0.079$, p=0.779, $\eta_p^2 = 0.001$). In both tasks, as expected, when geometric shapes morphed from diamond-like to circle-like, the choice proportion to the "likely" response (i.e., the one associated with preferred food) and the circle response (in perceptual decisions) increased ($F(2.505, 147.785) = 1213.829$, $p<.001$, $\eta_p^2 = 0.954$), and participants slowed down their responses in decisions with ambiguous shapes between diamond and circle categories ($F(1.858, 109.649) = 19.098$, $p<.001$, $\eta_p^2 = 0.245$) (Figure 4.2A and Figure 4.2B).

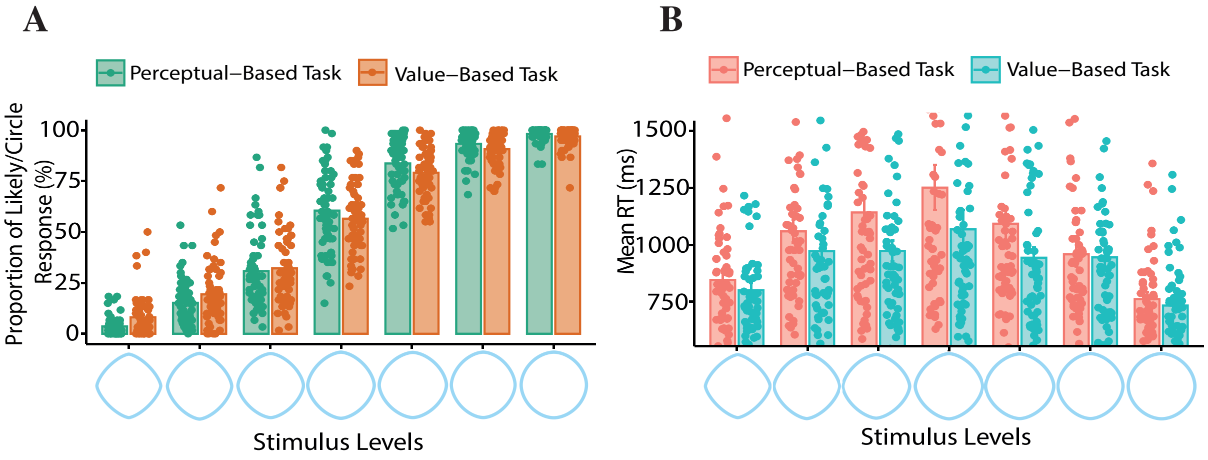

Figure 4.2 Behavioural results.

A. The percentage of likely and circle response (ratio of correct responses) between the perceptual-based decision-making task (green) and value-based decision-making task (orange) across all stimulus levels. **B.** The average of RTs between the perceptual-based decision-making task (red) and value-based decision-making task (blue) across all stimulus levels

Interestingly, there were significant interactions between decision contexts and stimulus levels in both choice proportion ($F(2.995, 176.711) = 6.501$, $p<.001$, $\eta_p^2 = 0.099$) and RT ($F(3.186, 187.997) = 3.243$, p=0.021, $\eta_p^2 = 0.052$, Greenhouse-Geisser correction). Hence, although there was no overall difference in behavioural performance between decision tasks, promoting the context of subjective preference varied participants' response strategy among different stimuli. For RT, the interaction between decision contexts and stimulus levels were mainly driven by the facilitation of RT in preference-based decisions of more ambiguous stimuli (i.e., shapes between diamond and circle, n=1.60, t(59)=-2.869, p=0.006; n=1.65, t(59)=12.069, p<.001; n=1.70, t(59)=19.878, p<.001), as there was no RT difference between decision contexts in trials with unambiguous stimuli (n=1.45, t(59)=-1.599, p=0.115; n=1.5, t(59)=-1.060, p=0.294).

To further characterise the context-dependent changes in choice proportion, for each session, we calculated the Weber fraction (WR) and the point of subjective equality (PSE, the 50% threshold) from the psychometric function fitted to individual participants' choice proportions across stimulus levels (Figure 4.3C). Compared with perceptual decisions, preference-based decisions had larger WR (t (59) = 3.127, p = .003, paired t-test) (Figure 4.3B) but similar PSE (t (59) = 0.241, p = .81) (Figure 4.3A). Therefore, the addition of preference-based context during decision-making decreased participants' perceptual sensitivity towards visual stimulus, while maintaining the response bias across individuals.

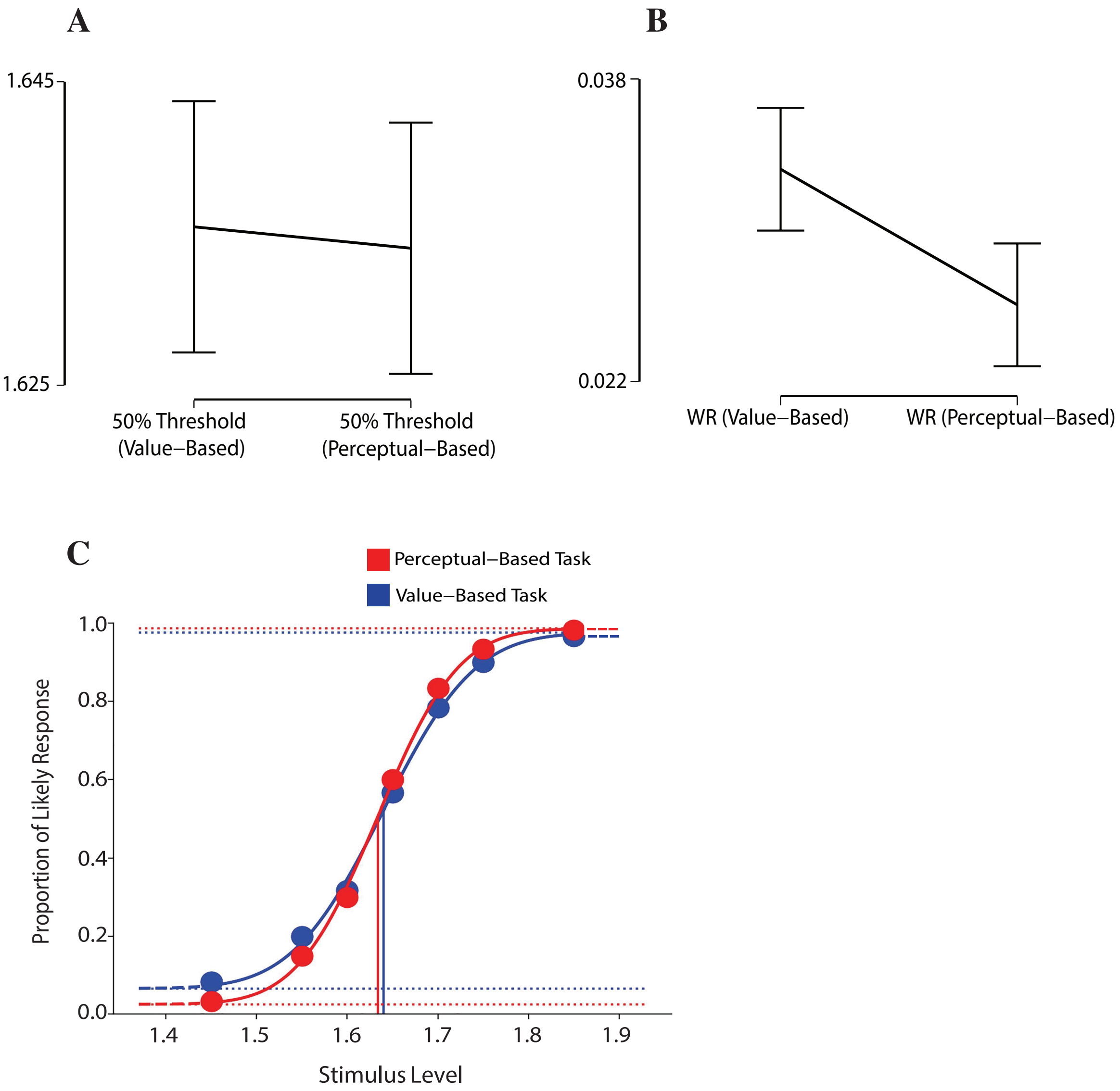

Figure 4.3 The behavioural performance comparison of preferential and perceptual decision-making tasks.

Both data were fitted with separate psychometric functions to compute the corresponding threshold and Weber ratio. **A.** 50% response thresholds define from the psychometric function for both decision types. **B.** Weber ratios calculated as half the distance between the 75% and 25% thresholds divided by 50% response thresholds. A smaller Weber ratio indicates steeper psychometric function and more sensitive to detect the shapes. **C.** Psychometric curves. The y axis shows the proportion of likely response for preferential decisions and the proportion of circle response for perceptual decisions, whereas the x-axis indicates the stimulus levels, which range from diamond-like to circle-like forms. Red dots and line correspond to human's perceptual decision-making performance. Blue dots and line represent performance of preferential judgments

To assess participants' consistency in their preferences towards food items, we compared individual participants' preference ratings for all food items before and after their main decision-making parts. On average, participants gave the same level of rating for over 90% of items Figure 4.4, indicating that the food stimuli used in the current studies are associated with stable preference-based information. Nevertheless, the rating consistency also varies between participants. Is it possible that participants with better preference rating consistency also exhibit superior behavioural performance during decision-making, indexed by higher sensitivity? Our results did not support this hypothesis, as there was no significant correlation between rating consistency and decision sensitivity (i.e., the WR) in preference-based (r = 0.048, p = 0.713) or perceptual decisions (r = -0.093, p = 0.479).

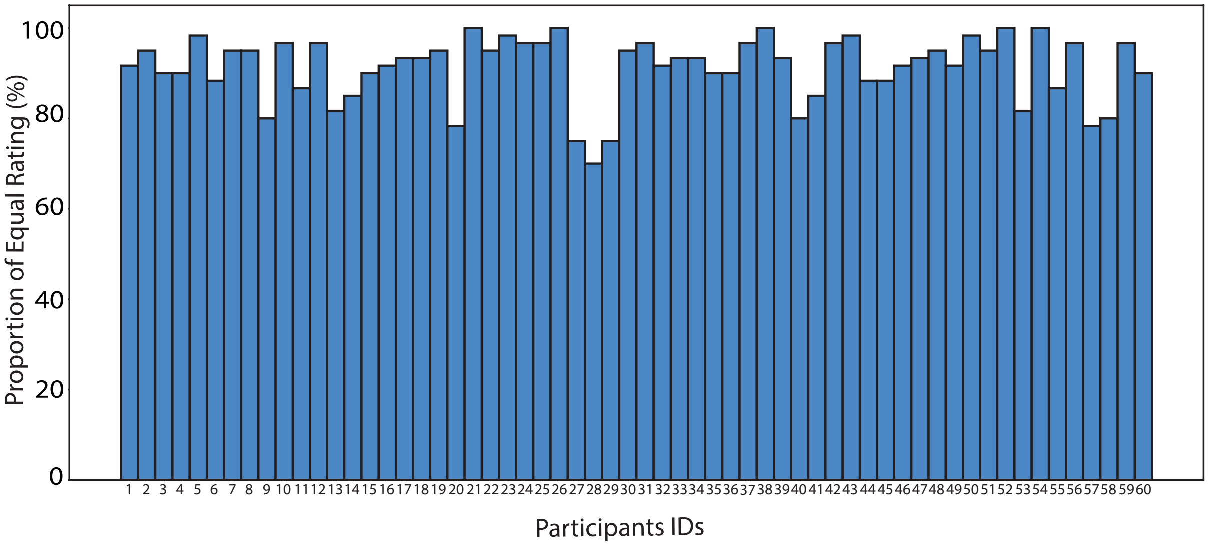

Figure 4.4 The proportion of equally graded food items between rating and re-rating phases for each participant

Overall, comparing preference rating scores in the two rating tasks allowed us to examine whether participants maintained a consistent preference for food items throughout the study. However, it is important to note that our data analysis did not specifically focus on examining items with the same preference rating scores in the two rating tasks. Our data was based on the first rating. The data analysis focused on examining decision-making performance based on the association between super ellipse shapes and preference levels of food items. The analysis did not specifically differentiate or focus on items with the same preference rating scores in the two rating tasks.

