Cardiff University

School of Psychology

The neurocognitive features of intentional decision-making in humans

A thesis presented for the degree of Doctor of Philosophy

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Dec 26, 2023

Abstract

This thesis investigated several aspects of intentional decision-making in humans. First, a meta-analysis revised that, comparing with exogenous, instructed behaviour, endogenous choices generated from intentional decisions increase the activation of a network consisting of the medial prefrontal cortex (pre-supplementary motor area (pre-SMA) and caudal anterior cingulate cortex (ACC)), the lateral frontoparietal cortices (dorsolateral prefrontal cortex (dlPFC) and inferior parietal lobe (IPL)) and the anterior insula cortex (aINS). According to the nature of the options in intentional decision-making, the intentions were categorized into four types: reactional intention (RI), perceptual intention (PI), inhibitory intention (II) and cognitive intention (CI). Second, a free-choice experiment on various cognitive tasks was proposed and conducted online to explore the cognitive intentions of heterogeneous cognitive processes. Participants showed consistent repetition bias and a preference for the perceived easier tasks. Notably, this perceived difference was not necessarily related to the actual task performance. Third, the MEG signatures of cognitive intentions and their subsequent stimulus processing were investigated through multivariate pattern analyses. Source-localized data showed the activities in the brain areas related to task rules, such as the middle cingulate cortex and the middle frontal area, were sensitive to both task types and transition types in cognitive intentions. Finally, to understand the cognitive intentions in a more naturalistic environment, an adapted version of the Pac-Man game was employed to investigate dynamic strategic decision-making. The behavioural modelling results together with the eye tracking and fMRI results presented the feasibility and a promising future of using video games as a continuous paradigm in intentional decision-making studies. To sum up, the abovementioned findings contribute to intentional decision-making with meta-analytic reviews, innovative experimental paradigms and multi-model neurocognitive evidence.

Acknowledgements

The completion of this thesis is inseparable from the assistance of those who helped me throughout the entire PhD study.

The person I want to thank most is my supervisor, Prof. Jiaxiang Zhang, who provided invaluable guidance and support over all my years at Cardiff. He is always available to help whenever I have problems. I appreciate his patience in explaining all those concepts and analyses that I often find confusing and his inspiring ideas that motivate me all the time. He is one of the best mentors I've ever had. I would like to extend my deepest gratitude to him.

I am also grateful to Dr Ulrich von Hecker, who has been both my friend and my panel reviewer over these years, for providing perceptive suggestions and precious advice in both academics and daily life.

Moreover, I am thankful to all my friends. I would like to give special thanks to Isa for being my academic and psychological shelter by sharing my experiments and sentiments, Ruikai for being my pilot participant for numberless times but still maintaining his friendship with me, and Ci’an for his technical support in programming and coding, and my dearest besties, Keke (and her cat, Nian-nian), Rui and Xinwei, for providing enormous emotional support that helped me through all the tough times. I also have to thank all the present and past members of the Cognition and Computational Brain Lab and all the colleagues I worked with in the CUBRIC community whose kindness and skills helped me out of countless issues.

Additionally, I would like to thank my family. They backed me to pursue my scientific dream and are always there for me. I could not have accomplished this work without their support and trust.

Last but not least, I would like to give my appreciation to the China Scholarship Council (CSC) and Cardiff University for offering a full scholarship to sponsor my study, which is a crucial material foundation for completing this thesis.

Contents

List of table

List of Figure

1. Introduction

1.1. Background

Decision-making is as old as organized human activities, encompassing the compelling needs of communities and the ethical parameters within which they operate. In classical antiquity, renowned philosophers such as Confucius and Aristotle emphasized the importance of ethical values and proposed their use in shaping moral and practically effective choices (Crisp, 2014; Waley & others, 2012). Their primordial ethical discourses can be considered to be the original exploration of decision-making, though these early thinks focused more on achieving practical ends and influencing others' decisions, rather than understanding the decision-making process itself. With the development of contemporary social science, scholars started to speculate on the motives and broader implications behind decision-making choices. Traditional approaches predicted customers' choices via a set of assumptions including rationality, self-interest, utility maximization, and consistency (Hollis & Nell, 1975).

By the time of the European Enlightenment, 18th-century philosophers had already identified the concept of the "economic man" as a theoretical construct to explain consumer behaviours (Edwards, 1954). This paradigm posited that individuals gather all the information related to a certain goal and make their choices with complete rationality, with a view to maximizing their benefits. Despite being criticized because of its oversimplification, the "economic man" paradigm still provides significant insights into understanding the fundamentals of the decision-making process, and it can be regarded as a prototype of subsequent decision-making models (Camerer & Fehr, 2006; Fox, 2015).

With the advent of modern psychology from the early 20th century onwards, an operational definition of "decision-making" was gradually formed, and it is now widely accepted to be the cognitive process by which a perceived appropriate option is selected from available alternatives to fulfil certain requirements (Shadlen & Kiani, 2013). Decision-making is the most fundamental mediator of daily life, ranging from mundane tasks necessary for the survival of the human organism (e.g., whether and what to drink), to meeting higher-order aspirations and sophisticated needs, governing the trajectory of the whole life span and interactions with changing social and physical environments, and the ability to adapt to changes and plan for the future.

In cognitive psychology research, two categories of decision-making scenarios are worth highlighting: perceptual decision-making and value-based decision-making. Perceptual decision-making is to choose the target with required perceptual features, like stopping or going in front of a traffic light (Summerfield & De Lange, 2014). Value-based decision-making is to select favourite items, like shopping for groceries in a familiar supermarket (Rangel et al., 2008). It is worth mentioning that one's preference is commonly considered to be consistent in the latter case, because it is a result of information or evidence accumulation via a trial-and-error process. An unexpected choice is usually treated as a wrong choice in value-based cognitive studies.

However, there are a large number of circumstances in real life where a choice cannot be judged with correctness, especially when the same goal can be achieved in various ways. For example, there is no "right" or "wrong" choice for dinner; while there can be a food preference in general, the specific dish choices can change daily, to fulfil incidental contextual goals. This kind of decision-making whereby all choices lead to homogenous outcomes is categorized as intentional decision-making, which has been referred to under various terms in the literature, such as "internal selection" (Van Oostende et al., 1997), "self-initiated movement" (Cunnington et al., 2002), "willed action" (Lau, Rogers, Ramnani, et al., 2004), "voluntary selection" (Forstmann et al., 2006), and "chosen action" (Zhang et al., 2012a). In this research, these terms are used interchangeably to denote "intentional behaviour".

1.2. Aims and Structures

This thesis aims to extend the research of intentional decision-making on both behavioural and neurocognitive aspects. On the behavioural aspect, innovative paradigms were used to explore the intentional decision-making on cognitions and strategies. On the neurocognitive aspect, a variety of neuroimaging methods were employed to reveal the brain activity patterns related to them. Below is a concise summation of each chapter.

Chapter 2 provides an overview of the theories on intentional decision-making. The overview starts with the definition and a common model of intentional behaviours, then presents discrete and sequential features of intentional choices, educes strategic decision-making with a Pac-Man example and introduces the multi-modal measurements employed in this thesis.

Chapter 3 summarizes the existing functional localization studies of *free-choice* paradigms, in which participants choose among options with identical values or outcomes. An Activation Likelihood Estimate (ALE) meta-analysis on 35 fMRI/PET experiments reveals a brain network related to intentional decisions including the medial and dorsolateral prefrontal cortex, the left insula and the inferior parietal lobule. The study then categorizes the free-choice paradigms into four types according to their experimental designs for further conjunction and contrast meta-analyses as well as meta-analytic decoding, suggesting the neurocognitive process underlying intentional decision incorporates anatomically separated components subserving distinct cognitive and computational roles.

Chapter 4 investigates behavioural patterns of intentional decisions on task rule choices. A novel paradigm was developed to examine the voluntary choices among different cognitive tasks. The performances on those choices and the accordant cognitive tasks were analysed. The study indicates a repetition bias in cognitive intentions, and implies this preference is associated with participants' subjectively perceived difficulty levels of the task. A follow-up experiment with independent difficulty levels in each cognitive task was then conducted and provided supportive evidence for this proposition.

Chapter 5 is a MEG study on cognitive intentions using the experimental paradigm adapted from Chapter 4. The behavioural results were largely consistent with the findings in Chapter 4. Two hypotheses were proposed to explain the phenomenon and there was supportive MEG evidence for both of them. The multivariate pattern analysis (MVPA) analyses were conducted on source-localised MEG data and identified brain areas associated different task rules. The transition types can also be detected at both sensor and source levels around the choice onset time.

Chapter 6 uses an adapted Pac-Man game as to experiment paradigm to explore the intentional decision-making on strategies. The study was inspired by a recent study on non-human primates, aiming to inspect the behavioural uniqueness of humans, and the neural correlates underlying human strategic decision-making. Behavioural modelling has shown that humans employed more intuitive strategies during the gameplay, but used a similar take-the-best heuristic in strategic decision-making. Neuroimaging analysis further showed that the different strategies had distinguished brain activation patterns, which validated the intuitive strategies selected in the study.

Chapter 7 recaps the results presented in the thesis, discusses both the contributions and limitations of the current work and proposes possible directions for future studies.

2. Literature Review

2.1. Intentional decision-making

In contrast to reflex or purely stimulus-driven reactions, intentional behaviour is characterized by volition and purposefulness. It is a goal-directed behaviour initiated by agents according to their internal or endogenous intentions rather than other external causes (Marken, 1982; Passingham, 1995). Intentional decision-making is conceptually different from perceptual or value-based decision-making; wherein specific cues incite a subsequent choice. Although the two latter types of decision-making allow participants to choose, they have “correct” answers for every single choice, based on either the objective properties or subjective preference of the stimulus (Dutilh & Rieskamp, 2016; Nakao et al., 2012). They are closed questions designed to understand the decision process for optimal choices, rather than the purpose-driven planning and evaluation of similar options.

Additionally, perceptual and value-based decision-making focuses on the trial-based discrete decision-making process, wherein individual trials are commonly considered to be mutually independent. This offers advantages in terms of simplicity when integrated with standard statistical hypothesis-testing, but also overlooks the potential richness in understanding how one trial might impact or be influenced by previous or subsequent trials, as natural behaviour is rarely discrete (Huk et al., 2018). Intentional decision-making, on the other hand, allows the extra exploration of inter-trial or sequential dependencies, which could contribute to a more comprehensive understanding of decision-making dynamics with long-range temporal correlation.

2.1.1. The What-When-Whether (WWW) model

One of the widely accepted models for understanding discrete intentional actions is the What-When-Whether (WWW) model (Brass & Haggard, 2008), which segments the unitary concept of intentional actions into the three eponymous components, as displayed in **Figure 1**, whereby one chooses *what* appropriate behaviour to execute, selects *when* to execute the action, and ultimately decides *whether* to execute the action.

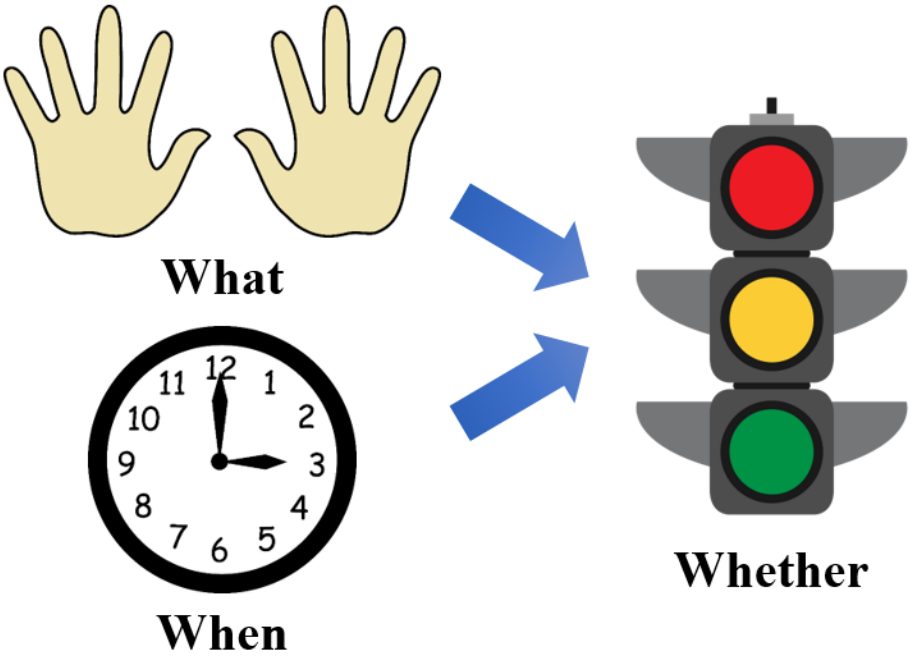

Figure 1. Schematic drawing of the What, When, Whether (WWW) model of intentional action (adapted from Brass & Haggard, 2008). The model assumes three component decisions relevant to intentional action.

In real-life situations, people are more aware of the *what* and *whether* components in decision-making, because the *when* component is accompanied by the other two components that are triggered by physiological and biological signals. In lab-based investigations, the *when* component is often studied with regard to internal motivations and the sense of agency (e.g., Haggard et al., 2002; Hoffstaedter et al., 2013; Libet et al., 1983), while the *what* and *whether* components pertain more on the effects of eliminating the external constraints.

2.1.1.1. When

The *when* component is about the timing of the intentional behaviour and is thereby initially and commonly studied with techniques of high temporal resolution such as EEG or MEG (e.g., Libet et al., 1983; Pedersen et al., 1998). One of the psychophysiological signals closely related to the *when* component is Readiness Potential (RP), a slow ongoing negative potential that occurs about a second preceding the voluntary actions (Deecke et al., 1969, 1983). RP started to be of great interest in neuroscientific and psychological studies after Libet et al. (1983) found that RP happens even before the subjective "urge to act" (**Figure 2**), the time of the conscious awareness of the action. The findings are consistent with the hypothesis that the (preparation) of voluntary action is not subjected to conscious awareness (Libet 1985), challenging the classical concept of free will.

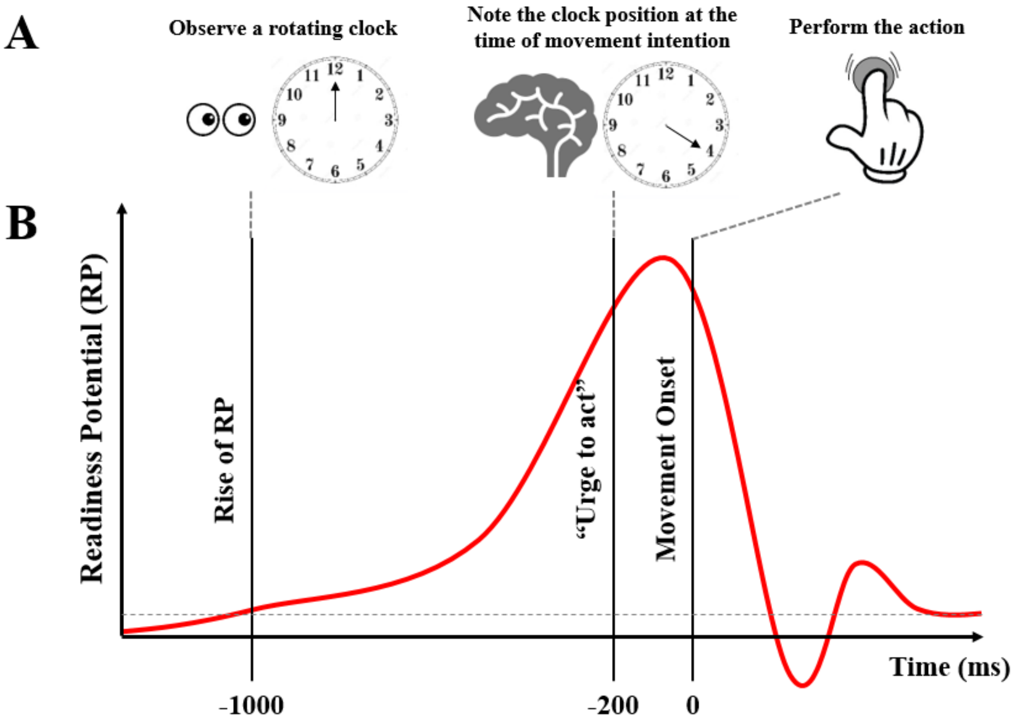

Figure 2. Demonstrations of Libet's task and corresponding readiness potential. (**A**) **The Libet's task**. Participants were asked to observe a rotating clock and remember the clock position at the time when they had the conscious intention to act and then perform the action. (**B**) **The readiness potential (RP)**. RP is a slow ongoing potential before the voluntary action. It starts to rise about a second before the movement onset, while the conscious "urge to act" will happen about 200 milliseconds before the movement onset.

With the deepening of RP research, its properties were further revealed (Alexander et al., 2016; Jahanshahi et al., 1996; Travers et al., 2020, 2021). First, RP is unique to self-initiated voluntary actions. Externally triggered action occurs in the absence of RP, compared with the temporally yoked self-initiated movements (Travers et al., 2020). Diseases that involve excessive involuntary movements, such as Parkinson's disease, are also correlated with reduced amplitude of RP in voluntary behaviours (Jahanshahi et al., 1996). Besides, RP can be detected before both voluntary motor action and non-motoric voluntary processes (Alexander et al., 2016). Researchers replicated Libet's (1983) task of estimating the time of conscious intention, and removed the final action request for half of the trials (i.e., participants only needed to orally report the time of their decision without any subsequent motor action), and found the RP still exists in those trials. The aforementioned studies revealed that the RP is associated with multiple types of self-initiated action intentions (Alexander et al., 2016; Jahanshahi et al., 1996; Travers et al., 2020). Moreover, this specificity was further suggested to have a link with the temporal expectation (Travers et al., 2021). After learning the optimal strategy to act in an imaginary free-timing situation, participants showed higher RP amplitudes than at the early learning stage. This indicated that RP reflects an anticipation of the action timing rather than the general action freedom from external constraints or uncertainty.

Functional localization studies in humans demonstrated that the *when* component is closely related to the activities of the middle cingulum and medial frontal cortex, including the supplementary motor area (SMA) and pre-SMA (Zapparoli et al., 2017). These results are consistent across multiple neuroimaging methods, such as intracranial EEG (Fried et al., 2011), PET (Jenkins et al., 2000), and fMRI (Hoffstaedter et al., 2013; Zapparoli et al., 2018). Moreover, the parietal lobe also plays a significant role in initiative action (Aflalo et al., 2022; Zapparoli et al., 2017). Clinical studies found that patients with parietal lesions exhibited a lack of ability to report their "urge to act" in the classical Libet's RP experiment, suggesting its necessity in the awareness of action timing (Sirigu et al., 2004). Later animal studies recorded the firing rate elevation of single neurons in monkeys' lateral intraparietal area, when they can proactively time their arm movements compared with the externally cued actions (Maimon & Assad, 2006). Correspondingly, direct electrical stimulations on the inferior parietal region in human patients generate movement intentions (Desmurget et al., 2009).

2.1.1.2. Whether

The *whether* component is about the decision of performing or inhibiting the intention formed. Deficient inhibitory control leads to impulsivity, a tendency to act immaturely on urges or desires, which is a common characteristics in addiction, attention-deficit/hyperactivity disorders, and other neurological and psychiatric disorders (Bari & Robbins, 2013). Therefore, the neural correlates of the *whether* component are always of greater interest. For example, electrophysiological research revealed the P300/delta oscillations generated from medial and pre-central sources are associated with the inhibition in humans (Huster et al., 2013). The P300 is considered to be related to cognitive processes such as attention allocation (Picton, 1992; Polich, 2007), and the delta oscillation could reflect the process of evaluating the motivational saliency of a given stimulus (Knyazev, 2012). Also, psychopharmacological studies indicated GABA, serotonin (5-HT) and noradrenaline as inhibition-related neurotransmitters across species (Eagle et al., 2008; Owens & Kriegstein, 2002).

The common paradigms used for studying inhibition are the stop-signal or go/no-go tasks, both relating to instructed inhibition (Rubia et al., 2001; Verbruggen & Logan, 2009). In the stop-signal task, participants are asked to continuously respond to a certain stimulus and cancel the prepared action when presented with a stop stimulus. In the go/no-go task, participants are presented with a series of stimuli and are asked to respond to a go stimulus, and withhold the response for a no-go stimulus. Therefore, the stop-signal task measures *controlled* inhibition, while the go/no-go task measures *automatic* inhibition, because of their inconsistent and consistent stimulus-stop mapping (respectively) (Littman & Takács, 2017; Verbruggen & Logan, 2008).

A meta-analysis by Zhang et al. (2017) suggested that action withholding in go/no-go tasks and action cancellation in stop-signal tasks have a shared brain activation pattern of the inferior frontal gyrus (IFG) extending to the insula, IPL, and the middle frontal area (including the SMA and pre-SMA). Albeit those areas were argued to be involved in multidimensional cognitive processes, such as attention and working memory rather than pure inhibition control (Criaud & Boulinguez, 2013; Zhang et al., 2017), a review paper on 43 non-invasive transcranial stimulus studies confirmed the crucial roles of pre-SMA and IFG in inhibitory behaviours in general (Borgomaneri et al., 2020).