4.4. Discussion

This current study aimed to examine whether preference-based information affects the decision-making process concerning external perceptual information. A choice paradigm was developed using an identical set of shape stimuli for both preference-based and perceptual decisions via intrinsic value-mapping. In both task contexts, when the information was more ambiguous (i.e., when the shape was between a diamond and a circle), behavioural performance was disruptively affected (i.e., decisions were slower and less accurate). Task contexts effect changes in participants' behaviour, such that preference-based contexts are associated with less sensitive yet more rapid responses than the perceptual contexts with regard to ambiguous decisions. The experimental results are discussed in more detail below.

4.4.1. Learning preference value not associated with response bias

Our results showed that learning the preference value associated with shapes did not introduce any response bias, supported by the null result in PSE between task contexts. The WR difference between decision contexts suggests that the presence of the preference context decreases participants' sensitivity to perceptual information. As discussed below these results are contradictory to previous studies on the effect of reward expectation on perceptual decisions.

Perceptual-based decisions and value-based decisions have been studied as two distinct but parallel fields. Value-based decisions have often been examined on the basis of external value (extrinsic value), whereby the value of the decision options is identified by the experimenter and an objectively "correct" answer exists. Such decision paradigms commonly associate choice options with rewards or losses. Learning reward associations has been found to lead to bias in the allocation of attentional priority across visual features (Anderson, 2013; Anderson et al., 2011a, 2011b; Anderson & Yantis, 2012; Awh et al., 2012; Chelazzi et al., 2013; Hickey et al., 2010; J. Lee & Shomstein, 2014; Maclean & Giesbrecht, 2015; Qi et al., 2013; Schiffer et al., 2014). Highly rewarded stimuli were attentionally prioritized compared to their low-rewarded counterparts (Anderson et al., 2011a, 2011b; Anderson & Yantis, 2012; Hickey et al., 2010), and made the stimulus more salient for making future decisions (Michel F. Failing & Theeuwes, 2014; Ikeda & Hikosaka, 2003; Kiss et al., 2009; Schiffer et al., 2014).

The above cited studies concluded consistently that reward probability influences attention, which leads to improved detection performance and changes people's behaviour. When people make decisions between alternatives with different payoffs based on sensory information, their responses are biased towards the more rewarded choice alternative (Fleming et al., 2010; Liston & Stone, 2008; Mulder et al., 2012; Christopher Summerfield & Koechlin, 2010). Furthermore, a higher reward probability of a choice option increases the attention to the option, which is suggested to increase participants' perceptual sensitivity to the more rewarding choice alternative (Engelmann et al., 2009; Mohanty et al., 2008; Small et al., 2005). However, it should be noted that different geometric shapes used in our study were associated not with probabilistic rewards, but with subjective preference. One possible explanation for the results on response bias and WR is that although the expectation on objective rewards plays an important role, subjective preference does not elicit the same effect on behaviour.

4.4.2. Preference-based context led to faster RT

The preference-based context also led to faster RT than the perceptual context, in particular in trials with ambiguous stimuli. Specifically, participants responded less cautiously in the preference-based context, which may appear counterintuitive at first glance. This is because the preference-based context involves the integration of internal (i.e., preference) and external (i.e., perceptual) information that likely takes longer than the perceptual context. However, the perceptual context may prompt participants to be more attentive to the visual stimulus, which in turn enhances perceptual sensitivity and prolongs decision time. Furthermore, the current study required participants to build associations between extreme shapes and preference levels, and decisions were based on the associative memory (G. E. Wimmer & Shohamy, 2012). Indeed, many value-based decisions have been found to be intertwined with the information from memory (Gluth et al., 2015; Murty et al., 2016; M. N. N. Shadlen & Shohamy, 2016; Weber & Johnson, 2006; Weilbächer & Gluth, 2016; X. G. E. Wimmer & Büchel, 2016). This associative memory process can trigger decision heuristics that facilitate processing speed (Kahneman, 2003, 2011).

Similar findings were reported by Dutilh and Rieskamp (2016), who suggested that different incentives during perceptual and preference-based decisions change people's behaviour. In their study, the participants performed a marble task, in which the relative proportion of black and white marbles was associated with different monetary payoffs. In the perceptual choice, participants were to decide the proportion of black marbles; in the preferential choice, they judged the proportion of white marbles with an underlying risk factor. Consequently, the criteria were defined according to the subjective goals of the decision maker, and the subjects responded as risk avoidance or risk seeking. Although their subjective criteria differed from the current study in this aspect, as they were objectively based on reward learning, they also found that participants responded faster in preference-based than perceptual decisions, similar to our study.

4.4.3. Summary

The current study was conducted online. Together with Chapter 3, our results demonstrated that participants in online tasks can make direct preference-based decisions and make decisions on abstract shapes in preference-based or perceptual contexts. Thus, our research contributes to the increasing trend of online psychological and psychophysics experiments, confirming the validity and reliability of internet-based experimentation (de Leeuw & Motz, 2016; Germine et al., 2012; Semmelmann & Weigelt, 2017).

In conclusion, mapping preference-based context onto perceptual information reduces perceptual sensitivity and facilitates response speed during decision-making. The following chapter further investigates preference-based and perceptual decisions when preference-based information is associated with different spatial locations.

Chapter 5

MEG Signatures of Task Relevant Information During Preference-Based and Perceptual-Based Decisions

5.1. Introduction

Neuroimaging literature has extensively investigated the neural representation of task rules during decision-making processes. Task rules play a crucial role in guiding behaviour and determining appropriate actions based on sensory information and subjective preferences. Understanding how the brain encodes and represents task rules can provide valuable insights into the underlying cognitive processes involved in decision-making.

The previous chapter presented an internet-based choice paradigm that subjective preference and perceptual information are presented as geometric shapes. We demonstrated that participant could make different types of choices with the same set of information based on task context. Such decision-making process requires the brain to have robust encoding of task rules for the same set of stimuli, and the flexibility of encoding task-specific information to switch between task rules. This relates to the literature of the task rule representation in the brain. For simple decision-making, task rules can be defined as the context establishing the relationship between stimulus features and their corresponding actions, i.e., task rules providing and constraining task-relevant information (Dreisbach et al., 2012). Previous studies considered comparable task rules about perceptual and conceptual aspects of visual stimuli such as colour discrimination versus orientation (Cai & Leung, 2009; Sakagami et al., 2006). It has been showen that the neural encoding of the task rule is represented in the frontoparietal network for a variety of experimental contexts (Bode & Haynes, 2008; Cole et al., 2011; Haynes et al., 2007; Hebart et al., 2012; Momennejad & Haynes, 2012; Reverberi et al., 2012a, 2012b; Soon et al., 2013; Waskom et al., 2014; Woolgar, Hampshire, et al., 2011; Woolgar, Thompson, et al., 2011; J. Zhang et al., 2013). For instance, J. Zhang et al., (2013) conducted experiments using functional magnetic resonance imaging (fMRI) to examine brain activity while participants performed perceptual decision tasks that required them to follow specific task rules such as motion discrimination, colour detection, and size discrimination. They found that distinct frontoparietal regions were involved in representing and implementing different task rules. Specifically, the study identified separate neural networks associated with rule selection and rule implementation. The rule selection network, located in the dorsolateral prefrontal cortex, was responsible for encoding and maintaining task rules to guide decision-making. The rule implementation network, located in the posterior parietal cortex, was involved in translating the selected rule into appropriate motor responses. Interestingly, the researchers also observed some overlap between these networks, suggesting that certain frontoparietal regions are engaged in both rule selection and implementation processes. Similar to fMRI research, electrophysiological studies revealed that the prefrontal network displayed task-specific activation patterns that were dynamically modulated by the presented cues (Mante et al., 2013; Rigotti et al., 2013; Stokes et al., 2013). In addition, EEG/MEG-based neuroimaging studies have identified frontoparietal activations when participants encoded task rule information (Cunillera et al., 2012; Hall-McMaster et al., 2019; Liegel et al., 2022; Rawle et al., 2012) .

In conjunction with MEG/EEG, a more recent technique called multivariate pattern analysis (MVPA) offers additional understanding of the cognitive control processes. MVPA utilizes pattern classification methods applied to neuroimaging data in order to ascertain what information is being encoded in the brain (Haxby, 2012). Time-resolved MVPA has been employed to examine how information processing unfolds over time (Carlson et al., 2011; Hebart et al., 2012). For example, Hebart et al., (2018) conducted a study where participants performed various tasks involving visual object stimuli while MEG measurements were taken. They discovered that object features relevant to the tasks were amplified during the later stages of processing, more than 500 milliseconds after the presentation of the stimuli. Other studies have revealed distinct patterns of task-relevant information during complex tasks, demonstrating separate dynamics for stimuli, tasks, and responses (Hubbard et al., 2019; Kikumoto & Mayr, 2020; Wen et al., 2019). These MVPA investigations have provided valuable insights into the neural processes underlying goal-directed behaviour.

In this chapter, we aim to build upon this existing literature by examining the neural representation of task rules before and during different types of decision-making processes. The study utilizes a choice paradigm where participants associate different spatial locations with their subjective preference for common snacks. During subsequent MEG recordings, participants make binary choices based on either the spatial locations (preference-based decisions) or the visual features (perceptual decisions) of the presented targets. The research questions addressed in this chapter are twofold. First, the study investigates the neural representation of task rules prior to the decision-making process. This will provide insights into how the brain encodes and represents task rules in anticipation of making a decision. Second, the investigation examines whether task-irrelevant features, such as spatial locations during perceptual decisions, influence the neurocognitive processes of decision-making. By exploring the impact of irrelevant information on decision-making, the study aims to uncover factors that modulate decision processes and shed light on the flexibility and adaptability of the brain in switching between different decision-making contexts. To investigate these research questions, the study employs cognitive modelling on behavioural data to gain insights into the decision-making processes. Additionally, multivariate pattern analyses (MVPA) are conducted on MEG data to examine the neural representation of task rules at different stages of a trial, from instruction to implementation. By combining these approaches, the study aims to provide a comprehensive understanding of the neural dynamics and cognitive mechanisms underlying decision-making and the encoding, switching, and implementation of task rules in different decision-making contexts.

5.2. Materials and Methods

5.2.1. Participants

31 participants (22 females, 9 males; age rage, 19-24 years; mean range, 20.67 years) were recruited from Cardiff University student panel. All participants had normal or corrected-to-normal vision, and they are right-handed. None of the participants had no history of any significant neurological or psychiatric illness and none of them had previous experience with the task. Table summaries demographic information about the participants. Subjects were informed about all aspects of the experiment, and they provided written consent before starting the experiment. We paid £56 for each subject for their participation in the experiment. The experimental protocol was approved by Cardiff University School of Psychology Ethics Committee.

Table 5 Demographic information about the participants. STD - standard deviation

Category	Value
gender	female (22), male (9)
age (years)	mean: 20.7, median: 20, STD: 2.61

5.2.2. Apparatus

The experiment was conducted in the behavioural testing room and MEG testing room. In the behavioural tests, stimuli were presented on a 22-inch CRT monitor with a resolution of 1600 by 1200 pixels and a refresh rate of 85 Hz, located approximately 120 cm in front of the participants. In the MEG sessions, visual stimuli were displayed on a MEG compatible PROPixx projector (VPixx Technologies Inc., Canada) with a resolution of 1920 by 1080 pixels and a refresh rate of 120 Hz, located approximately 120 cm in front of the participants. A chin rest was used to adjust the head position and viewing distance from the screen. Participants' responses were obtained from a response box (NATA button box). The experiment script was written in Python and used PsychoPy v3.1.0 library (Peirce, 2007).