For intentional inhibition, the adapted go/no-go task is commonly used as an experimental paradigm, providing additional cues for the intentional condition whereby participants can voluntarily choose if they want to respond or not, thereby allowing measurement of voluntary inhibition (e.g., Karch et al., 2009; Schel et al., 2014). There are also adapted stop-signal task that compares the instructed stop versus the voluntary stop for continuous stimulations (Lynn et al., 2016) or actions (Omata et al., 2019). Compared with the brain activities elicited by the instructed inhibition, intentional inhibition consistently activates the rostral cingulate zone (RCZ), including the ACC and pre-SMA, the anterior insula, the dlPFC and the IPL (Dall'Acqua et al., 2018; Lynn et al., 2016). Apart from this "choice network", Zapparoli et al.'s (2017) hierarchy clustering analysis suggested that subcortical structures such as the thalamus and the putamen (a part of the striatum) may also play a crucial role in deciding whether to initiate a voluntary act.

2.1.1.3. What

The *what* component is about choosing one of the homogeneous alternatives. Among the three components, it is the one characterized by the greatest level of cognitive awareness. In some experimental paradigms, the *when* component can also be presented in a *what* form, such as to act at one of several fixed time points (e.g., Krieghoff et al., 2009).

The *what* component has been mostly investigated with the "free selection paradigm" (Lau, Rogers, Ramnani, et al., 2004), which commonly has a control condition and a free selection condition. Both conditions are cued, and the cues can either be directly related to the motor responses, or can indirectly indicate movements by signalling a perceptual target. In the control condition, participants are required to make specified actions; in the free selection condition, participants can choose freely between the given actions.

A typical free selection paradigm can be adjusted from a traditional cognitive paradigm, such as the arrow flanker task that was originally designed to investigate the effects of distracting information by asking participants to respond as quickly and accurately as possible to the direction of the target stimulus (Eriksen & Eriksen, 1974; Hoffman & Eriksen, 1972). The adapted version of the Flanker task added a free-choice condition, whereby participants can respond to either side independent of the stimulus (e.g., Schouppe et al., 2014).

Schouppe et al. (2014) reported that participants did not show statistically significant behavioural differences under different conditions, but the fMRI contrast highlighted the pre-SMA, RCZ, IPL, left middle frontal gyrus, and left insula with a greater BOLD response in the free selection condition. Zapparoli et al.'s (2017) more recent meta-analysis on the *what* component revealed a similar pattern of the "choice network" concerning the *whether* component, and confirmed most of the above activation results except for the insula.

2.1.2. Intentions on high-level cognition

Apart from simple motor actions, real-life decision-making also involves high-level cognitions (e.g., language processing or mathematical calculations). However, due to the theoretical and practical difficulties in separating the intentions of a targeted cognition from other cognitive processes, only a modest number of studies have broached intentional higher cognition (Frith et al., 1991; Jarvstad & Gilchrist, 2019; Ort et al., 2019; Taylor et al., 2008; Wisniewski et al., 2016). Furthermore, the majority of such efforts were not focused on the high-level cognitive processes *per se*, as they looked at the saccadic selection (Jarvstad & Gilchrist, 2019; Ort et al., 2019). In such cases, both processes involve inevitable eye movements, and thereby are not independent of intentional motor actions.

Wisniewski et al. (2016) tried to investigate intentions during mental calculations, whereby participants were given two integers and were asked to add them up, subtract them, or freely choose one of the two operations according to the given cues. However, to select the correct answer, participants still needed to press corresponding buttons, leading to the indivisibility of the mathematical processes and the motor actions. Moreover, it is debatable if addition and subtraction are equivalent alternatives. Though the two operations are at the same level in mathematics, the ability to understand subtraction as a reverse operation of addition develops later than intuitive addition itself (Piaget, 1976).

Frith et al. (1991) studied cognitive intentions and successfully avoided the motor-related confounding effect by requiring participants to either repeat a specific word, or generate words with a given initial letter orally. However, this paradigm could be argued to have methodological shortcomings, as continuously generating words with the given initial might lead to random sequence generation rather than voluntary selection. In a broader definition, random sequence generation is also an intentional task, but the main difference between simple repetition and random generation lies more in the effort of creating variability (as explained in detail in **Section 2.1.3.1**).

In summary, having reviewed the experimental paradigms explained above, two main issues exist in current intentional studies on higher cognition: the intrinsic dearth of research *per se*, and the specificity of existent research paradigms. In the current research, Chapter 3 further elucidates and summarizes these issues, Chapter 4 proposes a novel paradigm for investigating intentions on higher cognition, and Chapter 5 provides the corresponding neural activity evidence for its effectiveness.

2.1.3. Sequential features of intentional decision-making

The WWW model provides a conceptual framework for trial-based intentional actions, but, as mentioned above, human behaviour exhibits interdependencies among consecutive trials. Multiple studies have shown that cognitive processes can be influenced by recently perceived information, and this influence can be either negative or positive (Kiyonaga et al., 2017). The positive trial-to-trial effect is called serial dependence, indicating the drifts in response to the previously received stimulus (Cicchini et al., 2018). Serial dependence has been profoundly investigated by visual perception studies, and has been confirmed with evidence arising from both behavioural (e.g., Fischer & Whitney, 2014; Liberman et al., 2014) and neurological (e.g., St. John-Saaltink et al. 2016) methods.

Conversely, the negative trial-to-trial effect is referred to as proactive interference, which corrupts the performance on the current trial (Kiyonaga et al., 2017). Proactive interference is one of the handicaps of working memory. Both human (e.g., Jonides & Nee, 2006) and animal (e.g., Papadimitriou et al., 2017) studies suggested that performance in memory tasks can be impacted by the previous relevant memory set. Both serial dependence and proactive interference represent the temporal smoothing of recent history, yet they lead to opposite effects on current performance, highlighting the significance of sequential features in cognitive studies. The rest of this subsection reviews two paradigms relevant to the rest of the thesis.

2.1.3.1. Random sequence generation task

One paradigm used to probe the sequential features of intentional behaviours is the random sequence generation (RSG) task. This has no structured or ordered response sets, and merely requires that participants make a series of choices with unpredictable patterns (e.g., Chapanis, 1953).

Early behavioural studies on the RSG task demonstrated that healthy human participants always have response preferences, and are not able to generate stochastic sequences regardless of the kind of symbol used (e.g., numbers, letters, and geometric figures) (Tune, 1964b). The initial explanation for this incapability attributed it to the limited capacity of the working memory (Baddeley, 1983; Tune, 1964a). It was proposed that participants are not able to remember and track back all their choices and thereby undertake repetition. However, more recent reviews suggested this is not the case, because memory impairments do not necessarily affect the RSG performance (Brugger, 1997), and there are also factors related to randomness being independent of memory performance (Towse & Valentine, 1997). For example, when tossing a coin, the tossing behaviour does not require any memory-related processes. Yet, it will lead to random results (head vs. tail) as long as the coin is fair. In fact, a recent study showed that when people were asked to mentally simulate a coin toss in the RSG task, their randomization scores were higher than simply being asked to make the choice randomly or freely (Guseva et al., 2023).

Besides, there are evolutionary views that regard repeating previous choices that have no adverse consequences in a stable environment as an inborn feature, because it helps individuals avoid uncertainty with minimized effort (Buss, 2005). In short, individuals tend to repeat the recent 'not wrong' choice. Since there are no wrong choices in each attempt of random generation, the tendency to memorize recent history can lead to repetition and lower randomness.

At the same time, randomness or variability is considered to be an acquired skill (Gutiérrez & Escobar, 2022; Nergaard & Holth, 2020; Neuringer, 2002). Some reviews deemed it as an operant, meaning the variability can be learned from contingent reinforcements on the diverse behaviours (Gutiérrez & Escobar, 2022; Neuringer, 2002; Stokes et al., 1999). For example, Gutiérrez and Escobar (2022) trained the mice with different levels of variability. They quantified the variability using a *Lag n* procedure, where the mice were rewarded with food only when they made a sequence of 3 lever presses that was different from the *n* number of previous sequences. The results suggested that higher *Lag* criteria lead to higher response variability.

However, Nergaard and Holth (2020) perceived it to be a result of the dynamic interaction between reinforcements and extinctions on individual responses, rather than being enhanced as a whole. In their view, the variability is a joint product of the variability-contingent reinforcement, and immediate consequences of every single response (Doughty & Galizio, 2015). That is, as the reward is contingent, reinforcements and extinctions occur unpredictably across individual responses, which results in variability from a macroscopic perspective.

Though having different explanations for the underlying mechanism, both abovementioned schools agreed that the variability is not an innate behaviour but is derived from operational conditioning.

Therefore, to generate random sequences, subjects need to voluntarily inhibit their automatic tendency towards repetition and execute response change (Guseva et al., 2023; Neuringer & Jensen, 2010; Nickerson, 2002). In this vein, it is unsurprising that an increased load on ancillary cognitive requirements during RSG interferes with subjects' task performance (e.g., Towse, 1998; Towse & Cheshire, 2007). This speculation corresponds with the brain stimulation evidence, which posits that stimulations on the dlPFC (the brain area associated higher-order cognitive processes, including inhibition and execution) influence the RSG performance. A continuous 60-second, 1 Hz repetitive transcranial magnetic stimulation (rTMS) on the left dlPFC enhanced randomness in RSG (Knoch et al., 2005). Similarly, the focal application of transcranial static magnetic field stimulation (tSMS) on the left dlPFC also increased the randomness index of the generated sequence (Soto-León et al., 2023). On the other hand, six pairs of 5-second, 10 Hz rTMS and 5-second rest in the same area decreased the performance (Knoch et al., 2005).

However, RSG is a minimalist paradigm with only one kind of symbol used in each experiment. Although it provides important insights into the sequential features of intentional behaviours, it lacks ecological validity, as behavioural patterns in real daily life are more varied and dynamic.

2.1.3.2. Task set and task switch

Humans inevitably engage in multi-tasking activities because of the dynamic environment in which we live. To fulfil different purposes at the same time, and prevent the information from different tasks from interfering with each other, individuals need to establish and remember an association between stimulus and the responses for each task. This kind of stimulus-response association has been termed a *task set* (e.g., Kiesel et al., 2010; Sakai, 2008). In cognitive studies, a task set is a configuration of the cognitive processes involved in a task, which directly influences participants' task performance (Koch et al., 2018). Early imaging studies suggested that the task set in general correlated with the activations of the prefrontal area, including the anterior prefrontal cortex (Sakai & Passingham, 2003b), dlPFC (BA 46) (Sakai & Passingham, 2006), and ventral prefrontal cortex (Bengtsson et al., 2009) (**Figure 3**).

Task sets are commonly studied with a task-switching paradigm (**Figure 4**). In a broad definition, task switching is also a kind of multi-tasking, because, although it does not require performing two or more tasks overlap in time, it does need the subject to keep different task sets in mind at the same time (Poljac et al., 2018). It has earned extensive acknowledgment that toggling between different task sets will result in a switch cost in task performance, manifested by the extended reaction times, the decreased accuracy, or both (Vandierendonck et al., 2010). That is, because additional cognitive effort is required for task switching, people will need additional time to complete the task, leading to delayed response. Alternatively, when responses are required within a limited time, accuracy may decrease. If instructions demand both quick and accurate responses simultaneously, individuals may exhibit delays and a decline in performance. The switch cost is a reflection of the reconfiguration of task sets to prepare for the coming event and the proactive interference of previous events (Vandierendonck et al., 2010).

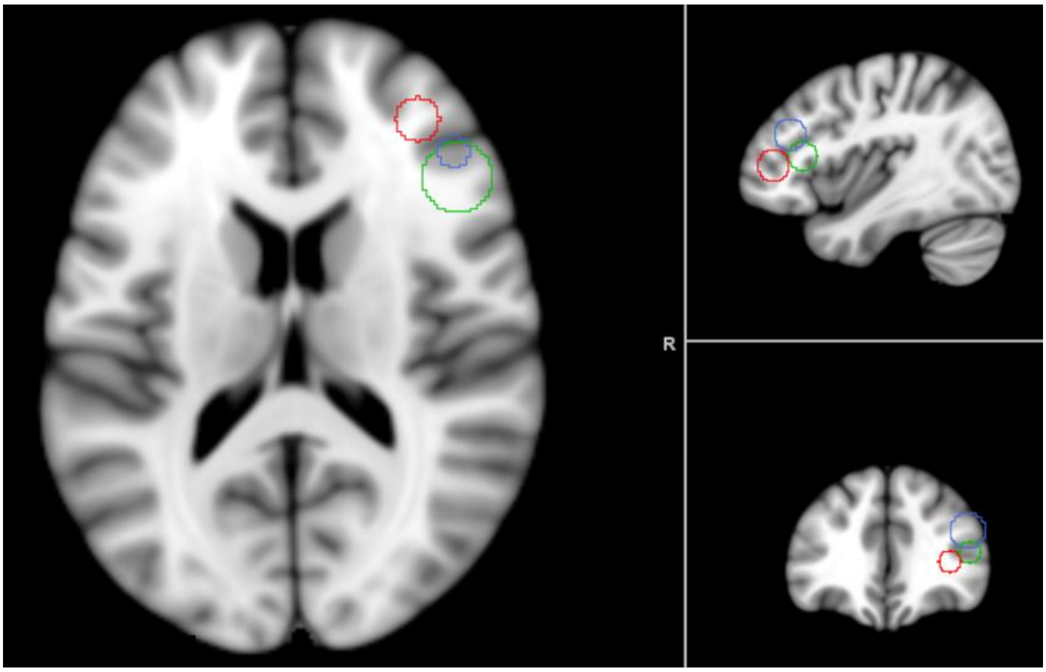

Figure 3. The task-set-related brain areas are presented in the MNI space. Red: Anterior prefrontal cortex (36, 44, 6); Green: Ventral prefrontal cortex (46, 28, 12); Blue: BA46 (45, 30, 20). The ROIs are generated from the peak coordinates provided by the abovementioned studies with a radius of 10 mm.

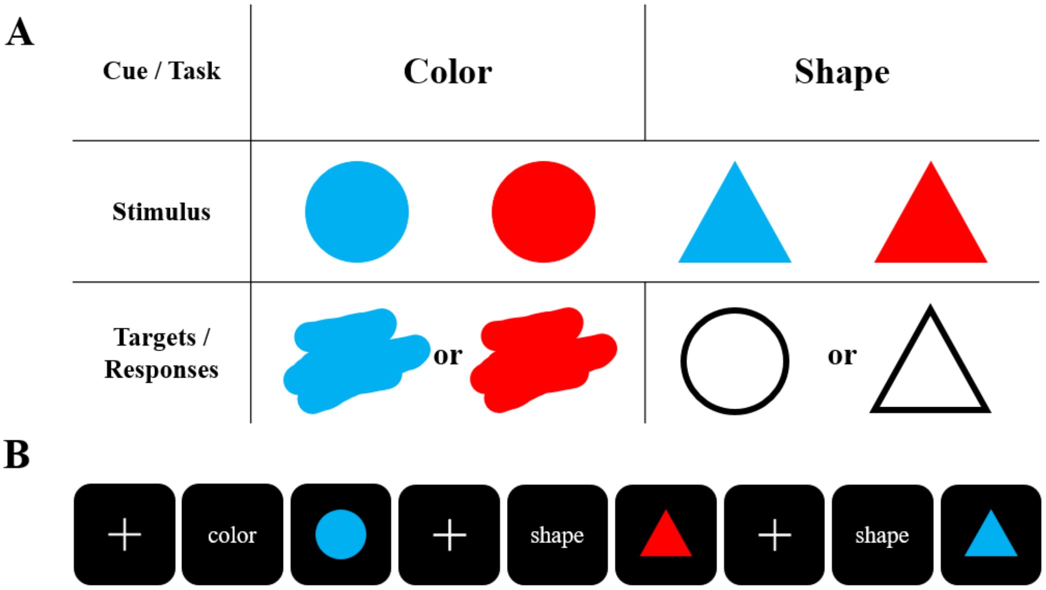

Figure 4. Task sets and task-switch paradigm. (**A**) An example of two different task sets. The colour and shape tasks share the same stimulus, but look for different targets due to their discrepancy in stimulus-responses mapping. (**B**) An example of a classical task-switch paradigm. Participants were explicitly instructed on tasks to perform in each trial, allowing the investigation of the task stay and task switch.

The classical task-switching task indicates the switch point with either sequence features (e.g., Rogers & Monsell, 1995) or explicit cues (e.g., Hsieh & Liu, 2005), which force participants to make a change. Arrington and Logan (2004) proposed the voluntary task-switching paradigm that allows the study of the intentional cognitive transition. This paradigm allows subjects to switch tasks whenever they want, as long as they complete each task roughly the same number of times by the end of the experiment. Similar to the classical task-switching paradigm, subjects also show switch costs in the voluntary tasks switch (Arrington & Logan, 2004), i.e., when subjects choose to switch between tasks spontaneously. This similarity adhered to the results from later neuroimaging studies. The fMRI imaging suggested that the task set switching is consistently correlated with the brain activities at the ventral prefrontal cortex (vPFC), regardless of whether the switch is forced or self-initiated (Bengtsson et al., 2009).

Jurczyk et al.'s (2022) recent EEG study also detected a common preparatory potential for the voluntary and forced switch by MVPA, and reported that reduced target-related negativity (TRN) was found in the voluntary switch trials, but not in the forced ones. TRN is a neurophysiological marker for attentional and inhibitory control (Polich, 2007), indicating that the voluntary switch is probably less interfered with by the previous event, or is more germane to the task set reconfiguration (Jurczyk et al., 2022). The implication matched early behavioural results indicating that the switching cost in the voluntary switch trial is lower than in the forced one (Arrington & Logan, 2005).

2.1.3.3. Limitations

The RSG and the task set partially explain the insufficiency of pure trial-based analysis, demonstrating the effects of recent history on coming events. However, natural behaviours are not trial-based and usually involves chains of sensory-cognitive-motor loops that cannot be easily separated into discrete trials (Huk et al., 2018). In other words, conventional trial-based paradigms restrain the understanding of cognition and perception. Continuous paradigms can be an alternative choice, as they allow experimenters to examine effects spanning across multiple actions (Huk et al., 2018).

2.2. Strategic decision-making

As highlighted above, continuous paradigms can have more dynamic and various information inputs for decision-making, as individuals need to find a way to efficiently utilize them. To employ continuous paradigms in research, two main questions need to be addressed: how to have a more naturalistic task that simulates the realistic environment, while at the same time allowing a certain level of control for experimental needs; and figuring out how people will deal with overwhelming information input and make proper choices with conditions of speed and frugality. This section reviews related literature to discern potential solutions to both issues, and provide a specific example of the combination of these two aspects.

2.2.1. Video games as decision-making paradigms

With the rapid advancement of technology, it has become feasible to track and record complicated behaviours in psychological or brain imaging studies, with a high temporal resolution. Researchers have started to use experimental paradigms that can bridge the gap between controlled laboratory experiments and real-world complexities. Video games gained prominence in this trend, because of their easy accessibility and diversity of genres (Dale et al., 2020).

Their easy accessibility means that most individuals have encountered video games at some juncture in their lives, making them a readily comprehensible tool in experimental settings. For instance, in terms of health psychology, video games are widely used as home-based interventions for psychological or neurological disorders, such as attention-deficit/ hyperactivity disorder (ADHD) (Peñuelas-Calvo et al., 2022), depression (Ruiz et al., 2022), and Parkinson's disease (Gallou-Guyot et al., 2022). Compared with traditional cognitive behavioural therapy, video games are observed to be more enjoyable and result in higher adherence (Gallou-Guyot et al., 2022; Ruiz et al., 2022).

The diversity in video game genres reflects the variety of in-game goals and the corresponding cognitive needs of players (Granic et al., 2014; Halbrook et al., 2019), allowing video games to be employed in a range of different research. For example, action games could enhance attentional control (Bavelier & Green, 2019), while focused video games with repeat practice and clear feedback may facilitate executive functions (Mayer et al., 2019). For experiments with more specific needs, a video game can also be customized to suit specific goals. Therefore, it is also possible to customize the features and the goals of a video game to satisfy the needs of individual studies, and this highly goal-oriented model perfectly fits with research on intentional decision-making.

2.2.2. Heuristics as a more naturalistic decision-making

When encountering situations of complicated decision-making, the classical logic and probability view considers the human mind as a mathematical machine that can gather all the available information to optimize the choices and make the best solution (Gigerenzer, 1989; Marshall, 2009). However, there are many situations where optimization can be impossible because of the characteristics of the environment (e.g., limited information inputs or time constraints) or the individuals (e.g., limited cognitive source or stress) (Gigerenzer, 2008). In those cases, an alternative way to satisfy the goal is to apply heuristics. The most prominent feature of a heuristic is to ignore a part of the information (Shah & Oppenheimer, 2008). It can help to make decisions more quickly, frugally, and accurately than complex computations under some circumstances (Gigerenzer & Gaissmaier, 2011).

Because of their robustness and potential efficiency in the uncertainty, heuristics are widely employed in nature. A part of the selection of the heuristics is hardwired by evolution (Gigerenzer & Gaissmaier, 2011). Even slime mold, a simple protist, can use heuristics to decide residency and departure (Latty & Beekman, 2015). More importantly, different kinds of slime molds can use different heuristics. For example, the *Physarum polycephalum* values food quality and environmental safety, while the *Didymium bahiense* only cares about the food amount (Latty & Beekman, 2015). Nevertheless, various species can also share the same heuristic. The gaze heuristic is a good example; this is usually used to catch a moving target, upon which the agent fixates and adjusts speed to keep a constant angle of gaze (Hamlin, 2017). This heuristic is used by both humans and other animals (e.g., eagles), with roots in predator-prey coordination (Gigerenzer, 2021).

Besides phylogenesis-based heuristics, there are also ontogenetic heuristics that are driven by individual learning (Gigerenzer & Gaissmaier, 2011). Creatures that are significantly more advanced than slime molds, such as ants, will further present individual differences in heuristics. Under the same food-searching circumstance, some black garden ants prefer the fixed direction, while others will just head to the most salient cues (Oberhauser et al., 2020). Besides, the social process will also play an important role in heuristic choices (Gigerenzer & Gaissmaier, 2011). For example, individual vervet monkeys are always able to find and use the most efficient heuristics in planning feeding routes, but when competing with others, only the dominants will continue this strategy, whereupon subordinates will adjust their heuristics to go for the nearest neighbours (Teichroeb, 2015). Humans, as advanced primates, employ even more heuristics as social tools, such as focusing on the similarities in developing trust, seeking strength or safety in numbers, or starting with cooperative response in interaction (Cardoso et al., 2020; Marsh, 2002b; Rand et al., 2014).

A recent neuroimaging study indicated that the discrepancy between heuristic and the optimal choices is positively correlated with the activities in the dorsal medial prefrontal cortex (DMPFC), extending to pre-SMA, ACC, dorsal striatum, and inferior frontal gyrus (IFG) (Korn & Bach, 2018). This pattern is very similar to the *whether* component of the WWW model, implying that ignoring a part of the contextual information is a process of voluntary inhibition.

2.2.3. Pac-Man as an example

The classic arcade game Pac-Man (Namco) is one of the typical examples that can be used as a continuous paradigm to investigate heuristic-based intentional decision-making (**Figure 5**).

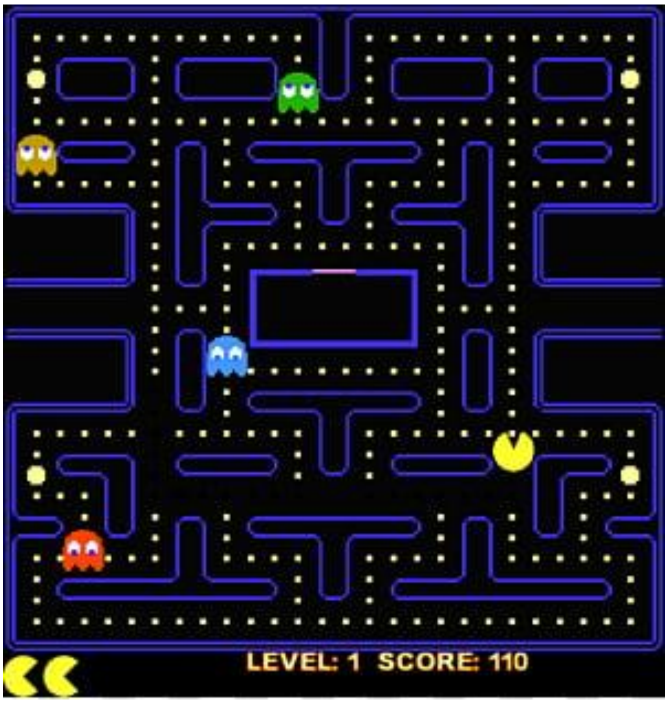

Figure 5. The Pac-Man game.
Pac-Man is a highly goal-oriented game, where players need to control eponymous yellow circular "Pac-Man" to navigate in the given maze, collect the pellets earning the scores, and avoid the ghosts to win the game. Compared with classical lab-based paradigms, the Pac-Man game is more dynamic and complex.

Pac-Man made its debut in May 1980 and quickly became a worldwide phenomenon. In the game, players need to control a yellow, circular character called Pac-Man, navigating a maze while eating pellets and avoiding ghosts. Early researchers already commented on Pac-Man as "an action system where skills and challenges are progressively balanced, goals are clear, [and] feedback is immediate and unambiguous" (Bowman, 1982, p.15). Because of these features, Pac-Man has been used as a task for exploring artificial intelligence in rule-based reinforcement learning and other evolutionary algorithms (DeNero & Klein, 2010; Rohlfshagen et al., 2018; Szita & Lorincz, 2007). However, although algorithms can play the game, they do so differently from living creatures, because they gather all available information all the time, while organisms select information to focus on based on their ecological rationality. For example, with the difficulty level of the game increasing, human players spend more time looking at the avatar (i.e.: the Pac-Man), rather than the other game elements such as the ghosts (Lankes & Stöeckl, 2020).

A recent monkey study by Yang et al. (2022) further illustrated this heuristic-based decision-making model concerning strategies during gameplay. They explained the monkeys' behaviours in terms of a strategy-based hierarchical model, whereby the players achieved an accuracy rate exceeding 90%. The model suggested that the monkeys adopted the take-the-best heuristic for Pac-Man in general, meaning they only followed one dominant strategy for decision-making at a given moment. Compound strategies were assembled with basic strategies and only used to handle particular game situations.

Chapter 6 described a Pac-Man-based study inspired by the abovementioned monkey research, aiming at exploring the behavioural differences between humans and monkeys and revealing the potential neural correlates involved in this process.

2.3. Multi-modal measurements

To provide physiological evidence for intentional decision-making, multiple data modalities were used, including fMRI (Chapters 3 and 6), MEG (Chapter 5) and eye movement (Chapter 6). The two brain imaging modalities have different advantages, rendering them suitable for different studies. This section briefly overviews these physiological measurements.

2.3.1. Magnetic Resonance Imaging (MRI)

MRI generates images using strong magnetic fields and radio impulses (Ai et al., 2012). Since its invention in the 1970s, MRI has been developed and clinically applied worldwide for nearly 50 years. It is now also one of the most popular neuroimaging tools in cognitive neuroscience, because of its non-invasiveness and high spatial resolution (with precision in the millimetre range). Two different kinds of MRI were employed in this research for different purposes.

Structural MRI was used to present the anatomical details of the brain. It can generate clear contrasts between tissues by measuring their water contents according to the number of protons (i.e.: ^1H).

Functional MRI was used to measure the change in brain activity induced by external stimuli or spontaneous modulations (Bandettini, 2012). It uses the blood oxygen level-dependent (BOLD) contrast that is sensitive to the concentration of de-oxyhemoglobin in the blood flow (Glover, 2011). The change in the BOLD response directly relates to the change in brain metabolism (or its energy consumption) (Peppiatt et al., 2006), and indirectly implies neural activities via the neurovascular coupling (Lecrux & Hamel, 2011). Due to the temporal delay in the heamodynamic response, fMRI inherently has a lower temporal resolution than direct neural activity measurements such as EEG or MEG. Additionally, the BOLD signal is not able to easily distinguish between neuromodulations and excitatory or inhibitory neural activities, as they all to some extent relate to metabolism. However, despite its limitations as an indirect measurement, fMRI is still a valuable tool for systematically investigating the functional localization of target cognitive processes or behaviours (Logothetis, 2008).

Chapter 3 presents an activation likelihood estimation (ALE) meta-analysis undertaken for the positron emission tomography (PET) and the fMRI studies on intentional decision-making, to reveal the common neural correlates of voluntary selections. Chapter 6 reports on the use of fMRI to detect the brain regions involved in heuristic strategy decision-making.

2.3.2. Magnetoencephalography (MEG)

Directly recording neural electrical activities is the gold standard for understanding the exact timing and characteristics of neural responses. Using single-electrode recording, multiple-unit recording (MUA), and local field potential recording (LFP), researchers have revealed neural firing rate and brain oscillations that reflect various cognitive processes (Hubel & Wiesel, 1962; Quiroga et al., 2005; Tort et al., 2008). However, all those recordings involve invasive procedures and hence are mainly used in animal studies or on patients who need to undergo invasive procedures in clinical settings.

Scalp electroencephalogram (EEG) was used to spot brain waves in a brain injury patient (Berger, 1931). Since then, EEG has been widely used in neuroscience as a non-invasive technique that directly records macroscopic brain electrical activities from the sensors placed on the scalp. EEG can detect the difference in the electrical potential changes of the coherent activation of a large number of pyramidal neurons (Murakami & Okada, 2006). The smallest possible area of the detectable current can be modelled as an equivalent current dipole (ECD). The complete current distribution in the brain can be broken down into the contribution of many dipoles distributed across the cortical sheet (Darvas et al., 2004).

However, EEG signal is affected by reference choices, as it can only detect the differences between electrodes. As the voltage fluctuations recorded by EEG sensors are influenced by the conductive properties of the tissues above brain tissues, such as the skull, cerebrospinal fluid, and scalp, reference electrodes are required to measure a baseline. The reference region can be at mastoids, earlobes or vertex. Mastoid reference is the most common choice with balanced advantages, earlobe reference is less affected by muscle artefacts and scalp activity, and vertex reference can help minimize spatial biases in recording. Second, EEG signal is highly sensitive to the conductivity of the brain, skull, and extracranial tissue, as it depends on the ohmic current flow throughout the head. Those unknown conductivity profiles limit the precision of spatial localization for recorded activities (Darvas et al., 2004). The skull and scalp can act as a low-pass filter, filtering high-frequency components that can be relevant to cognitive processes (Srinivasan et al., 1998). Additionally, EEG signals can be contaminated by eye movement artefacts, due to related muscle activities (Yuval-Greenberg et al., 2008). These artefacts are considerably larger in amplitude than typical EEG signals.

Invention of magnetoencephalography (MEG) by the early 1970s provided an alternative solution to these issues (Cohen, 1972). Ampere's Law indicates that magnetic fields are related to the electric current produced within them. Therefore, the

ECDs can also change the magnetic field around them. MEG takes advantage of this, and detects actual physical magnetic value at the local area instead of relative electrical differences depending on the references, which avoids the reference problem and the unknown conductivity profile (Lopes da Silva, 2013). This gives MEG a better signal-to-noise ratio, and thereby improves its spatiotemporal resolution.

The strength of the magnetic field changes caused by ECDs is on the scale of 10^{-15} T, while the earth's magnetic field is on the scale of 10^{-5} T. Therefore, the current generation of MEG has to use extremely sensitive sensors of superconducting quantum interference device (SQUID) in an electromagnetically isolated chamber, enabling it to capture reliable signals, and shield the signals from earth's magnetic field or other potential magnetic artefacts (Hansen et al., 2010).

Chapter 5 reports on the use of MEG to identify the spatiotemporal discrepancies between intentional choices and the cognitive processes for different cognitive tasks sharing the same stimulus.

2.3.3. Eye-tracking

Eye tracking is a non-invasive method that can monitor and record eye movements, eye positions, and eye fixations. The eye tracker used in this research works with pupil centre corneal reflection (PCCR), in which the pupil is illuminated with an invisible near-infrared or infrared light, and then the reflection generated on the cornea is captured using an infrared camera, to delimit the centre of the pupil. Eye movements, eye positions, and eye fixations are all deduced from the pupil centre and the corneal reflection via a mathematical algorithm (Holmqvist et al., 2011).

Because of its significance, the pupil centre delimitation needs to be accurate. The accuracy relies on a correction for the natural anatomical angle (known as angle kappa) between the optical and visual axes (Artal, 2014). The optical axis goes through the centre of the entrance pupil, and is perpendicular to the cornea. It is the light pathway that can be captured by the camera. In comparison, the visual axis connects the fixation point and the centre of the fovea. To calibrate the angle kappa, participants need to look at a series of fixed points on the screen. The eye-tracking system can then examine the pupil positions for those points to calculate the actual visual axis (Harezlak et al., 2014).

2.3.3.1. Pupillometry

Pupillometry refers to the measurement of pupil dilation. The pupil is the round opening in the centre of the iris, whose radius can change according to the external luminance to control the amount of light entering into the eye. In cognitive neuroscience, with the environmental confounders being controlled, pupillary responses can be the results of physiological changes or psychological processes, including but not limited to autonomic nervous system activity, arousal level, emotional reaction, attention change, and cognitive controls (Laeng et al., 2012; Mathôt, 2018).

Chapter 6 uses pupil dilation as an indicator of changes in decision strategy to guide subsequent fMRI analyses (De Gee et al., 2014; van der Wel & van Steenbergen, 2018)

2.3.3.2. Saccades

Saccades are ballistic eye movements that result in abrupt relocation of eye fixation. It is a rapid behaviour that cannot be easily interrupted once initiated. The usual length of a saccade is less than 50 ms, but it plays a significant role in visual perception, especially for gaining environmental information (Ibbotson & Krekelberg, 2011). Similar to pupillometry, saccades can also reflect cognitive controls such as attention shifts (Fischer & Weber, 1993; Perry & Zeki, 2000) or action preparation (Watanabe et al., 2013).

Chapter 6 uses the number of saccades in a unit of time as a marker to examine different heuristic strategies during decision-making.

3. Functional localization and categorization of intentional decisions in humans: a meta-analysis of brain imaging studies

3.1. Introduction

To fulfil our goals or desires, we constantly interact with the external environment through our voluntary behaviour. In contrast to reflexes that are beyond volition (e.g., a knee-jerk reflex), voluntary behaviours are characterised by choice (Passingham, 1995). Volition characterises the intentional choice or decision between multiple options, where the choice is not sufficiently explained by differences in expected or explicit rewards. The concept of intentional decision refers to this fundamental ability of human cognition: acting voluntarily based on internal or endogenous intentions (Marken, 1982).

The role of intention in decision-making occupies a broad spectrum. At one extreme lies externally guided perceptual decision such as stopping at a red traffic light, for which the involvement of internal intention is low because learned rules can dictate a correct choice (even if one can voluntarily break such rules). At the other extreme lies improvisational behaviour in music, painting or dance, which can be strongly determined by moment-to-moment intention. In between lies the common scenario of intentional decision-making, where the external environment constrains only which options are available while internal intentions dictate which of those options to choose. The ability to choose actions, cognitive strategies and behaviours in this way plays a key role throughout the life span and is essential to our understanding of human cognition. In child development from birth to 12 months, actions such as grasping and its coordination with vision gradually emerge from simple reflexes (Beilin & Fireman, 1999; Lewis, 2010; Piaget, 1976). In patients with neurodegenerative disorders, the inability to engage appropriate intentional behaviour can manifest as apathy (Starkstein et al., 2001), impulsivity (Dalley et al., 2011) and perseveration (Hughes et al., 2013). In addition, intentional behaviour is a foundation of social interactions via cooperation and collaboration (Bratman, 2017).

Intentional actions have been characterised by three components in the *what-when-whether* (WWW) model: (1) *what* action to perform, (2) *when* to perform it, and (3) *whether* to perform the chosen act (Brass & Haggard, 2008). The WWW model is based on evidence from two interlinked lines of research. First, the *when* component has been investigated by examining neural signatures immediately prior to intentional actions. Libet's intentional action paradigm is a classic example of this type (Libet, 1985; Libet et al., 1983), which has been used to localize electrophysiological and BOLD activity in the medial-frontal cortex preceding the conscious awareness of subsequent voluntary actions (Fried et al., 2011; Lau, Rogers, Haggard, et al., 2004) (but see Trevena and Miller, 2002; Nachev and Hacker, 2014 for critical evaluations). Second, research on the *what* and *whether* components, the focus of the current study, commonly use variants of the "free-choice" paradigm[1], to determine the neurocognitive mechanisms of voluntary decision processes.

In a typical free-choice paradigm, participants make a voluntary choice from multiple alternatives on each trial. The available alternatives can either be similar to each other (Zhang et al., 2012) or distinct (e.g., to choose voluntarily between stopping and acting in the adapted Go/NoGo task, Karch et al., 2009). Importantly, participants are made aware that all available options are homogeneous in terms of their objective outcomes, and the tasks do not introduce or manipulate rewards or costs according to the choices made. In other words, the task is not to identify a

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[1] In the literature, several terms have been used to refer to the free-choice paradigm, such as "voluntary selection" (Forstmann et al., 2006), "willed action" (Lau, Rogers, Ramnani, et al., 2004), "internal selection" (Van Oostende et al., 1997), "self-initiated" (Cunnington et al., 2002), and "chosen actions" (Zhang et al., 2012). The current study uses these terms interchangeably.

correct response. Rather participants can choose any of the available options. The alternate options are equally appropriate, and one's decision must come from intention. The intention could be influenced by endogenous factors, including subtly differential effort, preferences (Zajkowski et al., 2020), habits (Graybiel, 2008), incorrectly inferred arbitrary rules for the task, and recent actions (Phillips et al., 2018; Zhang & Rowe, 2015).

In recent years, there has been a substantial number of brain imaging studies adopting free-choice paradigms, enabling a well-powered meta-analysis. The current study focused on the hemodynamic and metabolic contrasts of intentional choice vs. specified response, which is the most widely reported task-related effect across free-choice studies. Here, specified responses serve as a control condition, in which participants need to make specific responses determined by the experimenter, rather than choose voluntarily from the same set of options in the free-choice condition. Therefore, the contrast between the two conditions offers a window to investigate brain activation associated with intentional behaviour, controlling for the common effects of stimulus encoding and response initiation.

The objectives of this study were three-fold. First, to identify brain regions consistently activated by intentional decision, we performed a systematic search of BOLD-fMRI or PET studies of intentional decision and conducted an activation likelihood estimation (ALE) meta-analysis. Increased BOLD and PET responses during intentional choices are commonly reported in a frontoparietal network centred on the medial frontal cortex (Brass & Haggard, 2008). However, some studies also observed activations external to this network during intentional behaviour, in particular in the insula (Brass & Haggard, 2010; Dall'Acqua et al., 2018; Thimm et al., 2012) and the inferior frontal gyrus (Wisniewski et al., 2016). Because results from a coordinate-based ALE meta-analysis are pooled from a large number of participants in multiple studies, they usually have higher statistical power than a single experimental study (Walker et al., 2008).

Second, we conducted further contrast and conjunction meta-analyses, assessing the distinct and overlapping neural correlates between different types of intentional behaviour. As highlighted above, the nature of options in a free-choice paradigm can vary significantly between studies and hence involve different cognitive processes. We reviewed all studies to date that met our predefined inclusion criteria (see *Study selection and inclusion criteria*). Based on the experimental design and implementational details of individual studies, we proposed four categories of the free-choice paradigm (**Figure 6**): reactional intention (RI), perceptual intention (PI), inhibitory intention (II) and cognitive intention (CI).

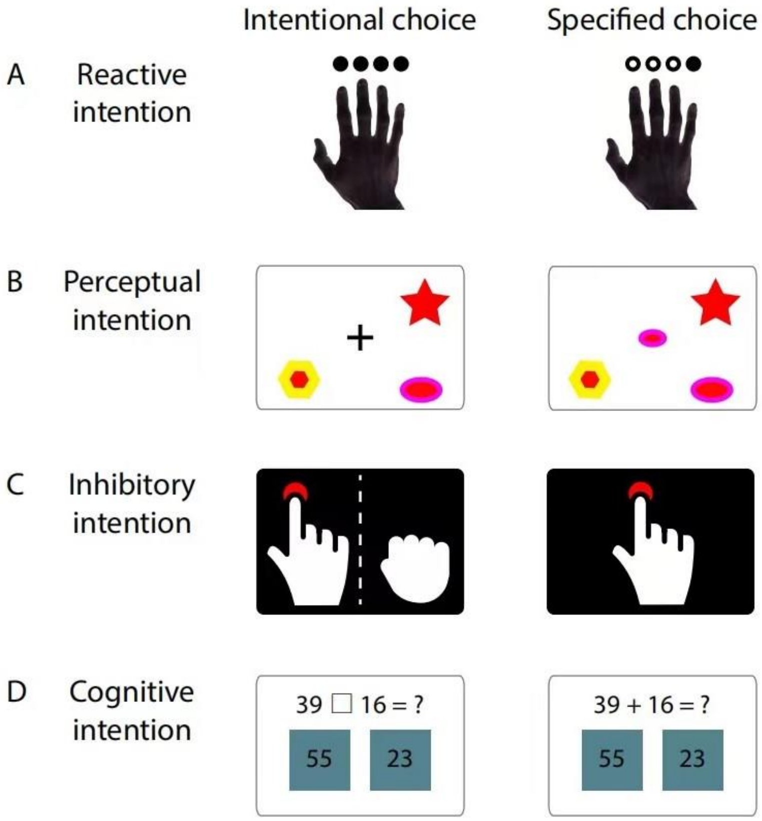


Figure 6. Schematics of four categories of intentional decision and their corresponding specified response conditions. (**A**) In the reactive intention (RI) paradigm, task cues indicate directly available options (e.g., any of the four fingers as in Rowe et al., 2010). (**B**) In the perceptual intention (PI) paradigm, task cues contain perceptually different options associated with options. For example, in Lau et al., (2004b), participants could choose any objects appeared the screen, and in the

specified response condition, participants needed to choose the object to match the fixation cue. (**C**). In the inhibitory intention (II) paradigm (e.g., Dall'Acqua et al., 2018), one of the options is to abandon or abort an intended action, and hence participants make voluntary choices between Go and Stop. In the corresponding specified response condition, participants are instructed to execute or cancel their actions. (**D**). In the cognitive intention (CI) paradigm, participants choose between different operations that require higher-level cognitive processing (e.g., addition vs. subtraction as in Wisniewski et al., 2016). Behavioural responses are dependent on the execution of the chosen operation.

Third, to undertake an exploratory data-driven analysis, testing whether consistent BOLD-fMRI/PET patterns of intentional behaviour correspond to specific cognitive processes. We quantified the similarity between the meta-analytical whole-brain activation pattern estimated from free-choice studies and brain activation patterns from 100 specific cognitive topics, extracted from a database of over 11,000 brain imaging studies (Rubin et al., 2017; Yarkoni et al., 2011). This reverse inference approach raises hypotheses about the putative cognitive processes underpinning intentional behaviour, where different cognitive processes are associated with specific networks of the human brain. We then reviewed results from these meta-analyses in the context of current cognitive models of intentional choice.