5.2.3. Stimuli

The initial rating and learning stages used 30 pictures of snacks were taken. The snack items were chosen to be easily accessible from the supermarkets. Each snack item was presented in the centre of the white circle with a grey background. In the main decision-making stage, Gabor patches were used as the stimuli, and they were displayed on a grey background. We set the Gabor patches with fixed 90˚ orientation and 5 cyc/deg spatial frequency. Gabor patches were placed on the screen according to the dimensions of a screen with standard 4:3 aspect ratio. On each trial, Gabor patches were presented in four spatial locations as to height units, including two at the bottom and the remaining two at the top ((-0.45, 0.25), (-0.25, -0.25), (0.45, 0.25), (0.25, -0.25)).

5.2.4. Task and Procedure

Participants completed this study in four different days, including one behavioural session, two MEG sessions, and one MRI session. This experiment consisted of five stages: (1) the initial rating stage; (2) the learning stage; (3) the staircase stage; (4) the decision-making stage (main task); and (5) the final rating stage.

1. Initial rating stage: Participants were instructed to provide preference rating for a set of 30 different snacks, indicating “how much they would like to consume the presented snack item” on a continuous scale from 1 to 100, with labelled two preference levels: "dislike" (1) and "like" (100). Each snack item was presented three times randomly so that participants completed a total of 90 ratings on the 30 snack items. Participants used mouse to move the value indicator on the rating scale to the left and right (Figure 5.1A). There was no time limitation for responding. At the end of this stage, the rating score for every snack item was calculated by averaging three ratings. Four snack items, two of which were graded with the highest scores and the other two with the lowest scores, were selected to be used as stimuli in the next stage.

2. Learning stage: We asked participants to associate four snack items with their spatial locations. These snack items were the two most preferred ones (preferred items) and the two least preferred ones (non-preferred items), that were chosen based on each participant’s individual rating scores. Their spatial locations were different between the first and second MEG session. In the first session, the two favourite items (preferred items) were placed at the bottom of the screen, whereas in the second session, they were presented on the right side of the screen (Figure 5.1B).

This stage started with the presentation of the four snack items (two good ones and two bad ones) on their corresponding spatial locations for 4.5 seconds. During this period, participants were instructed to learn snack items with their spatial mappings. Following, a random spatial location was displayed on the screen, which highlighted using a grey circle. The fixation point was then displayed for 0.8 seconds. Next, four snack items were presented side by side as choice options at the bottom of the screen in a random order. Participants were required to recall the snack item which was presented on the highlighted spatial location and then choose one of option from four snack items. There was no time limit for responses. The feedback was given after every trial, the correct and incorrect answers were shown on the screen as "correct" or "error", respectively. Participants responded by pressing buttons with their right hand using a button box. Four choices options correspond to 4 fingers (from left to right snack items: right index finger, right middle finger, right ring finger and right little finger).

3. Staircase stage: We used staircase procedure to identify participants’ individual perceptual thresholds. On each trial two Gabor patches were displayed on the screen. Participants were

performed perceptual task in which they required to choose the brighter Gabor patch. The contrast of the Gabor patch was continuously adjusted by a total of 20 trials via two-down one-up staircase procedure with the 75% threshold. Each trial was presented for a maximum of 2500 ms, during which time participants were instructed to respond with two arrow keys from the keyboard correspond to right or left choices. At the end of this part, the values of individual brightness level for each participant were obtained to use in the decision-making phase.

4. Decision-making stage (main task): This stage was completed in two separates MEG recording sessions. Participants made binary choices between two Gabor patches that could appear in four possible spatial locations. In preference-based decisions, participants were instructed to recall the mappings between four spatial locations and snack items, because these locations were associated with their two preferred and two non-preferred items. Then, they required to decide the location of which Gabor patch is associated with the snack item they prefer more. In the perceptual decisions, participants were instructed to choose Gabor patch stimuli with higher brightness. The order of the two task rules were randomized on a trial-by-trial basis. Task rules was conveyed by the different colours of the fixation points (blue or green), and the mapping between the fixation point colour and task rules was counterbalanced between participants (Figure 5.1C).

Each recording session consisted of 4 blocks of 120 trials. Hence, a total of 960 trials were completed across two MEG sessions. In each block, feedback was provided after every 25 trials and a short break was given after 40 trials. Half of the trials used preference-based decision rules and the other half used perceptual decision rules. Furthermore, in each block, 20 trials presented Gabor stimuli at the two preferred locations, 20 trials presented Gabor stimuli at the two non-preferred locations, and the remaining 80 trials presented Gabor stimuli at one preferred and one non-preferred locations.

Each trial began with the presentation of a fixation point at the center of the screen for 800 ms, indicating whether the upcoming trial represents a perceptual decision trial or a preference-based decision trial. Next, two Gabor patches (each option demonstrates one of the four spatial locations by means of the Gabor patches) appeared on the screen for a maximum of 2500 ms, during which participants make their preference-based (based on spatial locations) or perceptual (based on Gabor patches' brightness) choices by pressing the left or right button on a button box. After the response, choice options disappeared, and an inter trial interval was presented with a random latency between 1200ms and 1800ms. If the participants did not respond within 2500 ms, a warning message was given, and the participants proceeded to the next trial.

5. Re-rating stage: This part was performed outside the MEG scanner after the recording session. The original 30 snack items were rated with same procedure as in the initial rating phase in order to re-evaluate participants' preference after decision-making.

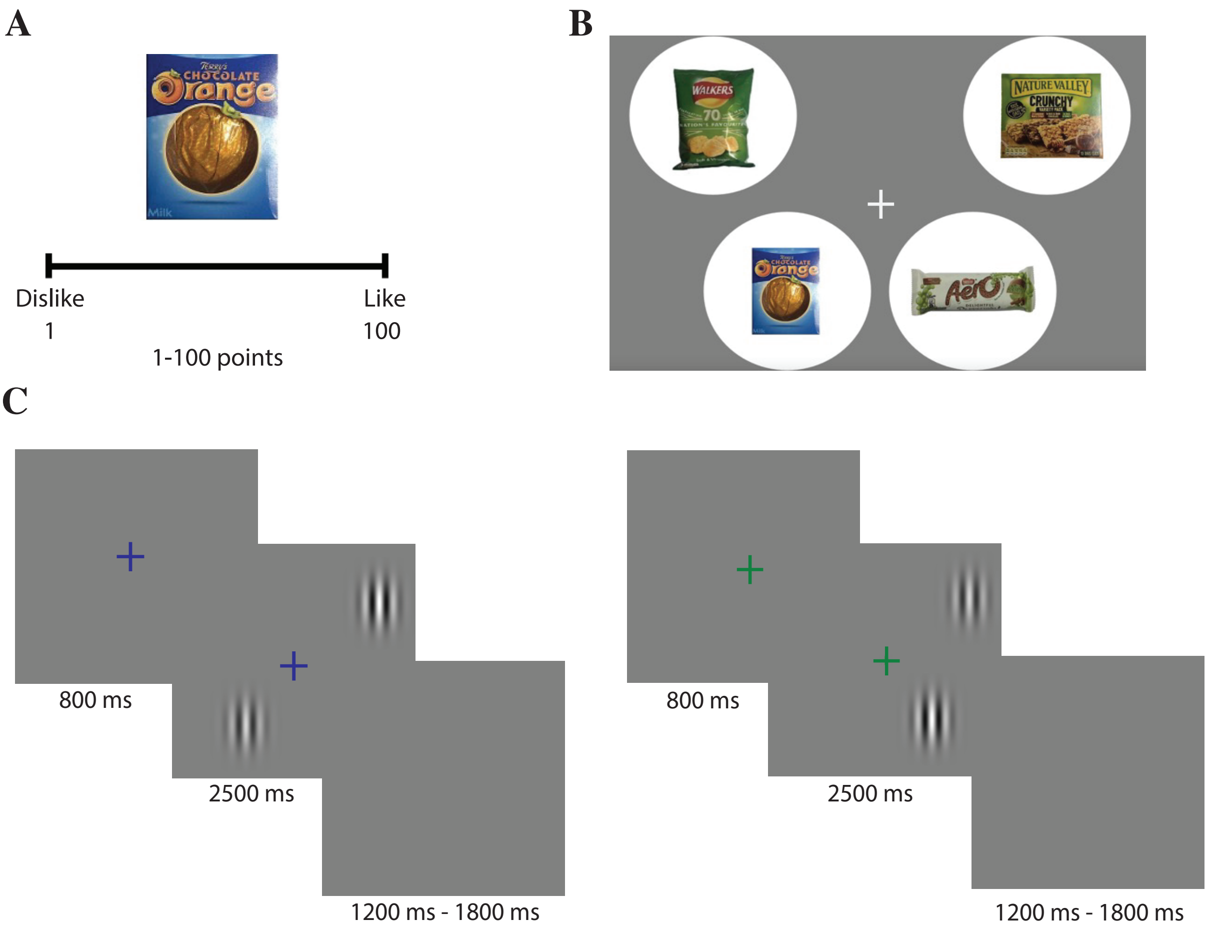

Figure 5.1 The representation of experimental procedure of the study

A. Rating phase. Participants were required to rate 30 food items according to subjective preferences (how much they would like to consume the presented food item) with using a continuous scale from 1 to 100. **B.** Learning phase. Participants were instructed to encode four snack items and their associated locations. These snack items were the two most preferred items and the two least preferred items. **C.** Decision-making phase. Two types of tasks were performed using the same stimulus (Gabor patches). Before the decision-making tasks, participants were instructed to encode the colour of fixation points as a task cue. After that, they made a binary forced choice task, indicating their response by pressing a button. In preference-based task, subjects were asked to choose the items according to their favourite food items location, while in the perceptual decision-making task, they were instructed to choose the items as to the brightness level.

5.2.5. Behavioural Measures

We quantified the response time (RT) of each trial as the time between the onset of the Gabor patch stimulus and the time of the behavioural response. For preference-based trials, response accuracy was quantified as the proportion of trials in which the option with a higher preference rating was chosen. To exclude fast guesses, trials with RTs faster than 100 ms were removed. The trials that were discarded accounted for 0.01% of all trials. To make group inferences on mean decision accuracy and RT, we used frequentist and Bayesian ANOVA, with task rules and task difficulty levels as within-subject factors. We used JASP (jasp-stats.org) to perform post-hoc comparisons and Bayes Factors (BFincl, BF10) to characterise the strength of evidence (Wagenmakers et al., 2018). Similar to Chapter 3, the hierarchical drift-diffusion model (HDDM) (Wiecki et al., 2013) was used to fit the DDM to the reaction time distribution and accuracy of each participant. Then, we assessed the fit of different model designs with varying parameter constraints to the behavioural data.

5.2.6. MEG and MRI data acquisition

A 275-channel CTF axial gradiometer system was used to obtain whole-head MEG recordings, at a sampling rate of 1200 Hz (0 to 300 Hz band-pass). An additional 29 reference channels were recorded for the aim of noise cancelation, the primary sensors were analyzed as synthetic third-order gradiometers (Vrba and Robinson, 2001). One sensor was turned off during recording due to excessive sensor noise (i.e., Nx = 274 gradiometers). Subjects were seated upright in a magnetically shielded room with their head supported on a chinrest in order to minimize movement. The task was presented on either a CRT monitor or LCD PROPixx projector (VPixx Technologies Inc., Canada). Horizontal and vertical electro-oculograms (EOG) were recorded to monitor eye blinks and eye movements. For MEG/MRI coregistration, the head shape with the position of the electromagnetic head coils was digitized using a Polhemus FASTRAK (Colchester, Vermont). Fiduciary coils (head shape digitization: Polhemus Fastrack – head shape, location of head position electrodes on the fiducials) were placed at fixed distances from three anatomical land-marks (nasion, left and right pre-auricular). Each recording session lasted approximately 30 minutes.

All participants also underwent a whole-brain MRI scan on a Siemens 3T Connectom MRI scanner and a 32-channel receiver head coil (Siemens Medical Systems). We used a T1-weighted magnetization prepared rapid gradient echo sequence (MPRAGE; echo time: 3.06 ms; repetition time: 2250 ms sequence, flip angle: 9◦ ,field-of-view: = 256 × 256 mm, acquisition matrix: 256× 256, voxel size: 1 × 1 × 1 mm).

5.2.7. MEG Pre-processing

All MEG analyses will be carried out using MATLAB. Continuous raw data was bandpass filtered at 0.1-100 Hz, 0.1Hz high pass filter and 100 Hz lowpass filter. The recordings were decomposed into 50 components using independent component analysis (fast ICA). Then, ICA components which belong to eye movements and cardiac activities were manually removed from the original data. Identification of visual artefacts was provided by simultaneous EOG recordings. Between 3 and 5 components were removed for each subject. Before the epoch data, 30Hz filter was applied. Following the above steps, cleaned data was obtained, which was then be further processed into epochs based on different triggers. Then, the data was down sampled to 200 Hz and the baseline was corrected using the time interval 200ms before task cue onset.

5.2.8. MEG Source Space

We analyzed the MEG source activity using an established source localization method, the linearly constrained minimum variance (LCMV) beamformer (Hillebrand et al., 2012; Van Veen et al., 1997). This approach combines the forward model and the data covariance matrix to construct an adaptive spatial filter. Beamformer weights were normalized by their vector norm to alleviate the depth bias of MEG source reconstruction (Hillebrand et al., 2012). For each run of each participant, the structural MRI scan was coregistered to MEG sensor space using FreeSurfer. The structural MRI scan was segmented, and a volume conduction model was computed using the semirealistic model (Nolte, 2003).

Te inverse source reconstruction using an LCMV beamformer on a 6 mm template with a local sphere forward model in Fieldtrip (version 20161101, http://www.fieldtriptoolbox.org). We then used the Automated Anatomical Labeling atlas (AAL; (Tzourio-Mazoyer et al., 2002) to derive source-level time courses for every voxel in each of the 78 AAL cortical regions (excluding the cerebellum and subcortical structures). In the univariate analysis, MEG activity from left and right ROIs were averaged to obtain bilateral cortical activity. In multivariate analysis, we performed pattern classification for each ROI and averaged classification accuracies from left and right ROIs.

5.2.9. Multivariate Pattern Analysis

We use time-resolved Multi-Voxel Pattern Analysis (MVPA) on source-localized MEG data (Dima et al., 2018; Zajkowski et al., 2021) MVPA combines information represented across multiple sources, which has been shown to be sensitive in decoding information representation from human electrophysiological data (Cichy et al., 2014; Dima et al., 2018).

We conduct three MVPA analyses to identify the latency and spatial distribution of the MEG multivariate information. The first is to decode task rules (e.g., preference-based vs. perceptual decisions). The second is to decode difficult vs easy choices (e.g., choices between two preferred or non-preferred options vs. choices between one preferred and one non-preferred options). The third is to decode choices of high preference vs choices of low preference values.

Each analysis is formed as a binary classification problem. The data feature for classification included MEG source-level time courses of each ROI. In each analysis, at each sampled time point and for each participant, we trained Linear Discriminant Analysis (LDA) classifier and calculated the mean classification accuracy following a stratified fivefold cross-validation procedure. LDA offers supervisor training speed than other classifiers such as the support vector machine.

For each ROI, each timepoint, classification accuracy was tested against the chance level 50%.

In each cross-validation, 80% of the data issued as a training set, and the remaining 20% as a test set. In some analysis, the number of trials belonging to the two classes is unbalanced in the training set. We use an under-sampling approach to randomly select the number of trials in the majority class to match that of trials in the minority class. To reduce data dimensionality, we perform principal component analysis to the training set data and selected the number of components that explained over 99% of the variance in the training set. The test set data are projected to the same space with reduced dimensions by applying the eigenvectors of the chosen principal components. We then train LDA to distinguish between the two classes and evaluate the classification accuracy using the test set data. The procedure is repeated five times with different training and test sets, and the classification accuracies are averaged from the fivefold cross-validation. We use the LDA implementation in MATLAB Machine Learning and Statistics Toolbox.

To estimate the significance of the classification performance, we use two-tailed one-sample t test to compare classification accuracies across participants against the 50% chance level. To account for the number of statistical tests across ROIs and at multiple time points, we use cluster-based permutation (Maris & Oostenveld, 2007) to control the family-wise error rate at the cluster level and the ROI level from 2000 permutations.

5.3. Results

5.3.1. Behavioural Results

Participants performed binary choices in two decision-making tasks, involving perceptual decisions based on brightness discrimination and preference-based decisions based on subjective preferences. The behavioural performance of the participants was quantified by accuracy measurement (proportion of correct response) and reaction time (RT). In preference-based decisions, the selection of the visual stimuli showing the positions of higher graded snack item was considered the correct response, while the selection of higher-brightness visual stimuli was marked as the correct response in perceptual decisions.

The behavioural performance was compared between two decision-making tasks; perceptual vs. preference-based on three difficulty levels (high versus high, low versus low, and high versus low, which were generated from the subjective preferences). Participants performed with a higher accuracy and longer reaction time in perceptual task (mean accuracy = 82.04%, mean RT = 922.22 ms, Figure 2A) than in preference-based task (mean accuracy = 68.42%, mean RT = 825.32 ms). A repeated measures ANOVA revealed that there was significant main effect of task rules on participants' behavioural performance (Accuracy: $F\ (1,30) = 21.396$, $p < 0.001$, $\eta_p{}^2 = 0.416$, $BF_{incl} = 1457.595$; RT: $F\ (1,30) = 11.369$, $p < 0.05$, $\eta_p{}^2 = 0.275$, $BF_{incl} = 7.774e{+}6$) (Figure 5.2A and Figure 5.2B).

The ANOVA also revealed that behavioural performance differed significantly between subjective preference levels in the preference-based task (Accuracy: with Greenhouse-Geisser correction, $F\ (1.524, 45.715) = 17.717$, $p < 0.001$, $\eta_p{}^2 = 0.371$, $BF_{incl} = 352403.592$, RT: $F\ (2, 60) = 14.531$, $p < 0.001$, $\eta_p{}^2 = 0.326$, $BF_{incl} = 2310.527$). Participants had better accuracy and faster RT when deciding between high and low value conditions (mean accuracy = 86.048%, mean RT = 794.41 ms) compared to two high value conditions (mean accuracy = 46.35%, mean RT = 804.35 ms) and two low value conditions (mean accuracy = 72.98%, mean RT = 878.47 ms). As expected, behavioural performance was comparable difference in perceptual task between difficulty levels (Accuracy: with Greenhouse-Geisser correction, $F\ (1.231, 36.927) = 1.923$, $p = 0.172$, $\eta_p{}^2 = 0.06$, $BF_{incl} = 0.435$, RT: $F\ (2, 60) = 0.997$, $p = 0.375$, $\eta_p{}^2 = 0.032$, $BF_{incl} = 0.210$). These results suggested that the behavioural performance in preference-based decisions were sensitive to the subjective value difference, whereas participants were able to ignore this value information making perceptual decisions.

Furthermore, there was significant interaction between the tasks and difficulty levels (Accuracy: with Greenhouse-Geisser correction, F (1.510, 45.312) = 15.335, $p < 0.001$, $\eta_p^2 =$ 0.338, BF$_{\text{incl}}$ = 56417.869, RT: F (2, 60) = 16.30, $p < 0.001$, $\eta_p^2 = 0.352$, BF$_{\text{incl}}$ = 1.872) indicating that the differences between task difficulties differ between the two types of tasks. Comparing the two sessions, the behavioural performance was not significantly different between the sessions across the participants (Accuracy: F (1,62) = 0.045, $p = 0.832$, $\eta_p^2 = 7.27\text{e-}4$, BF$_{\text{incl}}$ = 0.171; RT: F (1,62) = 0.037, $p = 0.847$, $\eta_p^2 = 6.013\text{e-}4$, BF$_{\text{incl}}$ = 0.464).

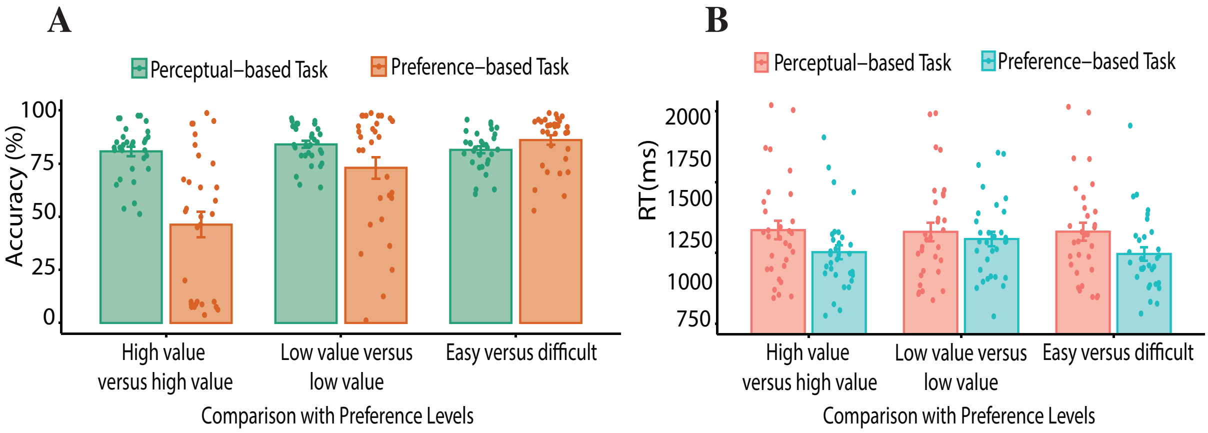

Figure 5.2 Behavioural results

A. Across all stimulus levels, the percentage of choosing brighter stimuli and choosing preferred snack items (ratio of correct responses) for the perceptual-based decision-making task (green) and preference-based decision-making task (orange), respectively. **B.** The average of RTs between the perceptual-based decision-making task (red) and preference-based decision-making task (blue) across all stimulus levels

We additionally compared the score of subjective preference on each snack item between the rating and re-rating phases. We found a strong correlation between the two times of ratings across the participants ($r = 0.882$, $p < 0.001$). This finding indicated that the individuals' preferences for the snack stimuli were consistent (Figure 5.3).