3.2. Materials and Methods

3.2.1. Study selection and inclusion criteria

We defined intentional choices as experimental paradigms involving self-initiated, voluntary selections of an action from two or more alternatives (Zhang et al., 2012). The experimental procedure would need to instruct participants that there are no correct or incorrect choices, and they should make a fresh choice among available alternatives on each trial, regardless of what they had done in previous trials. This contains an expectation that participants should not stick to doing always the same thing or produce any obvious predefined sequence of choice, but still allows participants to make voluntary choices in each trial. The advantages of this instruction outweigh the disadvantages, as by doing this, researchers can collect more balanced data for proper statistics and hypothesis tests with limited resources. This type of intentional choices differs from conventional goal-directed or externally cued behaviour, in which a correct or instructed response could be defined or identified. We focused on existing studies investigating the *"what"* (which action to choose) or "*whether*" (whether or not to execute an action) component of intentional behaviour (Brass & Haggard, 2008). Studies focusing on the "*when*" component (i.e., when to execute, as in Libet et al., 1983) is not considered here, because of the low temporal resolution of haemodynamic and metabolic responses.

We conducted a systematic literature search in accordance with the PRISMA guidelines (Moher et al., 2015) to identify brain imaging studies of intentional choice. The literature search was performed on both PubMed and PubMed Central (PMC) databases, because the two databases may contain different publications. The PubMed database was searched with specified keywords as following: ("volitional decision" OR "volitional choice" OR "voluntary decision" OR "intended decision" OR "intentional decision" OR "voluntary choice" OR "intended choice" OR "intentional choice" OR "free decision" OR "free choice" OR "volitional action" OR "voluntary action" OR "intended action" OR "intentional action" OR "free action" OR "volitional selection" OR "voluntary selection" OR "intended selection" OR "intentional selection" OR "free selection") AND ("fMRI" OR "functional Magnetic Resonance Imaging" OR "BOLD" OR "Blood Oxygen Level-Dependent" OR "Positron Emission Tomography"). For the PMC database, the same keywords were employed in the interrogation and a filter on the search field was set to "Body - Key Terms" to constrain search in a more concrete range. The search results from PubMed and PMC databases were combined with duplicated records removed, resulting in 332 publications as of October 2020.

We then inspected every publication from the literature search (**Figure 7**). The further inclusion criteria for our meta-analysis were applied as follows:

i. Studies reported first hand data that comes from experiments rather than reviews or meta-analysis. 291 of the 332 publications met this criterion.

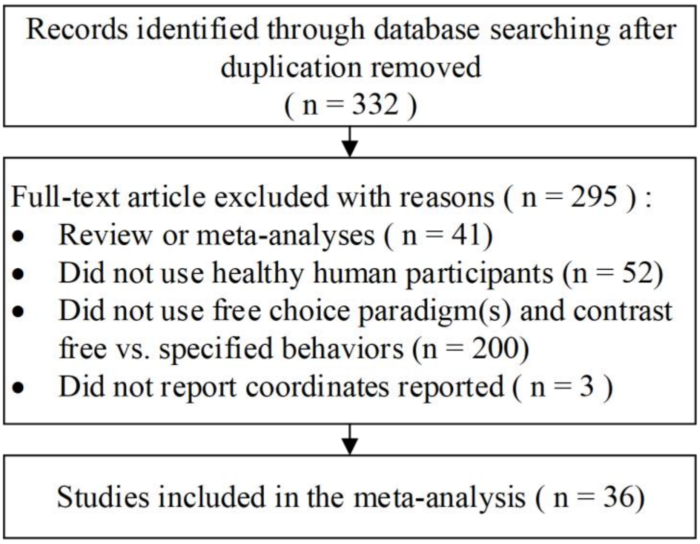
ii. Studies included results from healthy adult human participants. 239 of the remaining 291 publications met this criterion.

iii. Studies employed an intentional choice paradigm(s) and reported a fMRI/PET contrast of intentional choice vs. specified response conditions. Here, in the specified response condition, participants responded with the same set of possible actions as in the intentional choice condition, but the identity of which action to respond (or whether to respond) was determined by the experimenter. 39 of the remaining 239 publications met this criterion.

iv. Studies reported whole-brain analysis with MNI or Talairach coordinates of the cluster peaks. 36 of the remaining 39 publications met this criterion.

v. If more than one appropriate contrast with the same group of subjects were reported in a single study, only one contrast was included in the meta-analysis.

Figure 7. The PRISMA style flow diagram of study selection



Records identified through database searching after duplication removed (n = 332)

Full-text article excluded with reasons (n = 295) :

- Review or meta-analyses (n = 41)
- Did not use healthy human participants (n = 52)
- Did not use free choice paradigm(s) and contrast free vs. specified behaviors (n = 200)
- Did not report coordinates reported (n = 3)

Studies included in the meta-analysis (n = 36)

3.2.2. Activation Likelihood Estimation (ALE) meta-analysis of intentional decision

After the screening, the 36 fMRI/PET studies met the selection criteria, which included 38 independent experiments for meta-analysis. 26 studies recruited only right-handed participants, 1 study recruited thirteen right-handed and one left-handed participants, and the other 9 studies did not specify participants' handedness. These studies contained a total of 683 participants and reported 340 peak foci of increased fMRI/PET responses to the intentional choice vs. specified response contrast. Less than 3% foci (10 out of 340) were out of the brain mask in the GingerALE toolbox (Eickhoff et al., 2012; Turkeltaub et al., 2002), which was within the normal range due to spatial smoothing and potential registration errors (Eickhoff et al., 2012). Therefore, all foci were included in the study to maximize the usage of the original dataset. For activation foci reported in the Talairach space, we converted them to MNI coordinates using the Lancaster algorithm (Lancaster et al., 2007).

The coordinates-based activation likelihood estimation (ALE) meta-analysis was conducted over all the 38 experiments using the Ginger-ALE toolbox (www.brainmap.org, version 3.0.2) (Eickhoff et al., 2012; Turkeltaub et al., 2002). This analysis aimed to determine, across independent experiments, significant spatial convergence of fMRI/PET activation probabilities for the intentional choice vs. specified response contrast, under the null hypothesis that the activation foci are distributed randomly throughout the brain. First, for each experiment, the activation probabilities of all foci reported were modelled as 3D Gaussian probability distributions with their full-width half-maximum (FWHM) estimated from the between-subject variance of the experiment (Eickhoff et al., 2009). Second, an ALE activation map was then calculated by combining all experimental-level activation maps, yielding a voxel-wise ALE score to quantify the convergence of results across experiments at each voxel location. Third, an analytical approach was used to determine the null distribution of voxel-wise ALE scores. A non-parametric *p*-value map of ALE scores was then generated under the null distribution (Eickhoff et al., 2012). Finally, the *p*-value map was thresholded at $p<0.001$ and corrected for multiple comparisons across voxels using a cluster-level family-wise error (FWE) correction from 5,000 permutations (*p*<0.01, cluster-corrected).

3.2.3. Paradigm-specific meta-analysis

We categorized the 38 experiments into four intentional choice paradigms based on their experimental designs and procedures (**Figure 6**). The first category of paradigm is referred to as reactional intention (RI), in which participants voluntarily choose cues that associate to specific motor actions. We considered this category as the simplest form of intentional choice because a cue in the RI paradigm is directly linked to a target action. The second category is referred to as perceptual intention (PI), in which participants voluntarily choose between perceptually distinct targets (e.g., icons or pictures). Compared to the RI paradigm, the PI paradigm involves an additional matching process: an option is associated with a perceptual target, and the target is then associated with a specific motor action. The third category is referred to as inhibitory intention (II), in which at least one option is not to act (i.e., withholding responses). A cue in the II paradigm is associated directly with a specific action or the inhibition of action. The final category is referred to as cognitive intention (CI). The free choice condition in CI paradigm requires the participants to choose between options that require higher-order cognitive processes such as doing arithmetic or generating words. The categorization yielded 17 studies on RI paradigm, 9 on PI paradigm, 7 on II paradigm, and 5 on CI paradigm.

For studies employing each of the four paradigm categories, we performed the same ALE meta-analysis to identify the spatial convergence of fMRI/PET activation for the intentional choice vs. specified response contrast. The same procedure to correct for multiple comparisons was applied as in the meta-analysis across all studies (see section 0).

Based on the thresholded ALE maps from individual paradigms, we then conducted further conjunction and contrast meta-analyses between the RI and PI paradigms as well as the RI and II paradigms, using the “contrast study” function implemented in GingerALE. This allowed us to localize voxels commonly (i.e., conjunction) or differentially (i.e., contrast) activated across intentional choice paradigms. The conjunction images were created using the voxel-wise minimum value of the input ALE images. To correct for study sizes (Eickhoff et al., 2011), the contrast analyses were conducted through permutation tests. First, the ALE differences image was created by directly subtracting one input image from the other. Second, the simulated data was created by pooling the foci datasets and randomly dividing them into two new groups with the same as the original groups. Third, a new ALE difference image was created by directly subtracting of the two new datasets and then compared to the true data. Fourth, with multiple permutations, a voxel-wise *p*-value image was created to illustrate where the true data sit on the distribution of the ALE differences in each voxel. A lenient threshold (cluster threshold 200 mm^3, uncorrected voxel-level threshold $p<0.01$, permutation tests with 5,000 iterations) was applied to the contrast analyses between paradigm categories to avoid type II errors (Lieberman & Cunningham, 2009). No conjunction or contrast meta-analysis was conducted on experiments using the CI paradigm due to the limited number of studies available in that category.

3.2.4. Meta-analytic decoding of intentional decision

ALE activation maps indicate brain regions of consistent fMRI/PET activations between studies. We then used NeuroSynth (Yarkoni et al., 2011) to further perform a “reverse-inference” type of meta-analysis. That is, we meta-analytically decoded which cognitive functions or processes are likely to give rise to the consistent brain activations observed in ALE activation maps. As highlighted previously, one should interpret results from reverse inference with caution (Poldrack, 2011). Most functional brain imaging results are correlational. The involvement of a brain region in a certain cognitive function does not directly support the notion that the region is exclusively associated with the cognitive process. Nevertheless, meta-analytic decoding against large, unbiased imaging databases did provide useful information about the engagement of cognitive processes (Poldrack, 2006). In the current study, we consider our meta-analytic decoding analysis to be contributory rather than confirmatory, which offers insights for future studies of intentional decision.

We considered a set of 100 cognitive topics that were previously generated from over 11,000 brain imaging studies. The 100 topics were extracted by fitting a generative statistical model of sematic topics (Blei et al., 2003) to the abstracts of over 11,000 brain imaging articles in the NeuroSynth database (for details see Poldrack et al., 2012). We ignored the topics related to general methods (e.g., fMRI) and focus only on the topics related to cognitive processes. For each cognitive topic, a whole-brain association-test map (also referred to as the reverse inference map) was generated from all the articles in the database. A whole-brain association-test map was generated by comparing (i.e., subtracting) the ALE map of studies that contain the terms in a given topic and the ALE map of all studies in the database (Yarkoni et al., 2011). Higher ALE scores in a voxel indicate a more consistent activation pattern of studies containing the given cognitive topic compared to all studies in the database, and vice versa. Therefore, the value at each voxel of the association-test map quantifies the extent to which studies loaded highly on the current topic reported more consistent activation at this location than all the other studies (Yarkoni et al., 2011).

We estimated the similarity between each unthresholded ALE activation map with respect to the association-test maps of the 100 cognitive topics by calculating their Pearson correlations across voxels. The resulting correlation coefficients were rank ordered to identify the cognitive topics that are most likely to be present during intentional decision and its specific paradigms.

3.2.5. Data availability statement

All data used in this meta-analysis study were obtained from original publications. We have made the aggregated data open access (https://osf.io/bhwj5), which include the imaging data entered meta-analyses and unthresholded statistical maps from meta-analyses.

3.2.6. Ethics statement

This study did not include data from new participants. In all meta-analyses, we only considered studies that had obtained informed consent from human participants.

3.3. Results

3.3.1. Meta-analysis of intentional decision

Thirty-six brain imaging studies were identified from our symmetric literature search, which included 38 independent experiments of intentional decision. The number of participants, experimental paradigms and other details were summarized in **Table 1**.

Table 1. List of intentional decision studies that meet the inclusion criteria.

No.	Study	No. of subjects	Imaging modality	Experiment Paradigm
1	(Beudel & De Jong, 2009)	16	fMRI	RI: Press button with 2nd to 5th finger of one hand
2	(Deiber et al., 1991)	8	PET	RI: Push the joystick
3	(Deiber et al., 1996)	13	PET	RI: Move finger in response to visual cue
4	(François-Brosseau et al., 2009)	14	fMRI	RI: Press button with 2nd to 5th finger of one hand▲
5	(Frith et al., 1991)	6	PET	RI: Move finger in response to touch
6	(Gerardin et al., 2004)	9	fMRI	RI: Press button with left or right thumb▲
7	(Hoffstaedter et al., 2013)	35	fMRI	RI: Press button with right or left hand
8	(Hyder et al., 1997)	9	fMRI	RI: Move finger in response to touch
9	(Krieghoff et al., 2009)	16	fMRI	RI: Press left or right button with the index finger of one

				hand
10	(Mueller et al., 2007)	16	fMRI	RI: Press right or left button with the index finger of one hand
11	(Rae et al., 2014)	17	fMRI	RI: Press button with 2nd to 5th finger of one hand
12	(Rowe et al., 2010)	20	fMRI	RI: Press button with 2nd to 5th finger of one hand
13	(Schouppe et al., 2014)	22	fMRI	RI: Modified flanker paradigm
14	(Van Eimeren et al., 2006)	12	fMRI	RI: Press button with 2nd & 3rd finger of both hands
15	(Walton et al., 2004)	9	fMRI	RI: Press button with 2nd to 4th finger of one hand
16	(Walton et al., 2004)	9	fMRI	RI: Press button with 2nd to 4th finger of one hand
17	(Zapparoli et al., 2017)	32	fMRI	RI: Press button with right or left finger
18	(Bode et al., 2013)	15	fMRI	PI: Choose picture by button pressing
19	(Filevich et al., 2013)	23	fMRI	PI: Choose number with mouse cursor
20	(Forstmann et al., 2006)	22	fMRI	PI: Choose target(s) by button pressing
21	(Lau, Rogers, Ramnani, et al., 2004)	12	fMRI	PI: Choose target(s) by button pressing
22	(Orr & Banich, 2014)	28	fMRI	PI: Choose task by button pressing
23	(Rens et al., 2018)	24	fMRI	PI: Choose target door by button pressing
24	(Rowe et al., 2005)	12	fMRI	PI: Choose target(s) by button pressing
25	(Rowe et al., 2008)	20	fMRI	PI: Choose target(s) by button pressing
26	(Thimm et al., 2012)	28	fMRI	PI: Choose picture by button pressing
27	(Dall'Acqua et al., 2018)	24	fMRI	II: Adapted go/no-go paradigm*
28	(Karch, Thalmeier, et al., 2010)	8	fMRI	II: Adapted go/no-go paradigm*
29	(Karch, Feuerecker,	15	fMRI	II: Adapted go/no-go paradigm*

	et al., 2010)			
30	(Karch et al., 2009)	14	fMRI	II: Adapted go/no-go paradigm*
31	(Lynn et al., 2016)	21	fMRI	II: Pain stop or endurance by button pressing or not
32	(Omata et al., 2019)	26	fMRI	II: Whether to stop the continuous finger-tapping
33	(Schel et al., 2014)	24	fMRI	II: Adapted go/no-go paradigm*
34	(Frith et al., 1991)	6	PET	CI: Generate word or repeat word
35	(Jarvstad & Gilchrist, 2019)	23	fMRI	CI: saccadic selection
36	(Ort et al., 2019)	22	fMRI	CI: Redirect attention to target(s) without actual movement
37	(Taylor et al., 2008)	18	fMRI	CI: Redirect attention to target(s) without actual movement
38	(Wisniewski et al., 2016)	35	fMRI	CI: mathematical calculation (subtract or add)
Total	/	683	/	/

* All are adapted go/no-go task which has an intentional trial in addition to the tradition go/no-go trials. In the intentional trial, participants are free to choose whether to press the button.

▲ The study reported the contrast of intentional decision and specified response separately for left and right hands. Only the results from the dominant hand (right hand) were included in the meta-analysis.

Across all the 38 experiments, a Ginger-ALE meta-analysis on the contrast between free choice and specified response yielded greater BOLD-fMRI/PET activations related to intentional behaviour in a frontoparietal network (**Figure 8**). The analysis identified 17 peaks in 6 clusters, including bilateral pre-SMA, bilateral ACC, bilateral dorsal lateral prefrontal cortex (dlPFC), bilateral supramarginal gyrus (IPL) and left Insula (**Table 2**, $p<0.01$, cluster-level corrected).

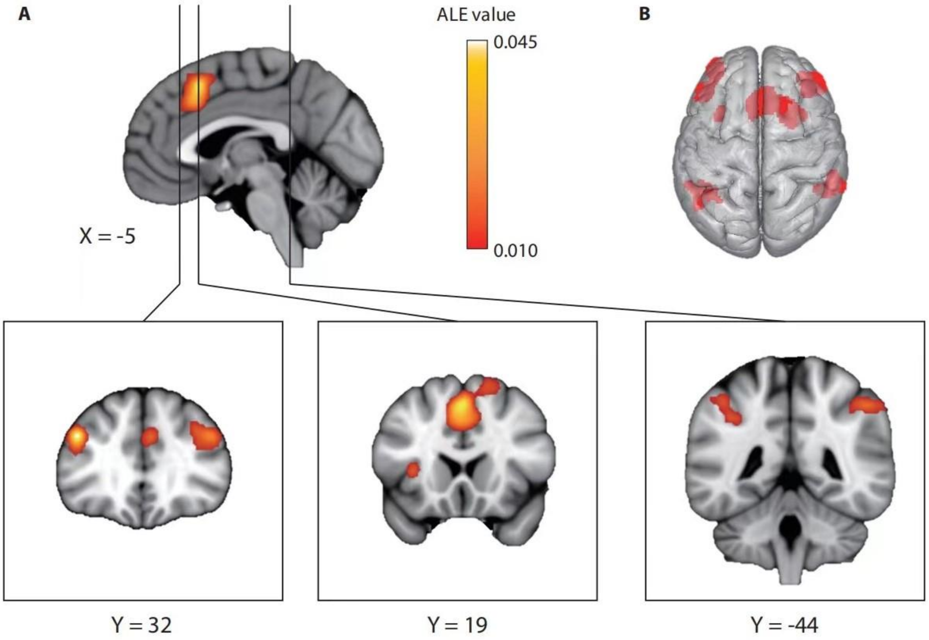


Figure 8. ALE meta-analyses of all free-choice studies showing significant activation clusters related to intentional decision ($p<0.01$, cluster-level FWE corrected from 5,000 permutations). (A) ALE value map. (B) 3D render of all the clusters. Table 2 lists the peak coordinates of each cluster.

Table 2. Meta-analysis results of intentional decision ("free choice" > "specified response") across all studies. Peak coordinates of clusters were reported in the MNI space (mm).

Cluster	Label	X	Y	Z	ALE score (max)	Cluster size (mm^3)
1	Left Pre-SMA	0	18	48	0.0448	13232
	Right Pre-SMA	28	10	52	0.0293	
		6	28	32	0.0270	
2	Right dlPFC	18	14	62	0.0242	5664
		44	34	30	0.0310	
		46	40	22	0.0303	
		34	42	18	0.0278	
3	Left dlPFC	-42	30	30	0.0468	5632
		-38	50	10	0.0313	
		-40	38	20	0.0186	
4	Left IPL	-42	-52	50	0.0273	3296
		-36	-46	38	0.0205	
		-52	-40	50	0.0163	
		-30	-52	44	0.0162	
5	Right IPL	54	-38	48	0.0275	2920
6	Left aINS	-34	14	2	0.0283	1208

3.3.2. Meta-analysis of contrasts between intentional decision paradigms

To investigate whether different types of intentional behaviour relate to selective brain responses, we assigned intentional decision studies into four categories (Figure 1), depending on their characteristics of experimental paradigms: reactive intention (RI), perceptual intention (PI), inhibitory intention (II) and other higher cognitive intention (CI).

Separate meta-analyses on individual intentional decision paradigms revealed overlapping and distinct clusters with increased activity in response to intentional behaviour (**Table 3**). Free choices in the RI paradigm were consistently associated with greater activations in 6 clusters with 14 peak foci, including bilateral pre-SMA and ACC, bilateral IPL, bilateral dlPFC and right premotor area. For the PI paradigm, the analysis revealed 3 clusters with 4 peak foci located in bilateral dlPFC and left ACC and pre-SMA cluster. For the II paradigm, there were 7 clusters with 14 peak foci located in bilateral IPL, right premotor area, bilateral prefrontal area and right Pre-SMA. No significant results were observed in the meta-analysis of the CI paradigm, possibly due to the limited number of studies in that category.

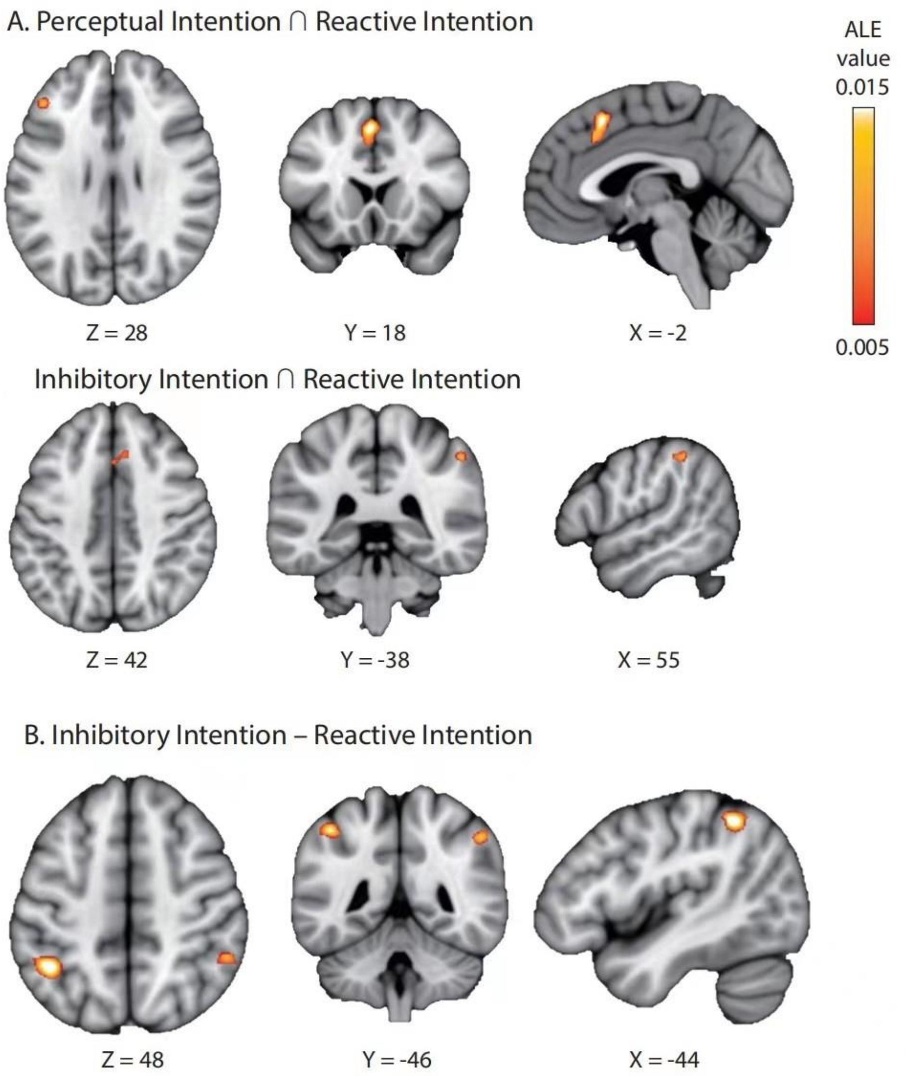
Table 3. Meta-analysis results of individual paradigms of intentional decision. Peak coordinates of clusters were reported in the MNI space (mm).

Cluster	Label	X	Y	Z	ALE score (max)	Cluster size (mm^3)
Reactive Intention						
1	Bilateral Pre-SMA	2	18	50	0.0219	4872
	Left ACC	-6	20	38	0.0200	
	Right ACC	6	24	42	0.0189	
2	Left dlPFC	-36	44	14	0.0162	2192
		-44	30	24	0.0155	
		-36	38	22	0.0129	

3	Left IPL	-38	-44	38	0.0198	1680
		-50	-40	42	0.0118	
4	Right dlPFC	36	28	34	0.0150	1344
		42	32	26	0.0108	
		36	18	34	0.0099	
5	Right IPL	54	-36	50	0.0179	1296
6	Right Premotor	24	4	56	0.0139	1280
		18	20	58	0.0133	
Perceptual Intention						
1	Left Pre-SMA	-2	20	48	0.0192	1920
	Left ACC	-2	24	38	0.0134	
2	Left dlPFC	-44	30	30	0.0197	1056
3	Right dlPFC	44	36	34	0.0138	912
Inhibitory Intention						
1	Left IPL	-44	-48	50	0.0192	1600
		-54	-42	50	0.0089	
2	Right IPL	52	-44	46	0.0171	1536
3	Right Premotor	28	12	56	0.0142	1272
		18	16	64	0.0133	
4	Right dlPFC	44	40	22	0.0126	768
		36	32	26	0.0092	
5	Left rlPFC	-38	50	6	0.0110	752
		-32	56	14	0.0108	
		-30	52	12	0.0107	
6	Left dlPFC	-42	32	30	0.0154	656
7	Right pre-SMA	4	28	50	0.0113	744

8	24	42	0.0096
2	18	42	0.0091

To quantify the distinction and similarity in brain response to different types of intentional behaviour, we conducted further contrast and conjunction meta-analyses, comparing both the PI paradigm (involving perceptual processing) and the II paradigm (involving inhibitory processing) with the most elementary paradigm (the RI paradigm). The contrast meta-analysis showed that the bilateral IPL is more likely to activate in the II than the RI paradigm (**Figure 9B, Table 4**). No significant difference was found between PI and RI paradigm. The conjunction meta-analysis showed that bilateral Pre-SMA/ACC complex and the left dlPFC are commonly activated in intentional behaviour across studies of PI and RI paradigms, and activations in the right IPL and right Pre-SMA are commonly observed in both II and RI paradigms **(Figure 9A, Table 4**).



A. Perceptual Intention ∩ Reactive Intention

Inhibitory Intention ∩ Reactive Intention

B. Inhibitory Intention – Reactive Intention

Figure 9. Conjunction and contrast meta-analyses. (A) ALE conjunction meta-analyses between PI and RI paradigms (top) as well as II and RI paradigms (bottom). (B) ALE contrast meta-analyses between II vs. RI paradigms. Table 4 lists the peak coordinate of each cluster.

Table 4. Contrast and conjunction meta-analyses between different free-choice paradigms. Peak coordinates of clusters were reported in the MNI space (mm).

Cluster	**Label**	**X**	**Y**	**Z**	**ALE score**	**Cluster size (mm^3)**
Inhibitory Intention > Reactive Intention						
1	Left IPL	-41.5	-50.4	50.3	0.0185	1336
2	Right IPL	52	-46	46	0.0138	488

Perceptual Intention ∩ Reactive Intention						
1	Left Pre-SMA	0	20	48	0.0173	1408
	Left ACC	0	24	38	0.0129	
2	Left dlPFC	-44	32	28	0.0126	240
Inhibitory Intention ∩ Reactive Intention						
1	Right IPL	54	-38	46	0.0128	336
2	Right Pre-SMA	8	24	42	0.0096	216
		2	18	42	0.0091	

3.3.3. Meta-analytic decoding of intentional decision

To probe cognitive processes underlying intentional decision, we assessed the spatial similarity (i.e., Pearson correlation across voxels) between the ALE activation maps from our meta-analysis and 100 association-test maps. Each of the association-test maps represents brain response selective to one of 100 psychological topics, generated from meta-analyses of >11,000 independent studies (Yarkoni et al., 2011). Therefore, a high correlation coefficient to an association-test map would imply the potential involvement of the corresponding cognitive process. The primary interest here is the relative ranking of the topics based on the similarity of their association-test maps to our results, not to perform null hypothesis significance testing on each correlation.

This reverse inference showed that the frontoparietal network identified in the meta-analysis of intentional decision across all studies (**Figure 10**) was strongly associated with several psychological topics. The top three are working memory (R = 0.436), task rules (R = 0.392) and conflict (R = 0.365) (**Figure 10**, and see **Supplementary Table 1** & **Supplementary Table 2** for full results).

We also applied the same reverse inference procedure to paradigm-specific ALE-activation maps. The RI paradigm was associated with the topic of working memory

($R = 0.395$), conflict ($R = 0.356$) and task rules ($R = 0.350$). PI paradigm was associated with the topic of working memory ($R = 0.419$), cognitive control ($R = 0.322$) and task rules ($R = 0.314$). II paradigm was associated with the working memory ($R = 0.307$), cognitive control ($R = 0.271$), task rules ($R = 0.260$) and feedback ($R = 0.227$).

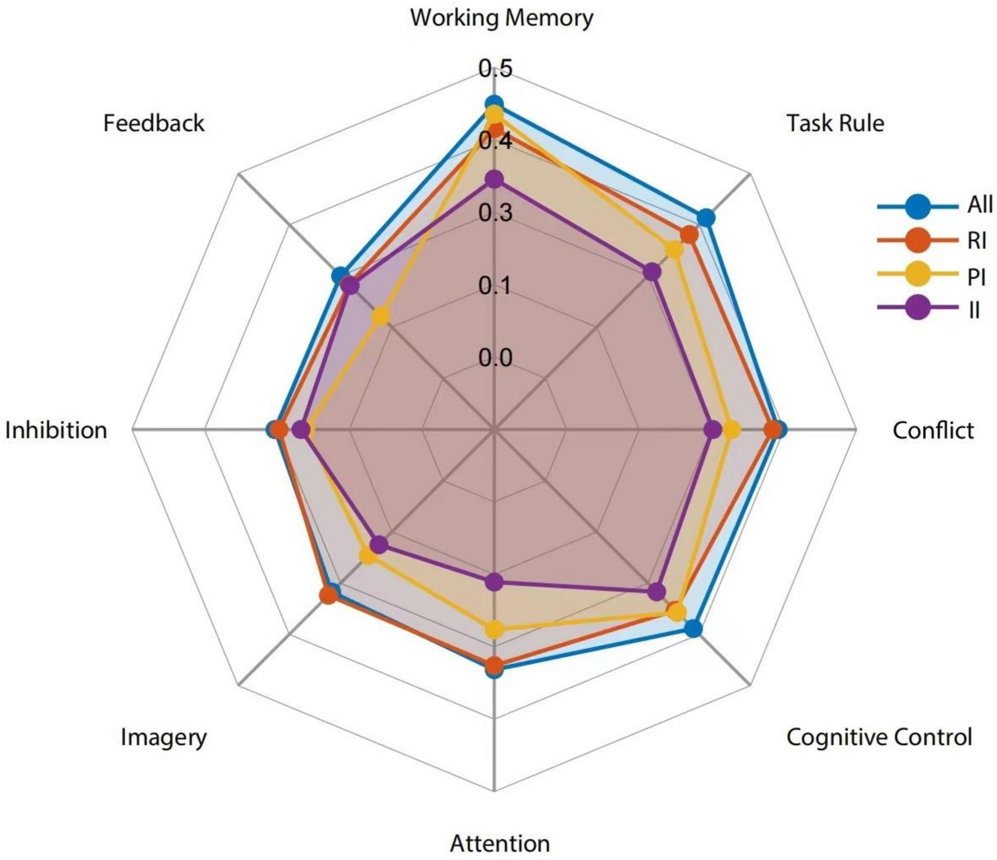


Figure 10. Meta-analytic decoding of intentional decision. Correlation coefficients between different cognitive topics' association maps and ALE maps of intentional decision were calculated. The correlation values for the top 8 topics were illustrated in a polar plot. Terms used to generate those topic-based association maps were listed in **Supplementary Table 1**.

3.4. Discussion

This study confirms, at the meta-analytic level, a consistent pattern of brain activation associated with intentional decisions for action, perception and cognition.

By contrasting between different free-choice paradigms, we also identified brain areas whose activities are dependent on specific categories of intentional behaviour. The meta-analytic decoding analysis suggested putative cognitive processes underlying intentional decisions. Our results provide insight into the cognitive roles of brain networks that mediate intentional behaviour in humans, which we discuss below together with their potential computational processes.

3.4.1. Functional localization of intentional decision in the brain

The ALE meta-analysis showed increased activities in the medial prefrontal cortex (pre-SMA and caudal ACC), the lateral frontoparietal cortices (dlPFC and IPL) and the aINS during voluntary behaviour originated from intentional decisions, in contrast of the same behavioural response prescribed exogenously (**Figure 8**). This result is in agreement with previous analyses that applied a similar method to smaller study samples (Rae et al., 2014; Zapparoli et al., 2017).

The brain areas involved in intentional decision overlap closely with the multiple demand network (Duncan, 2010; Duncan & Owen, 2000), a "task-positive" co-activation pattern associated with diverse cognitive demands (Dosenbach et al., 2006; M. Fox et al., 2005). A closer inspection of the literature indicates that subcomponents of this network may serve different cognitive roles during intentional decisions, which is also supported by our meta-analytic decoding results (**Figure 10**).

A large body of evidence indicates the central role of ACC in conflict monitoring (Botvinick et al., 2004). Conflicts in information processing arise from the presence of response competition. Greater ACC activation is consistently observed when (1) one or more prepotent responses need to be overridden, such as in the Stroop task (Barch, 2001; MacLeod & MacDonald, 2000) and the flanker task (Botvinick et al., 1999; Bunge et al., 2002), or (2) a voluntary choice is needed among multiple underdetermined options, like in all the free-choice paradigms discussed here (Zhang et al., 2012; Zhang & Bogacz, 2010). Although the existing literature of conflict monitoring is largely focused on the ACC, the adjacent pre-SMA is also sensitive to the presence of conflict, in particular the conflict in response selection, as lesions in this region lead to deficits in exerting voluntary control over immediate actions (Nachev et al., 2007). According to the conflict monitoring theory, as multiple options become available in the free-choice paradigm, increased ACC and pre-SMA activities may encode conflicts as an index of the need for greater cognitive demand, which in turn trigger voluntary choices to reduce or resolve the conflict (Botvinick, 2007; Botvinick et al., 2004). A direct prediction of this proposition is that the activity in the medial prefrontal cortex should increase proportionally, at least to some extent, to the number of available options in the free-choice paradigm, which has been validated in previous studies (e.g., Forstmann et al., 2006).

Beyond the medial prefrontal cortex, the frontoparietal network on the lateral brain surface has a distinct functional connectivity pattern relating to cognitive control (Corbetta & Shulman, 2002) and executive task performance (Seeley et al., 2007). Two functions of this network are essential to intentional behaviour. First, intentional decisions in the free-choice paradigm are, by definition, rendered endogenously. Nevertheless, the brain may still establish a “task set” that incorporates transient and arbitrary rules in addition to relevant exogenous information, such as associations of stimuli and imagined outcomes as well as available options (Sakai, 2008). Both single-unit recording in non-human primates (Asaad et al., 2000; Quintana & Fuster, 1999; Wallis et al., 2001) and brain imaging in humans (Bunge et al., 2002; Sakai & Passingham, 2003a) have identified neural representations of various task sets in the frontoparietal network. The encoding of a task set can be actively maintained in this network until its execution (Zhang et al., 2013), thereby facilitating the intentional decision process to unfold in time. Second, intentional behaviour is commonly accompanied by the subjective experience of volitional control (Haggard, 2008), which requires internal models that matches the consequences of the response against its initial intention (Wolpert et al., 1995). It has been proposed that the parietal cortex hosts such internal models (Desmurget & Grafton, 2000), as patients with parietal lesions exhibited altered behavioural and electrophysiological signatures of their intention to act (Sirigu et al., 2004).

Our meta-analysis across all free-choice experiments showed the consistent involvement of the aINS during intentional decision, in spite of the lack of significant insula activity in some studies (e.g., Van Eimeren et al., 2006). This supports an earlier account that the aINS is a key component of the integrated brain network involved in intentional behaviour (Brass & Haggard, 2010). Anatomically, the aINS connects directly to the ACC (Augustine, 1996; Moisset et al., 2010). Functionally, robust coactivation in the aINS and ACC was observed across multiple cognitive domains (Medford & Critchley, 2010) as well as in resting-state (Chang et al., 2013), and both regions are a part of the salience network (Chen et al., 2016). It may therefore be tempting to ascribe the aINS activity to conflict processing during intentional decision, similar to that of ACC. An alternative proposal originated from the aINS's unique function in signalling introspective awareness (Craig, 2009) or subjective salience (Menon & Uddin, 2010) of cognitive (Preuschoff et al., 2008), homeostatic (Craig et al., 2000; Farrer & Frith, 2002) and emotional (Jabbi et al., 2007) information, which is not shared with the ACC. According to this theory, aINS activity reflects the affective consequences of intentional decisions. In other words, the aINS may not directly associate with the formation of current intention; instead, it evaluates the outcome of the intentional act with respect to an internal model of one's long term goal (see Brass and Haggard, 2010 for a detailed review).

3.4.2. Computational processes of intentional decision

With the identification of the consistent brain network for intentional decision-making, a new question arises: what is the computational process underlying intentional decision? Converging findings from behavioural modelling (Ratcliff, 2006), single-unit recoding (Kim & Shadlen, 1999; Mazurek et al., 2003; Shadlen &

Newsome, 2001) and imaging (Heekeren et al., 2004; Ho et al., 2009; Ploran et al., 2007) experiments suggest that, when making choices based on external stimuli, an accumulation-to-threshold mechanism governs the decision-making process (Gold & Shadlen, 2007; Heekeren et al., 2008; Smith & Ratcliff, 2004): the evidence supporting one or multiple options are accumulated over time, and a choice is made when the accumulated evidence reaches a decision threshold. For perceptual decisions with noisy sensory stimuli, this accumulation process reduces the momentary noise in information-processing and in turn results in more accurate decisions (Bogacz et al., 2006, 2007; Zhang & Bogacz, 2010).

For intentional decisions, it has been shown that a computational model implementing the accumulation-to-threshold mechanism can well describe the behavioural performance (i.e., response time distributions and choice probabilities) of both RI (Zhang et al., 2012) and PI paradigms (Zajkowski et al., 2020). Furthermore, the accumulated evidence predicted by the model is associated with the BOLD response in the ACC and pre-SMA on a trial-by-trial basis (Zhang et al., 2012). These results raise an intriguing possibility that, during intentional decision, the medial prefrontal cortex implements the accumulation-to-threshold process to integrate over time the transitory intention of choosing different options, until the accumulated intention for one choice reaches a decision threshold.

This hypothesis is supported by several electrophysiological studies, which characterised the accumulation process during intentional behaviour at a high temporal resolution. First, in Libet’s paradigm of voluntary action, the readiness potential measured by scalp EEG precedes participants’ conscious awareness of their voluntary intention (i.e., the “urge to move”, Libet et al., 1983). An accumulator model can be fit to the time latency of participants’ urge to move, and the activity of the accumulator qualitatively reproduces the time course of the readiness potential prior to conscious intention (Schurger et al., 2012). Second, in a free-choice version of Libet’s paradigm, when participants made intentional decisions between responding with their left or right hands, single-neuron activity in the medial prefrontal cortex build up several hundred milliseconds before the onset of conscious intention (Fried et al., 2011). Further, medial prefrontal neurons contralateral to the acting hand exhibited larger activity than ipsilateral neurons (Fried et al., 2011). Therefore, the medial prefrontal cortex may host accumulated intentions of multiple responses as well as their mutual competition, from which voluntary acts are rendered via the accumulation-to-threshold mechanism.

The putative role of the medial prefrontal cortex in intention accumulation is not inconsistent with this region’s function of conflict monitoring discussed above, because more free options would be associated with larger accumulated intention across alternatives as well as higher conflict. In this regard, intention accumulation can be interpreted as a computational implementation of detecting and resolving conflicts among underdetermined options. Therefore, we consider the accumulation process as a parsimonious computational framework for intentional behaviour outlined by the conceptual *what-when-whether* model (Brass and Haggard, 2008), because accumulator models can explain quantitatively both *“what”* (i.e., choice probabilities) and *“when”* (i.e., response time distributions) components. Interestingly, accumulator models can also be fitted to behavioural performance in externally-triggered stopping tasks (Gomez et al., 2007; Zhang et al., 2016). Future research should investigate if accumulator models can incorporate the “*whether*” component, or voluntary stopping in the II paradigm.

3.4.3. Paradigm-specific activations during intentional decision

By categorizing free-choice studies into different types, we identified brain regions associated with consistent and specific activations between sub-categories of intentional decision (Figure 3). The conjunction meta-analysis of the RI and PI paradigms showed that the pre-SMA/ACC and dlPFC are associated with both types of intentional decision. This is expected, as the RI and PI paradigms have a similar task structure, involving rapid voluntary choices among multiple action plans (Table 3). However, the contrast analysis did not reveal any difference between the two paradigms.

The II paradigm includes a unique option of not to act or intentionally inhibit one's action (**Figure 6C**). The conjunction meta-analysis of the II and RI paradigms showed that the right supramarginal gyrus in the IPL and right Pre-SMA was associated with both types of intentional decisions, and the contrast meta-analysis showed that the bilateral supramarginal gyrus was more likely to be activated in the II than that in the RI paradigm. The paradigm-specific result of II paradigm was the brain activation difference between instructed and voluntary stops, while the result of RI paradigm was the brain activation difference between instructed and voluntary simple actions. In both RI and II paradigms, participants need to reprogram their response model according to available options in each trial, which fits the critical role of the supramarginal gyrus in action reprogramming (Hartwigsen et al., 2012). The same region is also sensitive to the content of action plans and their similarity (Quandt et al., 2017). It could be argued that options in the II paradigm are more dissimilar (i.e., acting versus stopping) than that in the RI paradigm (i.e., multiple but similar actions), which leads to the additional recruitment of the supramarginal gyrus in the II paradigm.

It is worth noting that the results of conjunction and contrast meta-analyses should be interpreted with caution, because of the limited number of studies available in each category. Furthermore, one potential confound of the contrast meta-analysis is that different paradigm categories may vary in their task difficulty, and hence the contrast between categories may not directly support the involvement of distinct cognitive processes. This issue can be examined in future studies that explicitly manipulate both task difficulty and intentional decision paradigms.