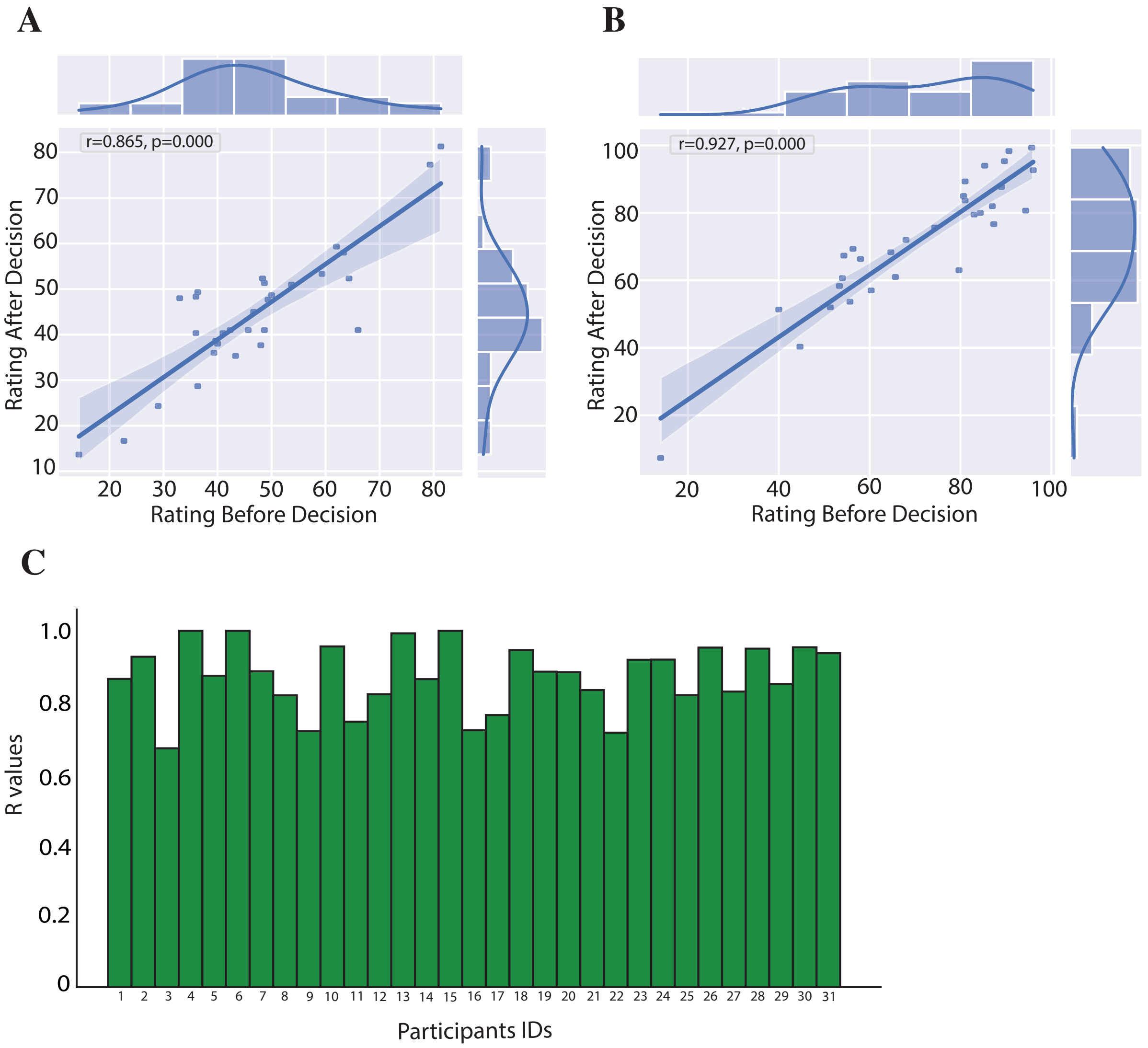

Figure 5.3 The correlation result from the subjective preference on each snack item between initial rating and re-rating phases.

A. and B. Examples from two different participants. C. The graph shows R values for all participants.

5.3.2. Cognitive Modelling Results

Similar to Chapter 3, the HDDM model was used to decompose each participant's behavioural data into internal components of cognitive processing (Wiecki et al., 2013). We allowed three model parameters (i.e., the drift-rate v, the non-decision time T_{er}, the decision threshold a) to be fixed or vary between difficulty conditions, task rules (i.e., preference-based or perceptual-based decisions) or both. For each model variant, we ran 5 MCMCs, with each one having 20,000 samples, discarding the initial 2,000 samples as the burn-ins. The Gelman-Rubin statistic was used to evaluate model convergence (Gelman & Rubin, 1992). After 20,000 samples, the maximum Gelman-Rubin statistic was R = 1.00022, indicating that all parameter estimations converged after 20,000 steps.

The best-fitting model (i.e., the one with the lowest DIC value) allows all three parameters (*v*, T_{er}, and *a*) to vary between task rules, *v* to vary between the difficulty levels, and *t* to further vary between the difficulty levels (Figure 5.4B). The observed data and model simulations were in good agreement for all conditions (Figure 5.4A).

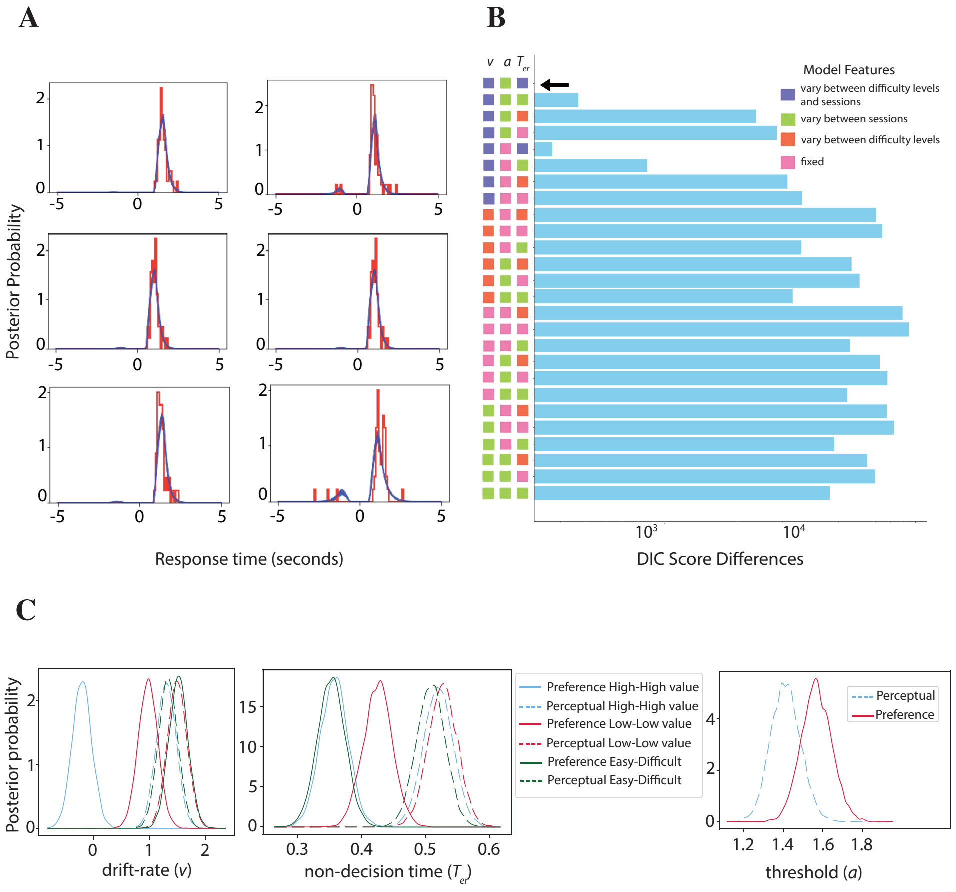

Figure 5.4 Cognitive modelling results.

A. Model simulations on the best fitting model are shown on six individuals. The red line provides data from the RT distributions of participants, whereas the blue line represents model fit with variable parameters. **B.** The DIC score of the 26 DDM model variants. The DIC score differences between all models and the best-fitting model are shown against the model dependencies depicted on the graph's left side. A square filled with purple indicates that the corresponding parameter can vary between the preference-based decisions and perceptual-based decisions across task difficulty levels. A square filled with orange indicates that the corresponding parameter can vary based on task difficulty levels (i.e., high-high value, low-low value, and easy-difficult conditions). Green-filled square indicates that corresponding parameter can vary between the preference-based decisions and perceptual-based decisions. The square containing the colour pink indicates that the corresponding parameter is constant between conditions. A black arrow pointed to the best-fitting model, which had a DIC score difference of 0 and was denoted by a score of 0. **C.** Group-level DDM model parameters for the best fitting model, which corresponds to second model variant in Panel B. Each posterior distribution was derived from 20,000 MCMC samples. Blue, red, and green lines reflect varying levels of preference for the parameter of v. On the parameter of v, T_{er}, and a, preference-based and perceptual-based information are represented by solid and dashed lines, respectively.

We calculated the proportion of non-overlaps between parameter posterior distributions using Bayesian statistics (Gelman et al., 2013; Kruschke, 2010). For the drift rate, there was strong evidence to support differences between task difficulty levels for preference-based decisions. The drift rate was also higher in choosing between high value versus low value options for preference-based choices. For non-decision time parameter, we observed that choosing between two low value items led to a significant increasement in the non-decision time for preference-based decisions. Furthermore, making preference-based decisions led to a small increase in the decision threshold than making perceptual-based judgements (Pp|D = 0.934) (Figure 5.4C and Table 6 Posterior comparisons of the model parameters (v and T_{er})

Table 6 Posterior comparisons of the model parameters (v and T_{er})

	v		T_{er}	
	Preference Based	Perceptual Based	Preference Based	Perceptual Based
x = Low-low value; y = High-high value	1.000	0.782	0.986	0.587
x = High-low value; y = High-high value	1.000	0.553	0.438	0.358
x = High-low value; y = Low-low value;	0.986	0.256	0.008	0.279

The table indicates the proportion of non-overlap between posterior parameter estimates x and y, which equates to a Bayesian test of the hypothesis $P_{p|D}(x > y)$. Experimental conditions are high-high, low-

low, high-low values refer to different preference levels and the DDM parameters are v drift-rate and T_{er} non-decision time.

5.3.3. MEG Results

We performed MVPA on source-localized MEG activity to identify cortical ROIs that contain significant information of 1) task rules prior to the decision-making process, 2) task difficulty and 3) preference levels during decision-making. Figure 5 shows the binary classification accuracy in the source space multivariate analyses and their corresponding univariate differences on three contrasts: preference-based vs perceptual decisions, distinct versus similar target values, and high value versus low value trials. In each figure, the black bars indicate the time in that region with significant classification or univariate difference ($p<0.01$, FWE corrected).

The first 800 ms of each trial was the rule instruction period, during which only task cues were presented without choice stimuli. During this period, there was significant pattern information of task rules (i.e., preference-based vs. perceptual decisions) in the occipital lobe and the superior parietal cortex. The significant decoding in the visual cortex may relate to the different task cues used in the task instruction period. The decoding in the parietal cortex is consistent with earlier studies on rule representation and supports the frontoparietal network of task rules (Waskom, Kumaran, Gordon, Rissman, & Wagner, 2014; Soon, Namburi, & Chee, 2013; Momennejad, 2012; Reverberi, Gorgen, & Haynes, 2012a, 2012b; Cole, Etzel, Zacks, Schneider, & Braver, 2011; Woolgar, Hampshire, et al., 2011; Woolgar, Thompson, et al., 2011; Bode & Haynes, 2009; Haynes et al., 2007). It is worth noting that there is no univariate difference in the initial 800 ms. After the initial 800 ms, task rule decoding was significant in large groups of occipital, temporal, parietal, and frontal ROIs. More importantly, we observed significant decoding of task rules in the medial prefrontal cortex including the supplementary motor area (SMA) and the anterior cingulate cortex (ACC), which has also been associated with task rule representation (Zhang, Kriegeskorte, Carlin, & Rowe, 2013) (Figure 5.5).

We expected that information representation relating to task difficulties or preference levels could only exist after 800 ms, because no choice target was presented during the rule instruction period (0-800 ms). Both univariate and multivariate analyses supported this prediction, as they yielded null results in the first 800 ms.

When contrasting trials with targets of distinct (i.e., one preferred and one non-preferred targets) or similar (i.e., two preferred targets or two non-preferred targets) values, occipital, parietal, temporal, and prefrontal (SMA) regions contain significant information of task difficulty levels during preference-based decisions. Interestingly, a similar analysis on perceptual decision trials demonstrated significant representation of task difficulty levels in a smaller set of ROIs, predominantly in the occipital and parietal lobules. Considering that there was no behavioural difference in perceptual decisions between targets with distinct or similar preference values, our MVPA results suggesting that the brain encodes task irrelevant information during perceptual decisions. In other words, when participants perform perceptual decisions, targets' value information in terms of their spatial locations can be reliably decoded from MEG activity, although such information is not relevant to the current task. For both preference-based and perceptual decisions, the contrast of distinct and similar target values yield no significant univariate difference in any ROI (Figure 5.7).

On the contrast of high vs. low value targets, during preference-based decisions, there was significant multivariate classification results in the occipital cortex, the superior parietal cortex, and the SMA. The same contract on perceptual decision trials lead to significant classification results predominately in the occipital cortex, indicating the presence of task irrelevant information. On univariate analyses, this contrast is associated with a transit difference ~100 ms after stimulus onset, likely relating to the difference in visual evoked fields (Figure 5.6).

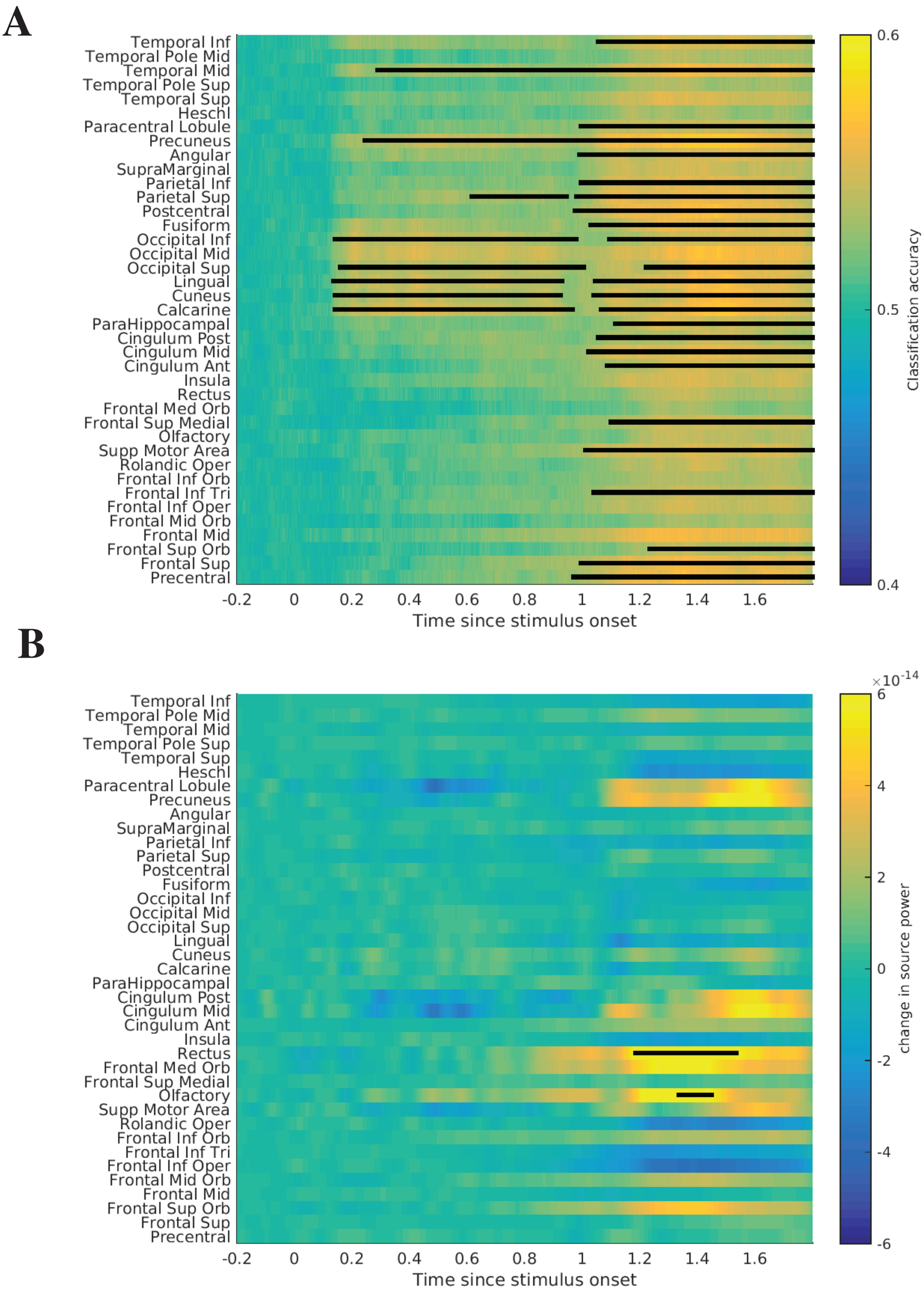

Figure 5.5 Combined MEG results for preference-based decisions and perceptual-based decisions. Each row represents decoding from each cortical region and the black bar indicates significant time points corrected across clusters and ROIs ($p<0.01$).

A. The results from multivariate pattern analysis **B.** The results from univariate analysis

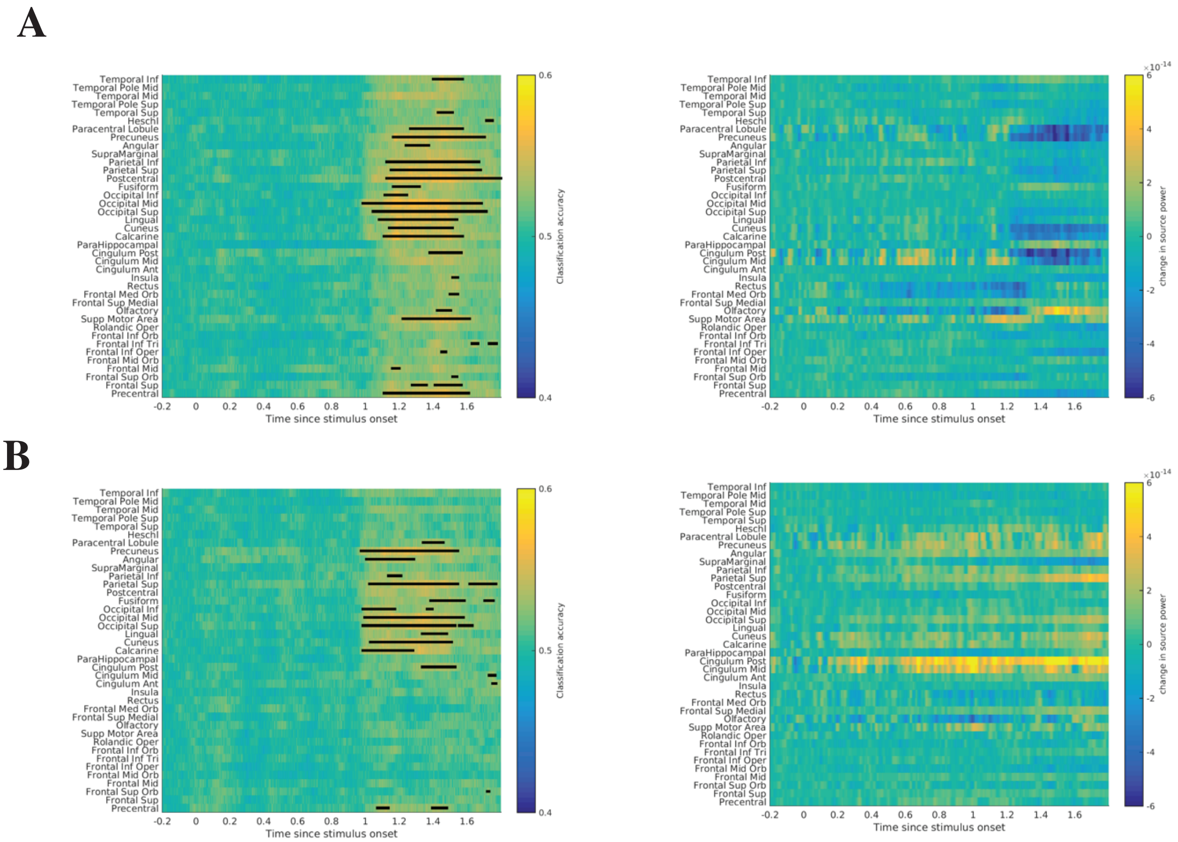

Figure 5.6 MEG results for preference-based decisions and perceptual-based decisions for easy versus difficult conditions.

A. This panel shows the results from preference-based decisions. The right figure depicts univariate analysis results for preference-based decisions, whereas the left figure shows multivariate analysis results for preference-based decisions. **B.** This panel shows the results from perceptual-based decisions. Similar to Panel A, the right figure indicates univariate analysis results for perceptual-based decisions, whereas the left figure shows multivariate analysis results for perceptual-based decisions

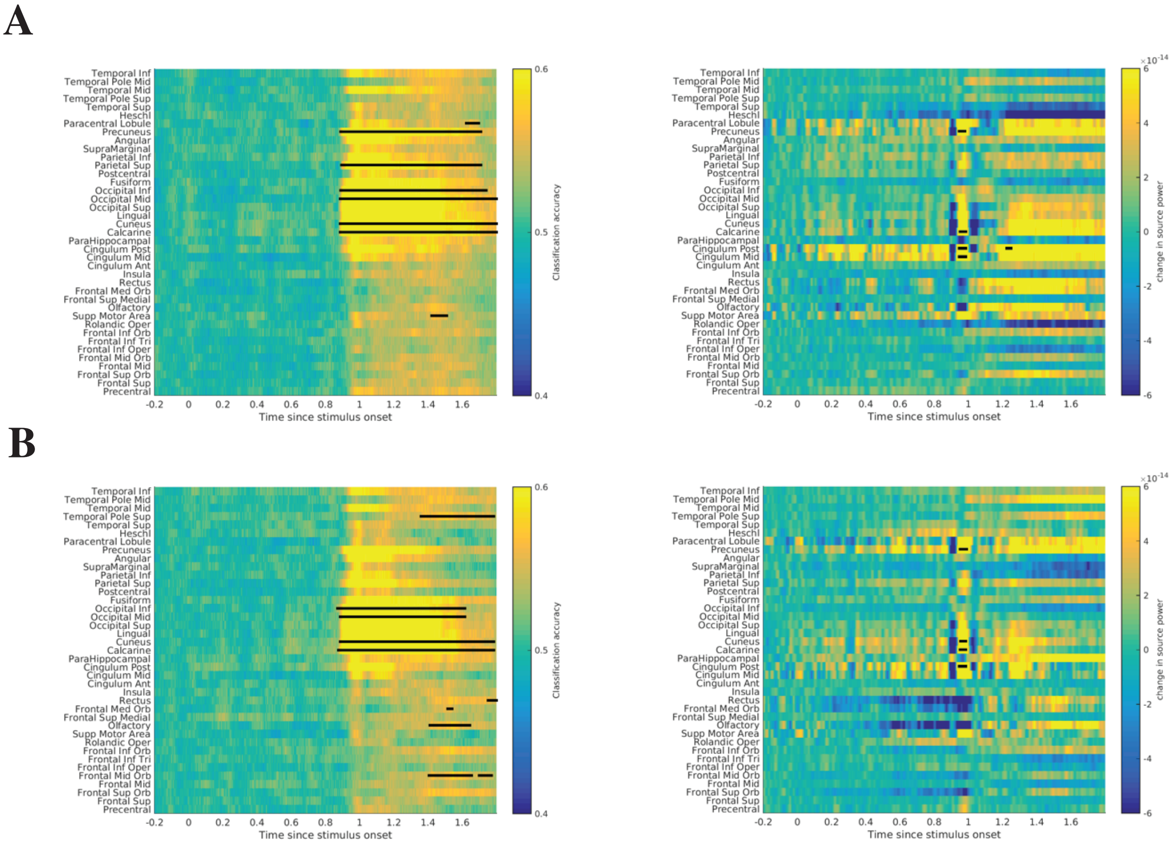

Figure 5.7 MEG results for preference-based decisions and perceptual-based decisions for choosing between two preferred items and choosing between two non-preferred items (i.e., choosing between high value versus high value and choosing between low value versus low value).

A. This panel depicts the results from preference-based decisions. The left figure shows univariate analysis results for preference-based decisions, whereas the right figure shows multivariate analysis results for preference-based decisions. **B.** This panel shows the results from perceptual-based decisions. Similar to Panel A, the left figure indicates univariate analysis results for perceptual-based decisions, whereas the right figure shows multivariate analysis results for perceptual-based decisions

5.4. Discussion

In this chapter, we studied preference-based and perceptual decisions using identical visual stimuli for both types of decisions. The aim of this study is to compare preference-based with perception decisions in terms of behavioural performance, cognitive modelling, and neural representations. Participants performed binary choice tasks guided by task cues on a trial-by-trial basis. The preference information is encoded at different spatial locations, whereas the perceptual information is presented within each target stimulus. The current study also demonstrates that, in both preference-based and perceptual decisions, MEG activity in selective cortical regions contains information of preference values (i.e., preferred vs non-preferred) and the level of value conflict (i.e., similar vs. distinct values).