3.4.4. Future directions and conclusion

This analysis leaves open some issues for future research on human intentional decision-making. First, our systematic review identified only four studies in the CI category: two studies included options with attention shifts (Ort et al., 2019; Taylor et al., 2008), one with verbal responses (Frith et al., 1991) and the other one with arithmetic rules (Wisniewski et al., 2016). The small number of CI studies did not yield any significant result in the paradigm-specific meta-analysis, but that may reflect type II error. We recommend future research to explore different types of CI studies and examine the robustness and consistency of existing results across a range of distinct cognitive processes.

Second, our meta-analysis of the II paradigm did not show conventional regions involved in inhibitory control (Swick et al., 2011). We propose that this is due to the fact that our analysis used the contrast of intentional choice vs. specified response, with the former including intentional stopping and the latter including externally triggered stopping - this contrast may therefore not detect differential response inhibition. Indeed, the BOLD response in the aINS was higher during intentional stopping than intentional action execution (Brass & Haggard, 2007), while the inferior frontal gyrus is consistently observed during instructed stopping (Aron et al., 2004). To examine how the brain switches effectively between intentional and instructed stopping in the II paradigm, one need to examine the effective connectivity between these two regions and the medial prefrontal cortex, which is involved in both types of stopping (Kühn & Brass, 2009; Sharp et al., 2010).

Third, the current imaging literature on intentional behaviour indicates that the main focus is to localize associated brain regions or their underlying computational processes. Less is known about how a participant would intentionally choose one option over other homogenous alternatives in a trial. The answer to this question is important because the sequence of intentional decisions over trials are not completely random (Zhang & Rowe, 2015) but dependent on executive control of working memory (Baddeley et al., 1998), the context of a given choice in a sequence (Rowe et al., 2010), and other sources of response biases (Zajkowski et al., 2020). We suggest that the free-choice paradigm provides an ideal testbed for future research to investigate the interplay between the intention accumulation process governing a single trial and modulatory effects that operate at a longer time span.

In conclusion, our meta-analysis identifies a brain network consistently activated when humans have the freedom to make intentional choices among multiple options. Some components of this network are recruited specifically in subcategories of the free-choice paradigm. Multiple cognitive and computational processes are involved in intentional decision, which collectively serve essential roles in shaping and maintaining volitional control.

3.5. Supplementary Materials

Supplementary Table 1. Top 8 cognitive topics and their corresponding correlation coefficients with brain maps from the main (**Figure 8**) and paradigm-specific (**Table 3**) meta-analyses. The ranking is based on the meta-analytic decoding result of the main analysis of all studies (**Figure 8**).

Topics	**ALL**	**RI**	**PI**	**II**
Working memory	0.4362	0.3945	0.4192	0.3072
Task rules	0.3919	0.3509	0.3143	0.2601
Conflicts	0.3648	0.3555	0.2845	0.252
Cognitive control	0.3609	0.3165	0.3218	0.2711
Attention	0.2895	0.2825	0.2203	0.1383
Imagery	0.2716	0.2795	0.1825	0.1563
Inhibition	0.2533	0.2463	0.2007	0.2084
feedback	0.2498	0.2289	0.1518	0.2266

Supplementary Table 2. Full list of terms associated with the 8 topics in **Supplementary Table 1**. The number of studies of each topic was extracted from the Neurosynth database (Yarkoni et al., 2011, https://neurosynth.org/analyses/topics/v4-topics-100/).

Topics	**Terms included**	**Num. Studies**
Working memory	memory, working, task, load, verbal, maintenance, performance, cognitive, activation, information, tasks, term, capacity, probe, manipulation, executive, spatial, phase, encoding, updating, performed, storage, network, span, rehearsal, retention, increased, delay, function, accuracy, functions, demands, vwm, delayed, phonological, loads, demand, performers, sternberg, binding	798
Task rules	switching, set, rule, task, switch, rules, flexibility, shifting, sets, sorting, trials, shift, shifts, anxiety, switches, card, wcst, anxious, costs, paradigm, single, ef, required, wisconsin, stimulus, trial, worry, repeat, switched, paradigms, execution, depending, component, chunk, cost, gad, lower, updating, types, iu	230
Conflicts	conflict, interference, control, stroop, incongruent, task, response, congruent, olfactory, resolution, trials, odor, behavioral, attentional, color, cognitive, odors, simon, congruency, word, flanker, effect, monitoring, irrelevant, processing, activated, conflicting, incompatible, neutral, relevant, mechanisms, detection, conflicts, situations, resolve, adjustments, pre, compatibility, compatible, counting	392
Cognitive control	cognitive, control, performance, task, executive, function, functions, cognition, ability, attention, behavioral, tasks, functioning, test, goal, effort, individuals, behavior, demands, recruitment, abilities, lateral, performed, attentional, neuropsychological, directed, domains, tests, level, individual, relevant, behavioural, evidence, speed, performing, impairment, stroop, deficits, impaired, domain	1098

Attention	attention, attentional, visual, spatial, search, orienting, target, top, selective, control, location, areas, attended, network, stimulus, irrelevant, cues, distraction, shifts, relevant, feature, modulation, task, cued, mechanisms, color, cueing, focus, bottom, processing, attend, event, endogenous, cue, attending, allocation, directed, resources, modulated, perceptual	841
Imagery	wm, imagery, mental, imagined, rotation, mi, tasks, visual, visuospatial, motor, areas, spatial, ltm, imagination, imagine, transformation, image, imagining, mentally, images, activated, ability, angle, degrees, physical, strategy, manipulation, visuo, poor, actual, rotations, simulation, kinesthetic, gifted, representational, clock, angles, rehearsal, future, instructed	355
Inhibition	inhibition, response, control, inhibitory, stop, task, motor, signal, activation, trials, nogo, suppression, responses, successful, inhibit, behavioral, error, inhibited, inhibiting, pre, performance, prepotent, reactive, stopping, ability, sst, monitoring, suppress, correlates, gating, action, rifg, success, proactive, errors, tasks, required, participants, voluntary, behavior	421
Feedback	feedback, error, errors, learning, prediction, monitoring, correct, negative, performance, response, outcome, reinforcement, positive, trials, processing, outcomes, task, trial, reversal, behavior, stimulus, expected, signal, detection, signals, events, expectations, incorrect, expectation, predictive, contingencies, correlated, event, reward, contingency, adaptation, probability, adjustment, actual, unexpected	501

4. The intentional choice pattern among different cognitive tasks: Online experiments

4.1. Introduction

Intentional choice plays a significant role in everyday human behaviours (Haggard, 2008). In the lab setting, researchers tend to use simple experimental paradigms to minimize the effect of confounding variables. A common experimental paradigm for studying intentional behaviours is the free-choice paradigm. It allows the participants to voluntarily choose between multiple homogenous alternatives. In our recent meta-analysis (Chapter 3), we identified four subtypes of the free-choice paradigms: reaction intention paradigm, the perceptual intention paradigm, the inhibitory intention paradigm, and the cognitive intention paradigm (Si et al., 2021).

Among the four subtypes of tasks, the intentional choice cognitive intention paradigm has the fewest studies, because it requires decisions to be made among higher-order cognitive processes rather than simple perception. The cognitive intention paradigm can use various types of cognitive processes including attention shifts (Ort et al., 2019; Taylor et al., 2008), verbal responses (Frith et al., 1991), arithmetic calculations (Wisniewski et al., 2016), saccadic-based attention selection (Jarvstad & Gilchrist, 2019), and rule selection (Orr & Banich, 2014; Rowe et al., 2008). However, those cognitive intention paradigms had one major similarity in that they only use similar types of cognitive processes in one experiment, and the alternatives are the different facets of this certain cognitive process. For example, in Wisniewski et al. (2016), the targeted cognitive process was always to do arithmetic calculations. What participants could freely choose from was the direction of the calculation such as addition or subtraction. Such a design makes it easy for the researchers to control confounding variables because the execution of different choice alternatives is similar. However, the pattern of the free choice behaviours itself was neglected and only a few studies report the choice pattern in the free choice condition. In those studies, participants more or less showed choice bias toward one of the alternatives (e.g., Krieghoff, Brass, Prinz, & Waszak, 2009; Rens, Bode, & Cunnington, 2018). A limited number of studies investigated this bias and suggested that the sequence of a series of intentional choices was not completely random (Zhang & Rowe, 2015) and can be affected by the various sources of response biases such as reward probability and spontaneous preference (Zajkowski et al., 2020), echoing the previous literature that demonstrated the non-random behaviour during random number generation (Baddeley et al., 1998; Tune, 1964b).

This study aimed to investigate the behavioural pattern of the intentional choices among different cognitive tasks along with the conventional task performance after task switch or repetition. A new free-choice paradigm was created to allow the participants to make intentional choices among different cognitive tasks. Three cognitive tasks were used in the experiment including a learning task, a memory task, and a perception task. We further conducted a follow-up experiment with additional freedom in choosing task difficulty levels.

There were two main hypotheses for the two studies: 1) the choice sequence of the task was not completely random, and a biased pattern of intentional choice among cognitive tasks was expected, and 2) the switch between different tasks will result in a switching cost in behavioural performance, akin to the conventional task-switch effect (Kiesel et al., 2010; Vandierendonck et al., 2010).

4.2. Experiment 1: Choices on cognitive tasks

4.2.1. Participants

A total of 101 participants (67 females and 34 males) were recruited from two different online platforms. 61 participants were recruited from the Prolific online platform. 40 participants were recruited from the Cardiff University School of

Psychology participant panel. The participants were aged from 18 to 50 years old with an average age of 22.95 ± 6.55 years old. All participants had current study levels at or above secondary education. Informed consent was obtained from all participants and all participants received momentary compensation for their time. The study was approved by the Cardiff University School of Psychology Research Ethics Committee.

4.2.2. Apparatus

The main part of the experiment was written with JavaScript and the execution of tasks was implemented using the jsPsych library (de Leeuw, 2015). The experiment was conducted online through the Pavlovia server (https://pavlovia.org) and was compatible with diverse web browsers including Google Chrome, Firefox, and Safari. To optimize the experiment, participants were required to complete the experiment with a tablet or a personal computer.

Two standard questionnaires on decision-making and information-processing styles were used in this study. One is the 14-item multitasking preference inventory (MPI, Poposki & Oswald, 2010) and the other is the 38-item cognitive style index (CSI, Allinson & Hayes, 1996). The MPI uses a 5-point Likert scale with possible scores ranging from 14 to 70. The CSI uses a 3-point Likert scale with possible scores ranging from 0 to 76.

4.2.3. Tasks

In the experiment, participants were able to voluntarily choose one of three cognitive tasks to perform in each trial.

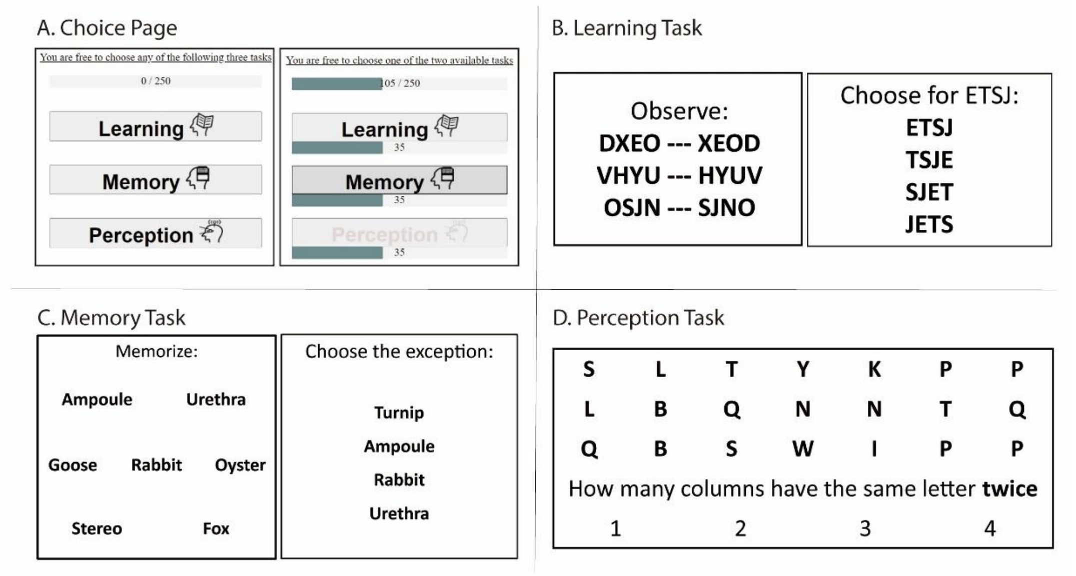


Figure 11. Examples of the choice page and the three different cognitive tasks.

4.2.3.1. Learning task

The learning task was adapted from *Visual Reasoning Tasks* which involves presenting participants with a sequence or pattern and testing their ability to understand the transformation rule and apply it to a new sequence (see Evans, 1964; Forbus & Lovett, 2021 for examples). In the learning task, participants were asked to observe three pairs of letter combinations, find the pairing pattern, and select the correct match from four options for a new letter combination (**Figure 11B**).

In each trial, four unrepeated letter combinations were used, and each combination consisted of four unrepeated letters. Three of them were given their corresponding pairs. A corresponding pair can be generated with one of the four possible rules: 1) same as the original letter combination (ABCD to ABCD); 2) moving the first letter to the end of the letter combination (ABCD to BCDA); 3) moving the first two letters to the end of the letter combination (ABCD to CDAB); 4) moving the last letter to the head of the letter combination (ABCD to DABC). One of the rules was randomly selected and applied to three of the chosen letter combinations in a trial to generate the three combination pairs in the question stem. The remaining letter combination was the one requiring a match to be found. Additionally, the four potential options were generated by the transformation of this combination via the four rules respectively.

4.2.3.2. Memory

The memory task was adapted from *Word Recognition Memory Tasks* that requires participants to remember a word list and then identify if a given word belongs to that original list (e.g., Schulman, 1971; Shepard & Teghtsoonian, 1961). In the memory task, participants were presented with 7 words and asked to memorize them in 5.5 seconds, followed by a decision page in which they needed to choose the words that were not presented before (**Figure 11C**).

There was a library of a total of 750 possible words in the memory task. All the words were nouns from thirteen categories including animals, occupations, body parts, furniture, vegetables, snacks, makeups, colours, electronic devices, fruits, vehicles, nuts/seeds, and stationeries. The category of vehicles, nuts/seeds, and stationeries contained 50 words each, while all the other categories contained 60 words. All words were between 5 to 12 letters long. However, their average length and frequency were not controlled across categories. In each trial, ten unrepeated words were randomly drawn from the library. Seven of them were presented in the question display for memorizing. The seven words were shown in three rows with two words in the first and the third row, and three words in the second row. The remaining three words and one of the seven presented words were set as four-choice options.

4.2.3.3. Perception

The perception task was adapted from the *Feature Search Tasks*, where participants are asked to quickly identify the presence or absence of a specific feature within a set of stimuli (see Quinlan & Humphreys, 1987; Trick & Enns, 1998 for examples). In the perception task, participants were asked to observe a letter matrix and count the number of columns that have the same letter occurring twice (**Figure 11D**).

A letter matrix consists of 3 rows and 7 columns and was randomly generated in each trial by columns. The possible number of columns that have a letter occurring twice was from 1 to 4. In those columns, the two same letters can occur in three possible positions: 1) the first and the second rows; 2) the first and the third rows; and 3) the second and the third rows. The options for the perception task were always number 1 to 4.

4.2.4. Procedures

The experimental session contained a behavioural experiment and two standard questionnaires.

The behavioural experiment consisted of three cognitive tasks including learning, memory, and perception. There were two ways to complete the behavioural experiment: 1) completing 250 trials in total, or 2) completing at least 70 trials in each task.

Participants went through an introductory session before they started the formal experiment. In the introductory session, they were introduced to the structure of the main choice page and given a chance to learn and practice all three tasks in several demo trials. The demo trials also provided tips for each task. There was only one demo trial for each task followed by a detailed explanation. The demo trials were a part of the instruction but not a part of the inclusion criteria. Hence, participants' accuracy was not measured in demo trials.

The formal experiment started with the main choice page. After each trial, participants were redirected back to the main choice page (**Figure 11A**). The main choice page, from top to bottom, consisted of an instruction line, a progress bar, three task buttons, and a time reminder. The instruction line emphasized that participants could freely choose from the available tasks. The progress bar shows the total number of trials completed. The task buttons were vertically arranged on the page. The sequence of the tasks was randomized across the participants. The time reminder showed the time that participants had spent on the experiment by minutes.

In the first trial, all three tasks were available, and participants were able to choose any of the three tasks. From the second trial, one of the three tasks would become unavailable, and participants could freely choose one of the two remaining tasks to perform. The button of the unavailable task was rendered in grey as an indication and would not respond to the participant's choice. According to the chosen task in the previous trial, the current trial can be divided into two types. 50% of trials were force-to-switch trials (FSTs), in which the unavailable task was the selected task in the last trial, hence the participants were forced to change to a different task. The other 50% of trials were stay-available trials (SATs), in which the unavailable task is one of the unselected tasks in the last trial. As a result, in SATs, participants could choose to repeat the previous task or switch to a different task. A fixed sequence of the FSTs and the SATs was used across the participants.

For about 15% of all the trials, additional progress bars appeared under each task button on the choice page. Those progress bars showed the number of trials completed in each task. This was for participants' reference if they chose to complete the experiment by doing at least 70 trials in each task.

After every 35 trials, the accuracy of the most recent 30 trials would be calculated after each trial. If the accuracy was lower than 40%, the experiment would terminate prematurely. Participants were not given specific instructions to prioritize either accuracy or speed in their responses. At the end of the instruction, a separate page was presented to emphasize the completion requirement on accuracy (i.e., at least 40%). The participants with premature termination would be removed from future analyses.

The behavioural experiment was followed by two questionnaires and a feedback session. The two questionnaires were divided into three pages. The first page contained 14 items from the MPI, the second page contained 19 items from the CSI and the third page contained the final 19 items from the CSI. The feedback session has a 7-point (0 to 6) Likert evaluation of the perceived difficulty levels of the three tasks and an open feedback box asking about the strategies that participants used in choosing the task for each trial.

4.2.5. Behavioural Measures

In each trial, the experiment recorded participants' choice of the cognitive task (i.e., learning, memory, or perception task), choice reaction time (RT) on the choice page, and the accuracy and RT on the chosen task.

4.2.6. Data Pre-processing

The trials with extra-long RTs were screened before data analyses because participants were allowed to take breaks during the experiment and the extra-long RTs were likely caused by those breaks or distractions from the experiment. The trials with RT being longer than two standard deviations above the group average were excluded from further analyses. There were 3.5% learning trials, 3.2% memory trials, 2.7% perception trials, and 0.38% of the RTs on the choice page that were screened out by this process.

4.2.7. Data Post-processing and Statistics

The statistical analyses focused on two aspects. One was the decision pattern on the choice page and the other was the performance in each task.

First, the decision pattern was illustrated by the transition rates. According to the task sequence that participants chose throughout the experiment, the transition rates were calculated by the actual times of the transition being made divided by the appearing times of a certain available transition. As the experiment had three tasks, there were nine possible transitions including each task to the other tasks and to itself (i.e., task repetition). If participants choose the tasks with no preference, the transition rate from one task to another should be .50 because there were always only two tasks available. Two different analyses were made on those transition rates. One took all the trials into consideration, aiming to investigate participants' behavioural patterns after each trial and their repetition rate. The other only included FSTs (i.e., force-to-switch trials), aiming at investigating participants' preference for different tasks when they were forced to switch. Additionally, we also analysed the time spent on the choice page and compared if staying and switching between different tasks would affect the time spent on intentional decisions.

Second, performances in each task were quantified by RT and accuracy. We further analysed the switching cost for each task. Switch cost is the difference in performance between a task switch and a task repeat, and is usually reported as a slower performance and decrease in accuracy (e.g., Jersild, 1927; Rogers and Monsell, 1995; Arrington and Logan, 2004), which is observed in a wide range of cognitive tasks (see Monsell, 2003).

The effects of task types (i.e., perceptual task or memory task) and transition types (i.e., staying at the same task or switching to a different task) on task choices and task performances were tested using repeated-measures analyses of variance (RMANOVAs). If the assumption of sphericity is violated, a Greenhouse-Geisser correction was applied to adjust the degrees of freedom and the frequentist *p*-values.

Third, we further compared all the measures in the two subgroups according to the strategy participants used to complete the task. One subgroup did more preferred trials and completed 250 trials in total (250-trial group); the other subgroup did three tasks evenly and completed less than 220 trials in total (210-trial group).

Finally, we used the linear support vector machine (SVM) to predict participants' intentional decisions based on the task availability and history of recent trials, and compared the prediction with a random choice sequence as a baseline.

4.2.8. Results

In the SATs (i.e., stay-available trials), the 3x3 transition matrix illustrated that participants had a difference in transition rates between tasks (**Figure 12A - left)**. The diagonal of the matrix shows the rate of staying on a certain task when it is available. The mean rates of staying in the learning, memory, and perception tasks were .61, .55, and .66, respectively. In each task, chi-squared tests on the numbers of stay and switch trials suggested that participants chose to stay more than to switch in all the tasks with $\chi^2(1, N=3744)$ 250.86 for the learning task, $\chi^2(1, N=3500) = 66.38$ for the memory task and $\chi^2(1, N=4552) = 674.32$ for the perception task (all corrected $p < .001$, **Figure 12B**). Moreover, an analyses of variance (ANOVA) showed that the repetition rates of different tasks were different ($F(2, 200) = 6.196$, $p = .002$). Post-hoc analyses suggested that the repetition rate of the perception task was higher than the memory task ($p = .001$), but the repetition rate of the learning task neither differed from the perception task ($p = .211$) nor the memory task ($p = .351$). The average repetition rate was .591 ± .023 for the learning task, .652 ± .021 for the perception task, and .547 ± .022 for the memory task.

In the FSTs, the diagonal of the transition matrix was invalid as the participants were forced to switch tasks (**Figure 12A - right**). The remaining two cells in each row suggested the choosing rates of different tasks when they were forced to switch from a certain task and thereby the sum of each row in the matrix is 1. The chi-squared test on the numbers of the trials switched to the other tasks from each kind of task suggested that participants had a preference for the perception task with a $\chi^2(1, N=3600) = 180.45$, $p<.001$ from the learning task and a $\chi^2(1, N=3268) = 324.30$, $p<.001$ from the memory task. Moreover, when being forced to switch from the perception task, participants chose more learning tasks than the memory tasks ($\chi^2(1, N=4520) = 11.61$, $p<.001$).

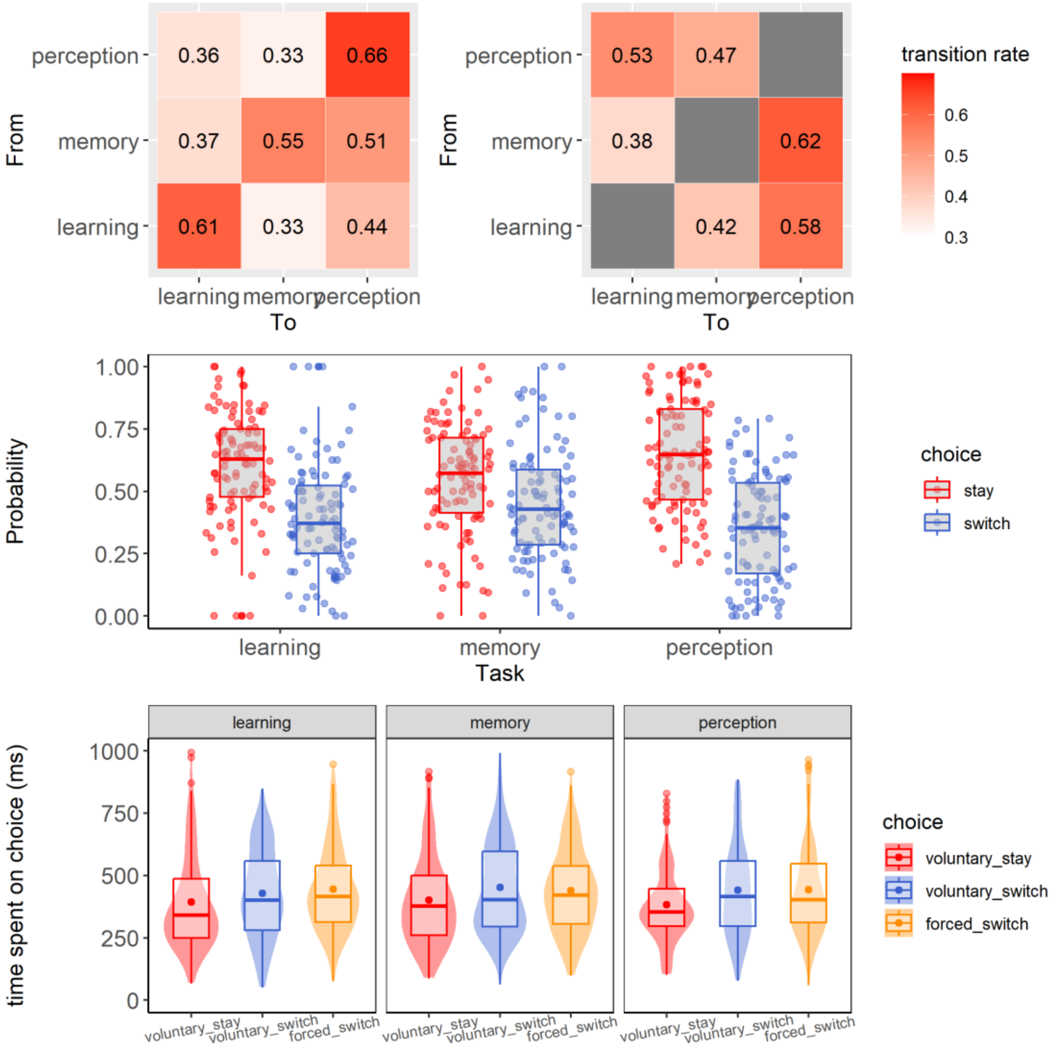


Figure 12. The performance on the choice page in Experiment 1. (**A**) The transition probability for the SATs (left) and the FTSs (right). (**B**) The possibility of staying and switching for each task. (**C**) The time spent on the choice of each task with three different types of choice behaviours.

We also analysed the time spent on choosing the tasks. There were three possible choice behaviours for each task including the voluntary stay, the voluntary switch, and the forced switch. A 3 task types (i.e., learning task, perception task and memory task) x 3 transition types (i.e., voluntary stay, the voluntary switch, and the forced switch) RMANOVA showed no interaction between the types of tasks and the types of choices (*F*(3.49, 296.83) = .276, *p* = .893, Greenhouse-Geisser correction) but a main effect on the three choice behaviours (*F*(2, 170) = 15.748, p<.001, **Figure 12D**). Further pairwise analyses suggested that time spent on voluntarily choosing to stay at certain tasks was shorter than both voluntary switch ($p < .001$) and forced switch ($p < .001$), but there was no difference between the voluntary and the forced switch ($p = .390$). In sum, participants exhibited different preference towards the three cognitive tasks when they had the freedom to choose among them, and the intentional decision of repeating the same task incurred faster RT compared with intentional switch or forced task switch decisions.

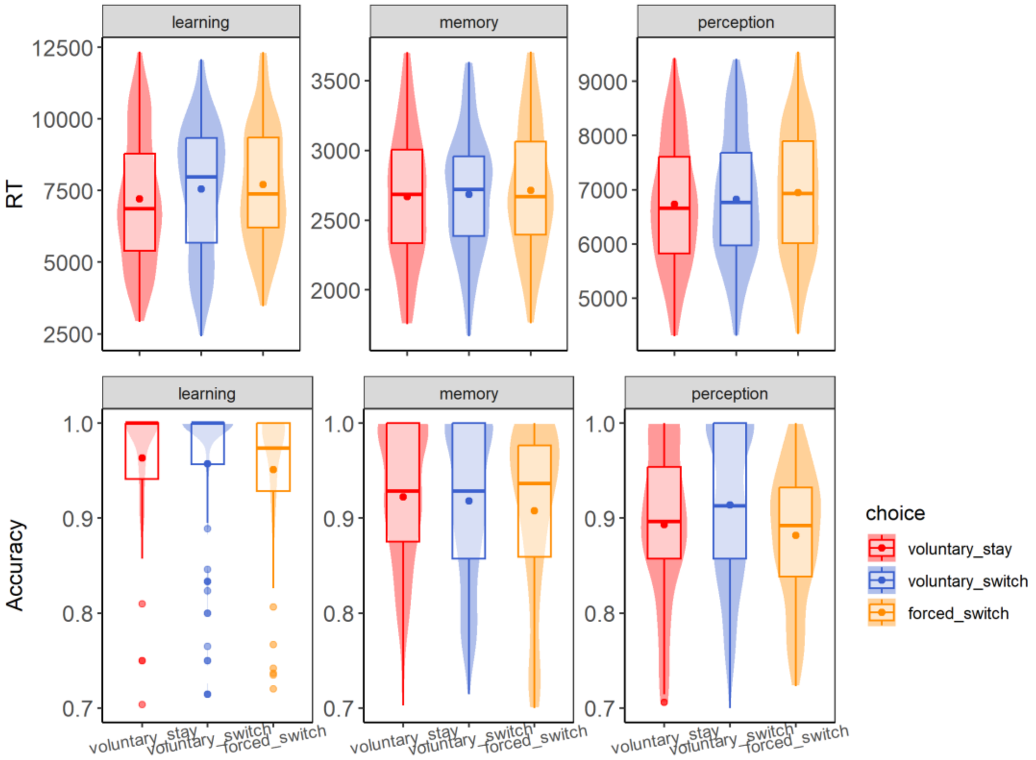


Figure 13. Task performance in Experiment 1. (**A**) The reaction times of the three tasks with three different types of choice behaviours. (**B**) The accuracies of the three tasks with three different types of choice behaviours.

The performance of each task was measured with accuracies and RTs. The accuracy of the learning task was 88.62% ± 20.09%, the accuracy of the memory task was 89.83% ± 8.87%, and the accuracy of the perception task was 85.19% ± 12.70% **(Figure 13B)**. The average RT for the learning task was 8793.61 ± 8260.47 ms, the average RT for the memory task was 3009.27 ± 1914.19 ms, and the average RT for the perception task was 7496.15 ± 4676.94 ms **(Figure 13A)**. The memory task had the stimulus page and the response page separately and the RTs of the memory task only calculated the time spent on the response page as the stimulus page was always shown for a fixed time period (5500 ms). The 3x3 RMANOVA suggested that neither the task types nor the choice behaviours had an influence on the accuracy. However, the task types and the choice behaviours had an interaction effect on the RT ($F(2.47, 225.27) = 4.260$, $p < .001$, Greenhouse-Geisser correction). There were significant main effects for both task types ($F(1.384, 125.96) = 7.955$, $p < .001$, Greenhouse-Geisser correction) and transition types ($F(2, 182) = 400.049$, $p < .001$). The RT of the learning task is longer than that of the perception task (corrected p =.002), which is greater than that of the memory task (corrected $p < .001$). The RT of stay trials is shorter than that of forced switch trials (corrected $p < .001$), but the RT of forced switch trials was not different from the voluntary switch trials (corrected $p = .450$). Further pairwise contrasts between individual conditions suggested that in the learning and the perception task, the RTs of the stay trials were shorter than both voluntary switch trials ($p < .001$ for learning and $p = .023$ for the perception) and forced switch trials ($p = .044$ for the learning and $p = .007$ for the perception), but voluntary switch trials and forced switch trials had no difference from each other. In the memory task, the RT of the stay trials was shorter than the voluntary switch trials ($p = .040$), but the RT of forced switch trials had no difference from both stay trials and voluntary switch trials. All p-values of the pairwise comparisons were corrected for multiple comparisons using Tukey's correction.

The questionnaire scores were calculated and analysed with the behavioural patterns. The scores of the MPI measure ranged from 14 to 59 with a mean score of 37.27 ± 10.34, and the scores of the CSI measure ranged from 20 to 75 with a mean score of 50.54 ± 11.02. Simple correlations were conducted between the questionnaire scores and the repetition rates, and 3 task types × 3 transition types analyses of covariance (ANCOVAs) with the questionnaire scores as covariates were conducted for the accuracy and the RT. However, there was no significant correlation between questionnaire scores and behavioural patterns (all corrected ps > .05).

The post-experiment feedback indicated that participants rated the difficulty levels of the three tasks differently ($F(1.71, 170.79) = 41.24$, $p < .001$, Greenhouse-Geisser correction). Post-hoc analysis suggested that the memory task had the highest self-report difficulty level (2.70 ± 1.45) followed by the learning task (1.93 ± 1.64), and the perception task had the lowest self-report difficulty level (1.23 ± 1.00). The differences between those tasks were statistically significant ($p < .001$, Bonferroni corrected).

Moreover, there were 47 participants in the 210-trial group and 43 participants in the 250-trial group. Our experimental design allowed the session to be completed within 210 trials (with each task chosen in 70 trials) or a maximum of 250 trials. Based on this completion criteria, participants were naturally divided into two groups (i.e., one group completed a total of 250 trials, and the other group completed 210 trials, with 70 trials in each of the tasks). The remaining 11 participants completed 220 to 250 trials which suggested that they didn't have a clear strategy for completing the experiment and were therefore excluded in the subsequent analysis. (**Figure 14A**). The two subgroups were comparable in gender, age, questionnaire scores, and subjective evaluation of the task difficulties (**Figure 14B**).

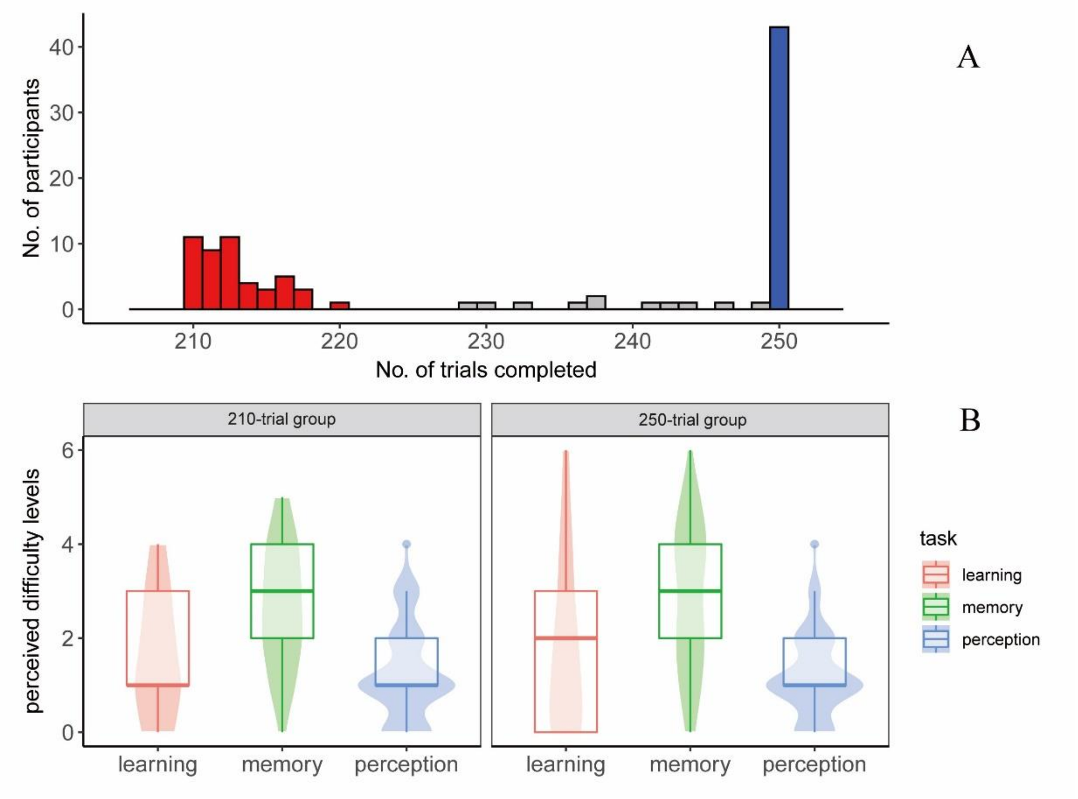


Figure 14. Subgroups in Experiment 1. (**A**) The grouping result with the distribution of the number of trials completed in all the participants. The red part indicates the 210-trial group and the blue part indicates the 250-trial group. (**B**) The perceived task difficulty levels of the three tasks in the two subgroups.

The two subgroups were different in the transition patterns. The repetition rates of the 210-trial group were .58 for the learning task, .53 for the memory task, and .55 for the perception task. On the other hand, the 250-trial group had repetition rates of 0.64, 0.56, and 0.77 for the three tasks, respectively (**Figure 15**). As expected, the 250-trial group had a stronger tendency to repeat the same task when possible.

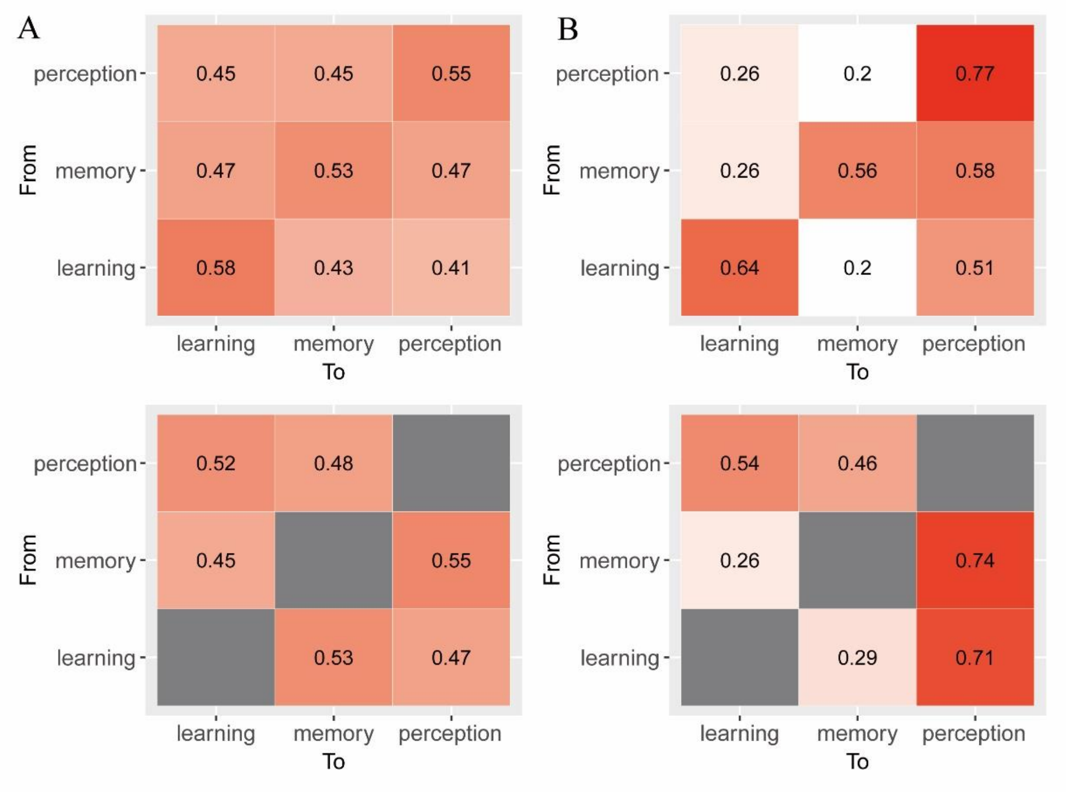


Figure 15. The transition probability for two subgroups. (A) the transition probability of the 210-trial group with SATs (upper) and the FTSs (lower). (B) the transition probability of the 250-trial group with SATs (upper) and the FTSs (lower).

Performance differences were found in RT on choice-making and task performance. The 250-trial groups spent less time making the choice of the next task than the 210-trial groups in both FSTs (Mean Difference (MD) = -120.884 ms, *t*(63) = 2.565, *p* = .013) and SATs (MD = -91.576 ms, *t*(70) = 20.38, *p* = .045) but also had averagely lower accuracy in the trials they completed (MD= -5.8%, *t*(88) = 2.853, *p* = .006). Additionally, the 250-trial group also had shorter average RTs in general than the 210-trial group (MD = -516.46, *p* = .026). This trend is consistent for all three tasks (**Figure 16**).

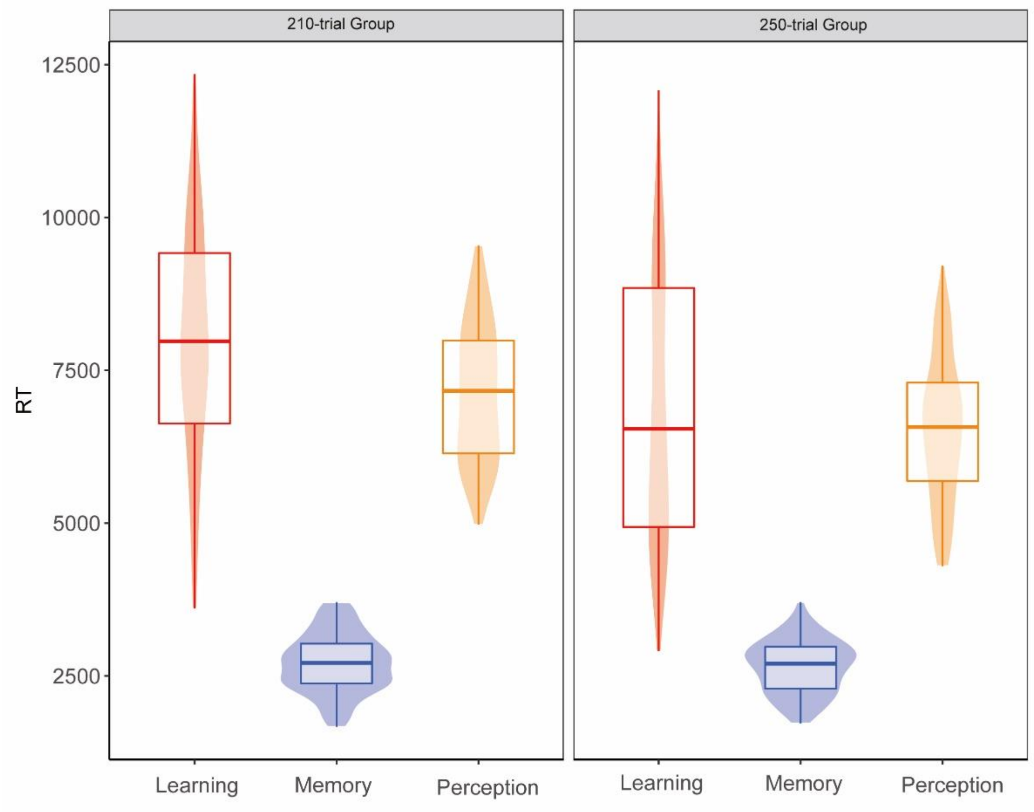


Figure 16. The reaction times of the three tasks for the two subgroups in Experiment 1.