We observed that when the decision based on perceptual information, the decisions were slower but more accurate. Similar to Chapter 4 findings, our behavioural results show that the perceptual stimuli were more ambiguous, and participants' response were slower. Moreover, the decisions rely on preference-based information also led to faster RT than the perceptual context. These findings support that the context of the perceptual information may encourage individuals to pay more attention to the visual input, which, in turn, enhances perceptual sensitivity and prolong the amount of time needed to make a decision. In addition, the value information or subjective preference embedded into spatial locations, and participants were required to remember value mappings among different spatial locations. Hence, when participants performing preference-based decisions, the associative memory also plays a role during the decision-making processing (G. E. Wimmer & Shohamy, 2012). In fact, numerous value-based decisions have been observed to be intertwined with the information retrieved from memory (Gluth et al., 2015; Murty et al., 2016; Shadlen & Shohamy, 2016; Weber & Johnson, 2006; Weilbächer & Gluth, 2016; G. E. Wimmer & Büchel, 2016). This process of associative memory can activate judgement heuristics, which in turn helps to facilitate processing speed (Kahneman, 2003, 2011). Taken together, these findings suggest that the task context influences participant behaviour, with preference-based contexts associated with less accurate but faster responses than perceptual contexts. Dutilh and Rieskamp, (2016) reported similar findings, indicating that changing incentives during perceptual and preference-based judgements influence people's behaviour. Although their subjective criteria differed from the current study since their value-based decisions based on reward learning, they also reported that participants responded faster in preference-based judgements than in perceptual decisions, similar to the findings in the current study.

SSM models have also been used to explain the evaluation of decision variables in value-based tasks (Busemeyer & Townsend, 1993; Gluth et al., 2012; Roe et al., 2001; Usher & McClelland, 2004). Here, the Bayesian hierarchical implementation of the DDM provided a good fit to response accuracy and RT data. First, our cognitive modelling results showed that value mappings on spatial locations affects the drift rate, when participants performing preference-based decisions. Between the task difficulty levels, there was a significant difference on preference-based decisions, but not on perceptual decisions. This is because perceptual judgements are only based on the luminance of the stimuli, which is irrelevant to spatial locations. Second, the non-decision time differs between the two types of decisions. The perceptual-based decisions had a higher non-decision time than preference-based decisions among task difficulty levels, and this change was accompanied by a reduction in the decision threshold. When participants making decisions based on more ambiguous information (i.e., perceptual information), behavioural performance was disruptively affected (i.e., decisions were slower) by increasing the non-decision time.

Using MVPA on MEG source localized activity, we identified cortical ROIs that contain significant information regarding task rules before the decision-making process, rule-relevant information throughout the decision-making process and task difficulty. First, we found significant decoding of task rules in the medial prefrontal cortex including the supplementary motor area (SMA) and the anterior cingulate cortex (ACC). These prefrontal regions have been associated with task rule representation (J. Zhang et al., 2013). Second, there was no univariate difference in the first 800 milliseconds of the measurement (the representation of the task rule). Following the first 800 milliseconds, significant task rule decoding was seen in broad clusters of occipital, temporal, parietal, and frontal ROIs. Third, or findings from the MVPA indicate that the brain encodes information that is not relevant to the task when it is making perceptual decisions. Since there was no behavioural difference in perceptual judgements between task difficulty conditions (which based on preference levels), we observed significant representation of task difficulty levels in a smaller set of ROIs, predominantly in the occipital and parietal lobules. This finding supports that the human brain remains sensitive to value information when participants performing perceptual-based choice. Our preference-based choices impact on perceptual decisions, based on the interaction between the two decision types. Recent research by Summerfield and Tsetsos (2012) supports our conclusion that perceptual decisions may involve value information or preference-based decision may be influenced by external perception. Since these two domains interact, our results consider that the two domains might be combined to develop a broad framework for comprehending human decision-making.

Two issues worth further consideration. First, this study used the DDM to draw inferences on behavioural data from both preference-based and perceptual decisions. Recent reserach support that same computational model can capture the information processing stages in those two types of decisions (Dutilh & Rieskamp, 2016; Polanía et al., 2014). As one potential limitation, here we analysed our behavioural data in the evidence accumulation framework, but we did not directly use this framework to interrogate the MEG data. Instead, we focused on our MEG signatures on pattern classification during the task rule encoding and the decision-making processing with specific task conditions. However, several previous studies applied evidence accumulation models to brain imaging data in order to investigate the neural basis of value-based decisions (Basten et al., 2010; Cavanagh et al., 2011; Gluth et al., 2012; Hare et al., 2011; Hunt et al., 2012; Lin et al., 2020; Pisauro et al., 2017; Polanía et al., 2014; Tajima et al., 2016). As a general assumption for the evidence accumulating framework for value-based judgments, the non-sensory evidence is provided by the subjective value that individuals assign to each option. Recent studies used HSMM model with EEG data to identify stages of the decision-making processing (Berberyan et al., 2021; Borst & Anderson, 2015; Dong & He, 2007; Joo et al., 2013). Further research might explore how to link cognitive processes and neural processing stages during preference-based decisions using HSMM.

Second, the current study mainly focused on broadband MEG activity, and future studies should investigate specific oscillatory activity. One previous study attempted to examine value-based and perceptual decisions using the evidence accumulation framework (Polanía et al., 2014). It showed that gamma band oscillations in parietal cortex is correlated with evidence accumulation, and this correlation is common for both perceptual-based and value-based decisions. Furthermore, the synchronization between parietal and fronto-polar regions was found stronger in value-based decisions than perceptual-based decisions. These findings suggest that the neural implementation of evidence accumulation process during decision-making may be frequency specific.

This study provides two main contributions to the field. First, the study revealed a temporal signature in the neural activity during the decision-making process. Initially, in the early visual areas, the neural activity was observed, and later it became more prominent in motor or frontal regions. This finding suggests a dynamic progression of information processing and suggests a temporal flow of neural activation from sensory areas to higher-order cognitive and motor regions. This temporal signature provides insights into the sequence of neural events involved in decision-making. Second, there are numerous studies in the field that have investigated the temporal signature of value-based decision-making using EEG and MEG. These studies have provided valuable insights into the neural dynamics and temporal patterns associated with decision processes. By examining the precise timing of neural activity, these investigations have contributed to our understanding of the temporal dynamics of decision-making and the underlying cognitive processes. However, in general, these studies focused on decisions based on reward/loss or external value decisions (Castegnetti et al., 2020; P. Chen et al., 2023; X. J. Chen & Kwak, 2022; Harris & Lim, 2016b; Huang et al., 2021; Itthipuripat et al., 2015; Thomas et al., 2013; Tyson-Carr et al., 2018; C. Wang et al., 2020). In this research, we examined the impact of different decision-making contexts, specifically preference-based decisions and perceptual decisions, on the neural activity. The results showed clear differences in MEG activity based on the representation of task rules and stimuli. This suggests that the brain's neural encoding and representation are influenced by the contextual factors of the decision-making process. The presence of extended contextual dependencies indicates that the brain flexibly adapts its neural processing based on the specific demands of the decision-making context.

For a future direction, an integrated model could be applied to behavioural and neuronal data. For instance, in one study, researchers aimed to establish a relationship between the decision-making process and EEG signatures. Behavioural and EEG data were integrated using a joint hierarchical Bayesian model in order to determine whether electrophysiological activity reflects trial-by-trial changes in the rate of evidence accumulation for decision-making (Zajkowski et al., 2021). Similar to this research, we could use a single trial trace of model parameters to integrate behavioural and neuronal signatures into a single model.

In conclusion, the study presented here is an attempt to further integrate our understanding of perceptual-based and preference-based decision making, from behavioural, cognitive modelling and neural representation perspectives.

Chapter 6

Discussion

This chapter provides a summary of the thesis in Section 6.1, and discusses the limitations of this research and potential future research directions in Section 6.2, in order to provide a comprehensive understanding of the outcomes of this inquiry, with a deeper knowledge of value-based decision-making.

6.1. Summary of contributions

The thesis began with a review of theoretical and experimental basis of decision making in Chapter 2. Decision-making problems were formalized with mathematical explanations based on the theory underlying cognitive models, and the classical drift-diffusion model (DDM) was utilised to define the decision-making process. In the context of DDM application, I reviewed behavioural aspects of perceptual decision-making through classical paradigms and described outlined the fundamental decision-making phenomena that influence behavioural performance in decision-making, such as the speed-accuracy trade-off. I provided a summary of seminal findings on the neurological process of perceptual decision-making through observations from animals via invasive electrophysiological recordings and from humans via non-invasive neuroimaging. Next, I reviewed the description of value-based decision-making, which allows broadening the scope of decisions from the simple to the complex and summarized its differences from perceptual decisions. I the reviewed the different concepts of values, the steps of value-based decisions, multiple value systems, existing experimental paradigms, and the neural signature of value-based decisions, as well as previous research findings.

The main contributions of the thesis were presented in Chapters 3-5, covering making preference-based judgments on combinations of multiple elements (Chapter 3) and examining the translation of the value information as well as their possible interactions with perception (Chapter 4-5).

6.1.1. Integrating multiple sources of value information

Chapter 3 investigated how preference-based decisions are made with the existence of the same types of multiple information sources, and how these multiple information sources affect decision performance and underlying decision processes. I addressed these questions by designing through two internet-based experiments in which participants made binary choices based on their food preferences, whereby each option involved the combinatorial of multiple food items.

Experiment 1 included two experimental sessions. In one session, each option contained two food items, and in the other session, each option contained four food items. Despite increasing the number of food items in the options between two sessions (which was a pivotal point of the experiments), all the food items combined in each option had the same preference level. Between two sessions and across four levels of preference difference, I compared behavioural measurements (Accuracy and RT) and the DDM parameters and found that increasing the number of items in each option led to less accurate and slower responses. The DDM results further showed that more pieces of information are associated with a lower drift rate. These findings established that when participants need to evaluate more pieces of value information, they are able to integrate the multiple information, but increasing information sources impeded rather than improved the decision accuracy.

Experiment 2 aimed to replicate and extend the main findings of Experiment 1 by using congruent versus incongruent information. In this experiment, participants made preference-based choices between two groups of food items, with each option containing four food items, and each choice option containing either fully congruent information or a piece of incongruent information. The results for incongruent information were less accurate and slower than those for the congruent condition, and this behavioural pattern is associated with a lower drift rate and reduced decision threshold in the incongruent condition. These findings suggest that individuals employ combinatorial of information sources during preference-based decisions. The number of information sources has an impact on behavioural performance, and such behavioural changes are related to the quality of evidence needed for rational and speed actions, but not the latency of sensory-motor encoding.

Chapter 3 laid the foundations for the following experiments by establishing the integration of combinatorial value information into a single source of evidence. To the best of my knowledge, the research described in the Chapter 3 is the first study to investigate the impact of the same types of multiple information sources in value-based decision-making.

6.1.2. Value information embedded into geometric shapes

Chapter 4 investigated decision performance under the context of internal preference and external perception. I developed an internet-based choice paradigm that allows examination of both value and perceptual decisions using the same visual stimuli. I parametrically morphed geometric shapes to vary between circle-like and diamond-like stimuli, and participants were instructed to perform categorization task based on internal value and perceptual information. In preference-based decisions, participants had the opportunity to establish the association between geometrical shapes and preference levels. They were then required to decide whether a visual stimulus was likely to be associated with preferred or non-preferred snack items. Using the same set of visual stimuli, the participants also performed perceptual decisions to determine whether a given stimulus was more like a circle or a diamond. This existing paradigm allowed investigation of how initial internal value mappings may affect subsequent perceptual decisions.

I observed psychometrical performance (sensitivity and bias) on the categorization task based on internal value and external perception information. The results showed that attaching internal values to geometric shapes led to lower discriminating sensitivity than perceptual decisions, indexed by a decreased Weber ratio. There was no difference in participants' response bias between the two types of decisions. Furthermore, value-based decisions were associated with longer reaction times than perceptual decisions across stimulus levels. These findings suggest that a common computational process may underlie value-based and perceptual decisions and mapping internal preference onto external perceptual information results in additional noise in the decision-making process.

Chapter 4 established an experimental design that used embedded internal value information for the geometric shapes. Participants used value mappings towards the shapes to indicate their snack item preferences, whereby the internal value information translated into geometrical shapes. Since internal value-based decisions are mostly influenced by memory representations, this design aimed to mimic scenarios in real-life decision making. Moreover, the identical visual stimuli design allowed investigation of interactions between internal value and external perception, and comparison of preference-based and perceptual-based decision-making.

6.1.3. Value information embedded into spatial locations

Chapter 5 presented an MEG experiment on preference-based and perceptual-based decisions. Participants were instructed to perform binary choice task in the contexts of internal preference and external perception using the identical visual stimuli on a trial-by-trial basis. The different colour of fixation points indicated the task rule of each trial. Rather than different geometrical shapes, internal values were mapped through different spatial locations by means of Gabor patches stimuli. In preference-based decisions, participants remembered value mappings among different spatial locations and snack items at different levels of subjective preference. The participants were then required to make binary choices between Gabor patches stimuli, according to which spatial location was associated with the snack item they prefer more. Using the same spatial locations and Gabor patches stimuli, participants made perceptual decisions to distinguish which Gabor patch stimulus was brighter than the other. This experiment aimed to compare internal value decisions and perceptual decisions in terms of behavioural performance, computational modelling, and underlying neural basis. Using the MEG recording, the spatiotemporal signatures of internal value-based decisions were identified and compared with perceptual decisions.

Using MVPA, I identified stimulus-task rule association with changes in multivariate data patterns in MEG signal. The results suggest that the brain actively maintain rule-relevant information before and throughout the decision-making process. MVPA on source space MEG data showed that more extended visual area activations are sensitive to value differences in value-based decisions. These findings provide a framework for further integrating perceptual and preference-based decision-making into a single framework.

6.2. Limitations

There are a few limitations in the methodological decisions and experimental work undertaken in this research that ought to be noted when interpreting its outcomes.

6.2.1. Value-based judgements

6.2.1.1. Single value preferences

In order to identify value-based judgments, I solely focused on one aspect of value in all of my projects, which is internal value in the context of subjective preference. Choices in this context of value-based decisions are based on the individual's own criteria rather than external criteria, hence there is no correct response (Johnson et al., 2005; Nakao et al., 2009, 2012; Paulus &

Frank, 2003). Previous research has described subjective preference with the preference judgment task using a variety of preference judgments, such as product choice (Knutson et al., 2007, 2008), brand choice (Santos et al., 2011), face selection (Chaudhry et al., 2009), holiday alternatives choice (Chaudhry et al., 2009), geometric figures (Jacobsen et al., 2005), and colour selection (Johnson et al., 2005). However, the majority of the studies used food item choices for preference judgment tasks during internal value decisions (Arana et al., 2003; Bielser et al., 2016; Hare et al., 2009; Harris et al., 2011; Harris & Lim, 2016; Linder et al., 2010; Milosavljevic et al., 2010; Polanía et al., 2014; Tashiro et al., 2019).

For instance, Arana et al. (2003) examined neural substrates during preference judgment for different incentive values by presenting a series of restaurant menus created with high and low incentive values. In the task, participants were not hungry, and the food items in the menus were customised for each individual. Participants were instructed to follow a set of menus and were asked to choose one from the menu halfway through the trials. Similarly, Hare et al. (2009) investigated neurobiological underlying of self-control during preference judgment for different factors of food items (health and taste). To identify differences between self-controller and non-self-controller decision-makers, participants were asked to rate the food items twice according to health and taste separately. Based on the rating results, an item rated as neutral for both health and taste was selected as the reference item for each participant. In the decision-making task, participants were asked to make a judgment between each of the food items and reference food item. Similar to the above studies, in all projects of this thesis, food items were utilised to evaluate preference judgments.

6.2.1.2. Rating tasks

Moreover, several papers about value-based decisions utilised rating tasks to indicate value on a scale (Bielser et al., 2016; Harris et al., 2011; Harris & Lim, 2016; Philiastides & Ratcliff, 2013b; Tashiro et al., 2019; Wimmer & Shohamy, 2012). In the same manner, in Chapter 4 and Chapter 5, before and after the experiments, two sets of ratings were performed on a Likert scale with using food items in order to indicate consistency. Those type of experimental procedure provide a robust measure of participants' preference towards food items.

6.2.1.3. Subjectivity issues

In Chapter 3 and Chapter 4, the representation of internal value was based on more abstract concepts. defined by subjective preferences towards the food items, which can reduce any potential bias or influences from branding. Philiastides and Ratcliff (2013) investigated how branding bias influences human behaviour and decision-making processes, demonstrating that branding does indeed affect people's choices (as intended). Furthermore, internal values are not limited towards food items: a broad range of internal values are instrumental in human decision-making. Moral decision-making stories are examples for other intrinsic value decisions (Heekeren et al., 2003; Greene & Paxton, 2009; Hare et al., 2010; Krueger et al., 2007; Kümmerli et al., 2010; Moll et al., 2006; Schleim et al., 2011; Sommer et al., 2010).

For instance, Sommer et al. (2010) investigated neural correlates during moral conflict situations in daily life. During tasks, the researchers did not assume that either one of the two options offered was correct. In the task, participants made choices when presented with morally conflicting situations in daily life in which moral rules crashed with personal desires, so that the decisions made were based on moral motivations or hedonistic behaviour. Both choices had their own advantages and disadvantages, but there may not be universally correct answer within the framework of the tasks. The choices, which entailed decisions, relied on participants' own criteria (i.e., participants could follow two behaviour strategies – making a decision based either upon their personal desire or their moral standards). The findings indicated that moral decisions were associated with increased activity in a large neural network involving the medial frontal cortex, the temporal cortex, the temporo-parietal junction, and the posterior cingulate cortex; conversely, hedonistic decisions were associated with increased activity in the amygdala/parahippocampal region.

In a similar vein, Moll et al. (2006) asked participants to decide between receiving money or donating to a charity, with neither option being presumed to be correct. In this case, the conclusion indicated that the participant earning money is not always the correct answer, because a charitable donation may be regarded the correct response from a moral perspective. Given the subject's personal viewpoint and financial interests, receiving the money rather than donating it to charities would be regarded the correct option. This choice signifies that the decision is motivated by self-interest or morality (depending on the criteria of the participant). The findings indicate that judgments based on moral beliefs are more significantly associated with medial frontal cortex activation than monetary reward decisions.

6.2.2. Internal value integrations

Throughout this thesis, I considered internal value integrations and the converse of preference-based decisions (i.e., internal value judgments) in relation to perceptual decisions. However, there is also a contrast between internal value judgments (i.e., preference-based decisions) and external value judgments. As a limitation, my research has no explicit consideration of external value judgments and their comparison with perceptual decisions. However, most research to date has focused on external value to elucidate the value-based decisions (i.e., extrinsic motivations and external incentives), in which decision options have objective characteristics; this means that the value of the options is defined externally by the experimenter, and correct answers exist. Such situations include objective utilities such as money, gambling, and other external incentives. Examples of tasks employed in external value judgments include gambling tasks and tasks in which one option is linked with a probabilistic better outcome than the others (i.e., a stimulus is associated with the probabilistic of a reward) (Abler et al., 2009; Bach et al., 2017; Bowyer et al., 2021; Gluth et al., 2013; Huettel, 2006; Hunt et al., 2013; Itthipuripat et al., 2015; Knutson et al., 2005; Lin et al., 2019; Oemisch et al., 2017; Steffen et al., 2011; Thomas et al., 2013; Tobler et al., 2007; Trimber & Luhmann, 2017; Volz et al., 2003; Wang et al., 2019; Zajkowski et al., 2021; Zhang et al., 2017; Zheng et al., 2020; Zhu et al., 2019).

For instance, when requiring participants to decide about different reward values, Abler et al. (2009) used cues to indicate different magnitude and probability of the monetary rewards. In the task, participants were instructed to follow the cue and make a decision based on the expectation of monetary rewards, whereby this value could be at different magnitudes, probabilities, and uncertainties. Research on extrinsic value judgments investigates the effect on decision making of circumstances with objectively correct responses, but it is difficult to predict outcomes due to the presence of uncertainty (Nakao et al., 2012). Thus, due to the implied correctness of the answers and decision criteria differences, there is a clear distinction between internal and external value judgments. Since external values affect behaviour as much as internal ones, it is important to investigate the potential interactions of internal and external values on behaviours, as they are as important as internal values in understanding value-based decisions. However, external value judgments are not the main focus of this thesis; it would be useful for future work to consider the interaction or influence of different effects from internal and external values on value-based decisions.

6.2.3. Online data collection

6.2.3.1. Dropout issues

The research presented in Chapters 3-4 was based on internet-based experiments. Although conducting online studies has the benefit of collecting data from large and diverse groups of participants in a relatively short period of time at much lower cost (such as employing the experimenter for a short time and average rate of the participants' compensation expenses), it also introduces a number of technical and scientific challenges (Birnbaum, 2004; Reips, 2000). First, an important challenge of interactive online experiments concerns participants dropping out before they complete the experiment. Participants rarely leave a session in physical laboratory experiments, whereas in online studies, participants are more likely to drop out. If dropouts occur for external reasons or technical challenges to the experiment, such as network connections, recording data over the internet, frozen screens, and so on, these reasons only lead to extra costs to the experimenter (Arechar et al., 2018) Internal dropouts are much more serious (when participants leave the experiment due to decreased motivation). Such dropouts may compromise the internal validity of experiments (Zhou & Fishbach, 2016). In our experiments, seven participants withdrew from the experiment before completing all their sessions because of external issues.

6.2.3.2. Technical issues

Furthermore, technical challenges can arise from conducting online studies, as this format does not allow full experimental control over participants' computer hardware factors that may affect the experimental conditions (e.g., screen size, computer speed, and a variety of web browsers).

6.2.3.3. Rapport

The absence of interaction between participants and experimenters during the experiment when using most forms of online data collection lose some of the potential engagement possible with traditional face-to-face methods. When the instructions are misunderstood by participants, there could be important issues affecting data quality and reliability. In my experiments, in order to address this challenge, feedback was provided sequentially after a part of the trials, and when the participants could not proceed to fulfil the task with higher than chance level they were removed from the experiment.

6.2.3.4. Oversimplification

Due to the particular challenges of online data collection adumbrated above, the experiments were designed as relatively simplified and repetitive psychological tasks. However, scenarios that include value-based decisions are typically more complex in real life. Nevertheless, these online experimental setups suggest the validity and reproducibility of online experiments to investigate the integration of subjective value and to examine psychometrical performance during value-based decision-making.

6.2.4. Summary

The behavioural and cognitive modelling results presented in Chapter 3 showed that humans are able to combine multiple pieces of information in preference-based decisions. The psychometrical performance from the experiments in Chapter 4 consider sensitivity and bias on the categorization task based on value and perceptual information. Our findings showed that mapping preference-based context onto perceptual information reduces perceptual sensitivity and facilitates response speed during decision-making. Chapter 5 further investigated preference-based and perceptual decisions when preference-based information is associated with different spatial locations. This chapter demonstrated that participant perceptual judgment is modulated or shaped by subjects' preference-based information. Future studies could look whether the reverse effect is also true (i.e., whether participant preference-based judgment is affected by perceptual appearance). Chapter 5 showed that there is a distinct neural signature of decision context between preference-based decisions and perceptual-based decisions. When performing perceptual or value-based decisions using identical stimuli, MVPA results showed that preference-based context engages a wider visual areas activation such as frontal parietal networks. Our results suggest that the brain actively sustains rule-relevant information before and throughout decision-making process. In conclusion, this thesis contributes to the research of value-based decision-making by integrating novel experimental approaches, cognitive modelling, and electrophysiological measures of the human brain.

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