Finally, we used a support vector machine (SVM) to predict participants' intentional decisions on tasks. The availability of the three tasks and the recent history of task choices were used to predict the choice of the next task, and a random choice sequence simulated by the computer was used as a control. The simulation was repeated 101 times (i.e., the actual number of subjects) for 250 trials. Because the numbers of observations were different in the simulation, 210-trial group and 250-trial group, a Kruskal-Wallis test was conducted for the classification accuracy, revealing a significant difference in them ($\chi^2(2) = 133.57$, $p < .001$). Further pairwise comparisons suggested that the availability of the task itself can help to predict participants' choice in the 250-trial group ($W = 1.00$, $p < .001$) but not in the 210-trial group ($W = 945.20$, $p = .124$) (**Figure 17A**). Additionally, one-way ANOVAs on the prediction accuracies with 4 levels of different number of recent histories were conducted in 210-trial group and 250-group trial separately. The recent history of task choice did not improve the prediction accuracy for either the 210-trial group

(*F*(1,186) = 3.143, *p* = .078) or the 250-trial group (*F*(1,170) = 2.161, *p* = .143) (**Figure 17B, Table 5**).

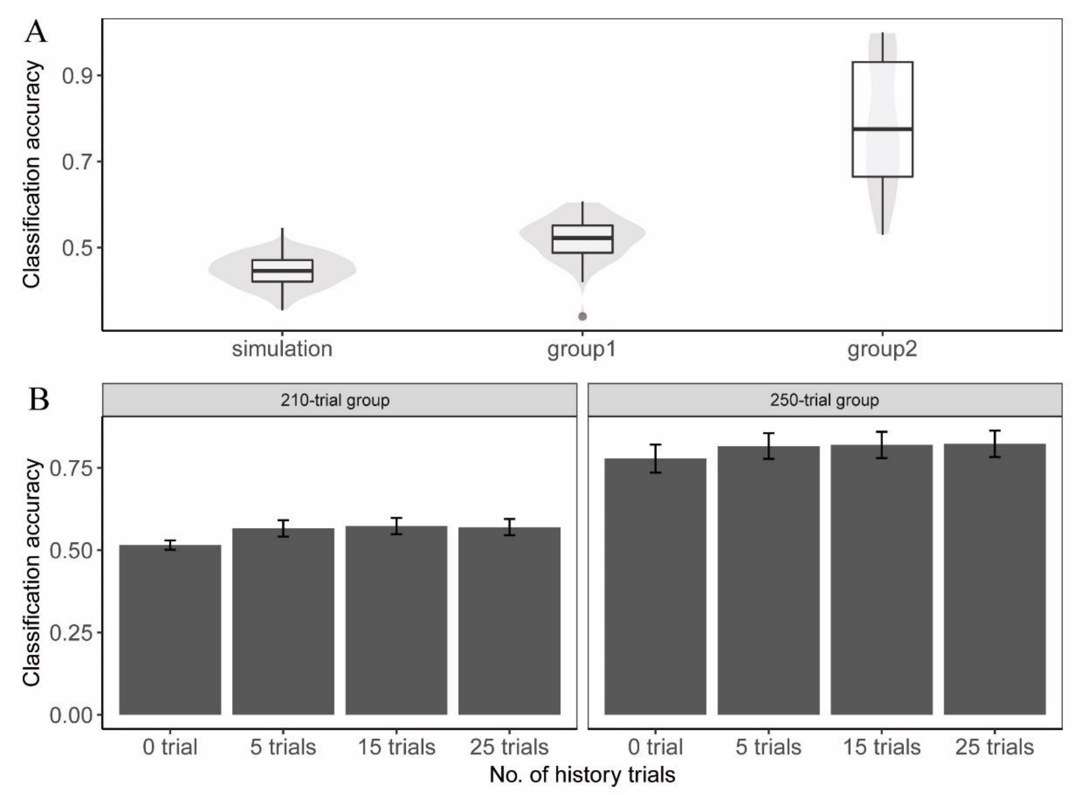


Figure 17. SVM prediction in Experiment 1. (**A**) The choice prediction accuracy with task availability only for each trial in random simulation, 210-trial group, and 250-trial group. (**B**) The choice prediction accuracy with task availability plus a different number of history trials in the two subgroups.

Table 5. The classification accuracy of two group with different number of recent history.

No. of Recent history	**210-trial group**		**250-trial group**	
	Mean	**SD**	**Mean**	**SD**
0 trial	51.53%	0.71%	78.79%	2.11%
5 trials	56.59%	1.23%	81.63%	1.93%
15 trials	57.32%	1.23%	81.97%	1.98%
25 trials	56.97%	1.22%	82.28%	1.98%

4.2.9. Summary of Experiment 1

Experiment 1 provided a new experiment paradigm that allows participants to choose among different cognitive tasks to investigate the intentional decision on higher cognitions.

On the group level, the results suggested that participants preferred to repeat the same type of tasks instead of switching to other types. The repetition rate is closely related to the perceived task difficulties of each task type. The perceived easiest task is the perception task, and it has the highest repetition rate. However, the perceived difficulty level does not reflect the objective behavioural performance in time cost or accuracy. Furthermore, the switch costs were not only found on RT of task performance but also on RT of the task choice for both voluntary and forced switches.

On the individual level, participants presented a large individual variability in their repetition preferences. With the extra benefits of task switch (i.e., to complete the task in fewer trials), there are still about half of the participants who chose to do the perceived easier task repeatedly.

4.3. Experiment 2: Influence of difficulty levels

In the previous experiment, participant's repetition rate was closely related to their perceived task difficulty of each task type. This conclusion is supported by the result that the perception task had the highest repetition rate and it was the perceived easiest task. However, the perceived difficulty level did not reflect the objective behavioural performance in time cost or accuracy. Therefore, Experiment 2 added an extra independent variable of difficulty levels to all the tasks, aiming at investigating the influence of difficulty levels on participant's task choice.

4.3.1. Participants

The effect size of the interaction effect of the 3 task types x 3 transition types RMANOVA on RT in Experiment 1 was .217. This effect size was transferred from the eta-squared value using G*Power 3.1 software (Erdfelder et al., 2009). The same software was used to calculate the needed sample size. Based on this effect size and an aimed power of 0.9, the minimum sample size needed for a 3 x 3 RMANOVA in

Experiment 2 was 48. Therefore, 75 participants (50 females and 25 males) were recruited from Prolific. The participants were aged from 18 to 68 years with an average age of 31.68 ± 10.16 years. All participants had current study levels at or above secondary education and had English as their first language. Informed consent was obtained from all participants and all participants received momentary compensation for their time. The study was approved by the Cardiff University School of Psychology Research Ethics Committee.

4.3.2. Apparatus

All the apparatus was the same as those used in the Experiment 1.

4.3.3. Tasks

In the experiment, participants were able to voluntarily choose both task types and task difficulty levels on each trial (**Figure 18**). The task type and the difficulty level were independent of each other as each task had two difficult levels: easy and difficult. The task forms were inherited from Experiment 1 but the patterns of the stimulus varied according to the difficulty level.

4.3.3.1. Learning task

In the easy learning task, the letter combinations consisted of 3 unrepeated letters. The corresponding pairs can be generated with one of the 4 possible rules as described in Experiment 1. In the difficult learning task, the letter combinations consisted of 5 unrepeated letters, and the corresponding pairs had 10 possible matching rules.

The other settings of the learning task were the same as the learning task in Experiment 1.

4.3.3.2. Memory

In the easy memory task, participants had 4 seconds to memorize 6 words. The 6 words were shown in three rows with two words in each row. In the difficult memory task, participants were asked to memorize 9 words in 4 seconds. The 9 words were shown in three rows with three words in each row.

The other settings of the memory task were the same as the memory task in Experiment 1.

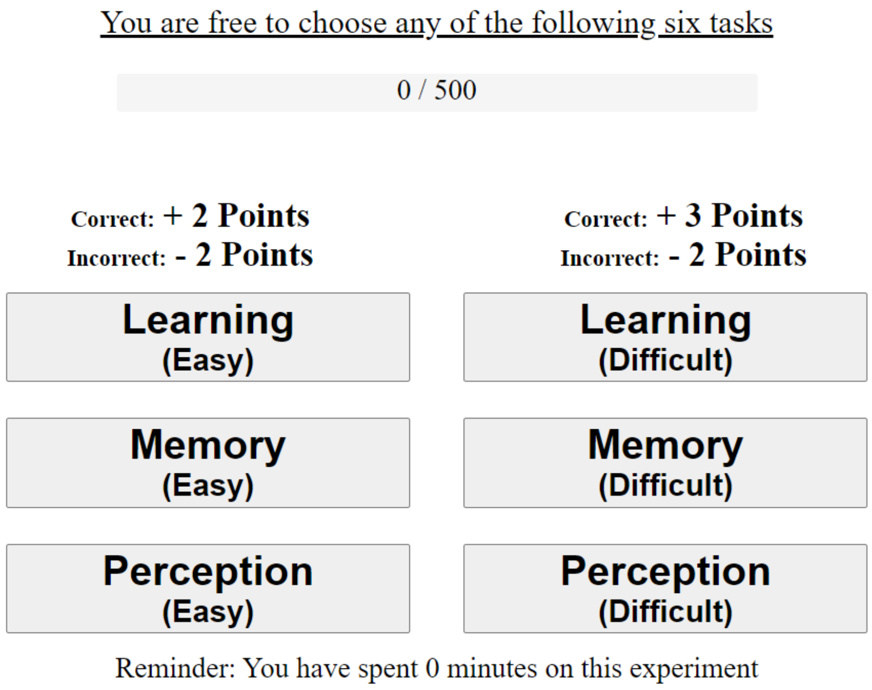
4.3.3.3. Perception

In the easy perception task, the letter matrices consisted of 3 rows and 6 columns. A column could have either none or two same letters. In the difficult task, the letter matrices consisted of 3 rows and 12 columns. A column could have none or two or three same letters.

4.3.4. Procedures

A complete experimental session contains a behavioural experiment and two standard questionnaires as in Experiment 1.

The behavioural experiment consisted of three cognitive tasks including learning, memory, and perception and each task had two difficulty levels. Every task contained an unlimited number of trials. Being different from Experiment 1, the behavioural experiment in Experiment 2 employed a point system to differentiate the objective value of two difficulty levels. A correct response was worth two points in an easy trial and was worth three points in a difficulty trial, while an incorrect response in either difficulty level would result in a two-point deduction. Participants needed to collect 500 points to complete the behavioural session. Moreover, this setting replaced the attention check algorithm in Experiment 1 as well. Because of the nature of the point system, the experiment completion also means that participants reached over 40% accuracy in the difficult task or over 50% accuracy in the easy task.



You are free to choose any of the following six tasks

0 / 500

Correct: + 2 Points
Incorrect: - 2 Points

Correct: + 3 Points
Incorrect: - 2 Points

Reminder: You have spent 0 minutes on this experiment

Figure 18. The choice page of Experiment 2. There were three cognitive tasks and each task had two independent difficulty levels. The point system and a progress bar were presented above the tasks, and a reminder on the time spent was presented under the tasks.

Before practice, participants were instructed to go through an introductory session as in Experiment 1. The introductory session would introduce them to the structure of the main choice page and give them a chance to learn and practice all kinds of tasks in the demo trials. The difficulty level of the demo trials was in the middle of easy and difficult for participants to build a baseline judgment of the difficulty levels.

The formal experiment was similar to Experiment 1 with adjustments in 6 aspects:

1) Each task was horizontally divided into two separate buttons for the two difficulty levels, resulting in six buttons arranged in a 2 x 3 format. The side that the selection button was presented on was also randomized across the participants. This additional variability was independent but secondary to the tasks. In other words, if a task became unavailable, the participant was not able to choose either the easy or the difficult version of the task.

2) Instead of showing the number of trials completed, the progress bar shows the

points that participants collected so far.

3) There were rules of the point system between the progress bar and the task buttons. The rules were arranged in two lines. The upper line was for correct answers and the lower line was for the incorrect answers.

4) After each trial, feedback about participants' performance in that trial was shown under the progress bar. For a correct answer, the feedback would be in blue and indicate that participants did the trial correctly and collected certain points (e.g., 'Correct! You collected 2 points'). For an incorrect answer, the feedback would be in red and indicate that participants made a mistake and lost two points (e.g., 'Incorrect! You lost 2 points!').

5) The type of a trial was randomized across the experimental session. FST and SAT trials were randomly selected with a 50% probability.

6) Because the completion criteria did not involve the points collection in each single task, there were no additional progress bars under each task.

The questionnaires and feedback session were the same as in the Experiment 1.

4.3.5. Behavioural Measures

In addition to the independent variables in the Experiment 1, an additional independent variable, difficulty levels, was recorded. The dependent variables were the same as in the Experiment 1.

4.3.6. Data Pre-processing

Different from Experiment 1, there was no pre-screening for the RTs because each task had two levels of difficulty level and would automatically increase the RT deviation of a single task. Also, because the number of the easy trial and the difficulty trials were not evenly distributed and the number of the easy trials was about 1/3 of the number of the difficulty trials in total, it is not reasonable to eliminate single trials with the same criteria in them as a smaller sample is more possible to associate with larger data deviation.

4.3.7. Data Post-processing and Statistics

The statistical analyses were mostly the same as the Experiment 1 with adjustments in 3 aspects to fit the settings of Experiment 2:

1) There were no subgroup analyses as there was only one way to complete the experiment in Experiment 2.
2) There was an additional analysis on the proportion of difficulty trials chosen by the participants.
3) The task performances were calculated and analysed with difficulty levels separated.

4.3.8. Results

In the SATs, the 3 x 3 transition matrix illustrated that participants had a difference in transition rates between different tasks in general (**Figure 19A - left**). The diagonal of the matrix shows the rate of staying on a certain task when it is available. The mean rates of staying in the learning, memory, and perception tasks were .63, .66, and .67, respectively. In each task, chi-squared tests on the numbers of stay and switch trials suggested that participants chose to stay more than to switch in all the tasks with $\chi^2(1, N=2751) = 674.26$ for the learning task, $\chi^2(1, N=3164) = 621.24$ for the memory task and $\chi^2(1, N=2466) = 756.68$ for the perception task (all corrected p-values < .001, **Figure 19B**). However, the repetition rates of different tasks were not significantly different ($F(2, 88) = .242$, p = .731, Greenhouse-Geisser correction).

In the FSTs, the diagonal of the transition matrix was invalid as the participants were forced to switch a task (**Figure 19A - right**). The remaining two cells in each row suggested the choosing rates of different tasks when they were forced to switch from a certain task and thereby the sum of each row in the matrix should be 1. The chi-squared test on the numbers of the trials switched to the other tasks from each kind of task suggested that participants had a preference for the perception task with $\chi^2(1, N=2546) = 306.93$, corrected $p < .001$ from the learning task and $\chi^2(1, N=2468)$ = = 232.81, corrected $p < .001$ from the memory task. However, when being forced to switch from the perception task, participants had no preference for the learning or the memory task ($\chi^2(1, N=3224) = 4.77$, corrected $p = .029$).

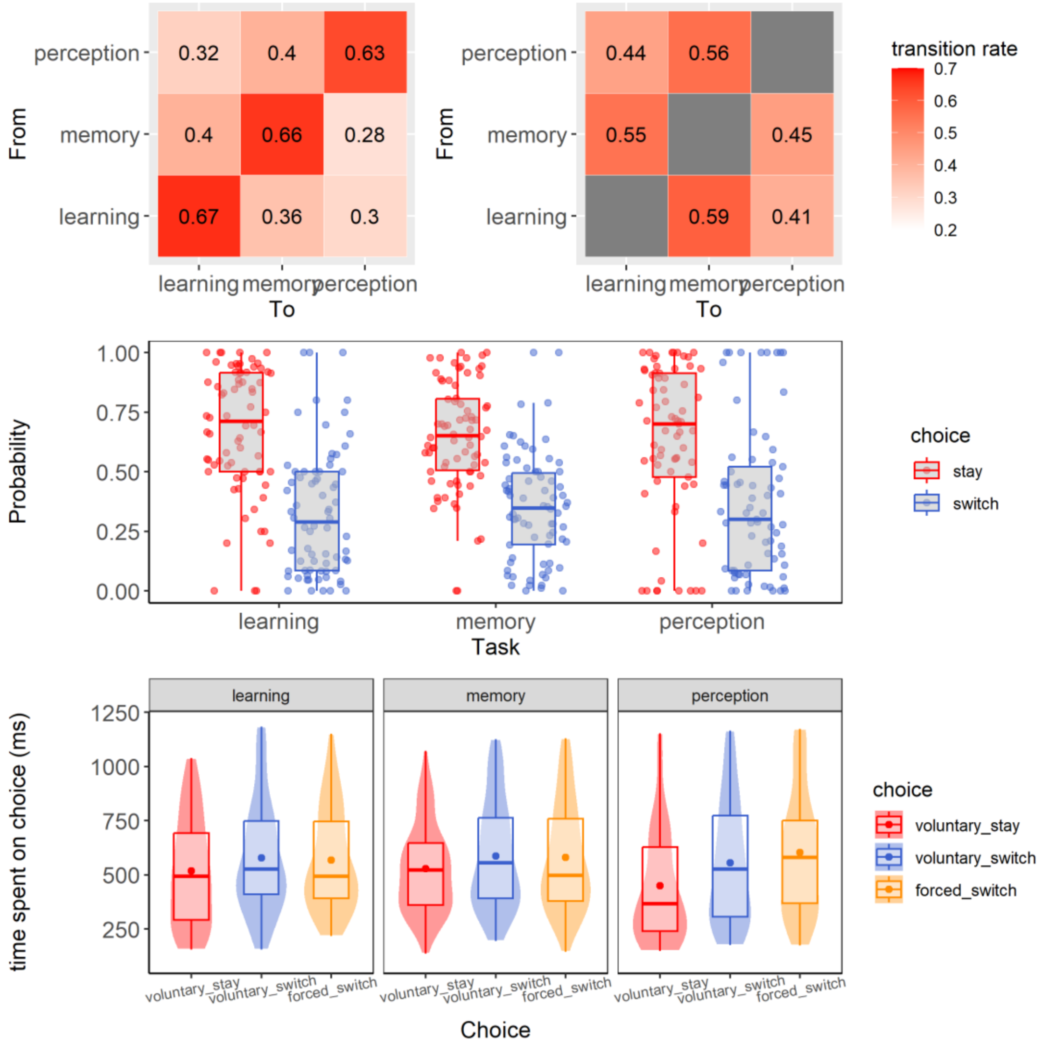


Figure 19. The performance on the choice page in Experiment 2. (**A**) The transition probability for the SATs (left) and the FTSs (right). (**B**) The possibility of staying and switching for each task. (**C**) The time spent on the choice of each task with three different types of choice behaviours.

We also analysed the time spent on choosing the tasks. There were three possible choice behaviours for each task including the voluntary stay, the voluntary switch, and the forced switch. A 3 task types (i.e., learning task, perception task and memory task) x 3 transition types (i.e., voluntary stay, voluntary switch, and forced switch) RMANOVA suggested no interaction effect between the types of tasks and the types of choices (*F*(1.96, 78.26) = .580, *p* = .678, Greenhouse-Geisser correction) but a main effect on the three choice behaviours (*F*(1.48, 78.26) = 4.64, p = .012, Greenhouse-Geisser correction, **Figure 19C**). Further pairwise analyses suggested that time spent on voluntarily choosing to stay at a certain task was shorter than both voluntary switch (MD = -138.637 ms, corrected *p* = .036) and forced switch (MD = -236.064 ms, corrected *p* = .017), but there was no difference between the voluntary and the forced switch (MD = 97.427 ms, corrected *p* = .929).

Additionally, the chosen rates of the two difficulty levels were different across the participants (**Figure 20A**). The proportion of difficult trials was calculated with the number of difficult trials completed being divided by the number of all the trials completed. The proportion of difficulty trials was not evenly distributed among the participants. About 57% of the participants completed their sessions with at least 75% of difficulty trials, while only about 13% of the participants completed their sessions with less than 25%. The average proportion of difficulty trials was .699 ± .375, .347 ± .354, and .507 ± .416 for the learning, memory, and perception tasks respectively (**Figure 20B**). A 3-level RMANOVA of task type effect on difficult chosen rate suggested that the rate of choosing the difficult task differed across task type (*F*(1.732, 128.190) = 12.221, *p* < .001, Greenhouse-Geisser correction). Further pairwise analyses showed that participants had a higher rate of choosing the difficult task in the learning task compared to the perception task, and also in the perception task compared to the memory task. (all corrected *p* < .05). At the same time, the post-experiment feedback showed that the perceived difficulty levels for the learning, memory, and perception tasks were 2.27 ± 1.78, 2.60 ± 1.68 and 1.90 ± 1.42, respectively (**Figure 20C**). Another 3-level RMANOVA of task type effect on perceived task difficulty levels revealed that participants rated the difficulty levels of the three tasks differently (*F*(1.80,123.88) = 3.603, *p* = .030, Greenhouse-Geisser correction). Post-hoc analysis suggested the memory task had a higher perceived difficulty level than the perception task (corrected $p = .010$), but the perceived difficulty level of the learning task was no different from either the perception task or the memory task (corrected $p > .05$).

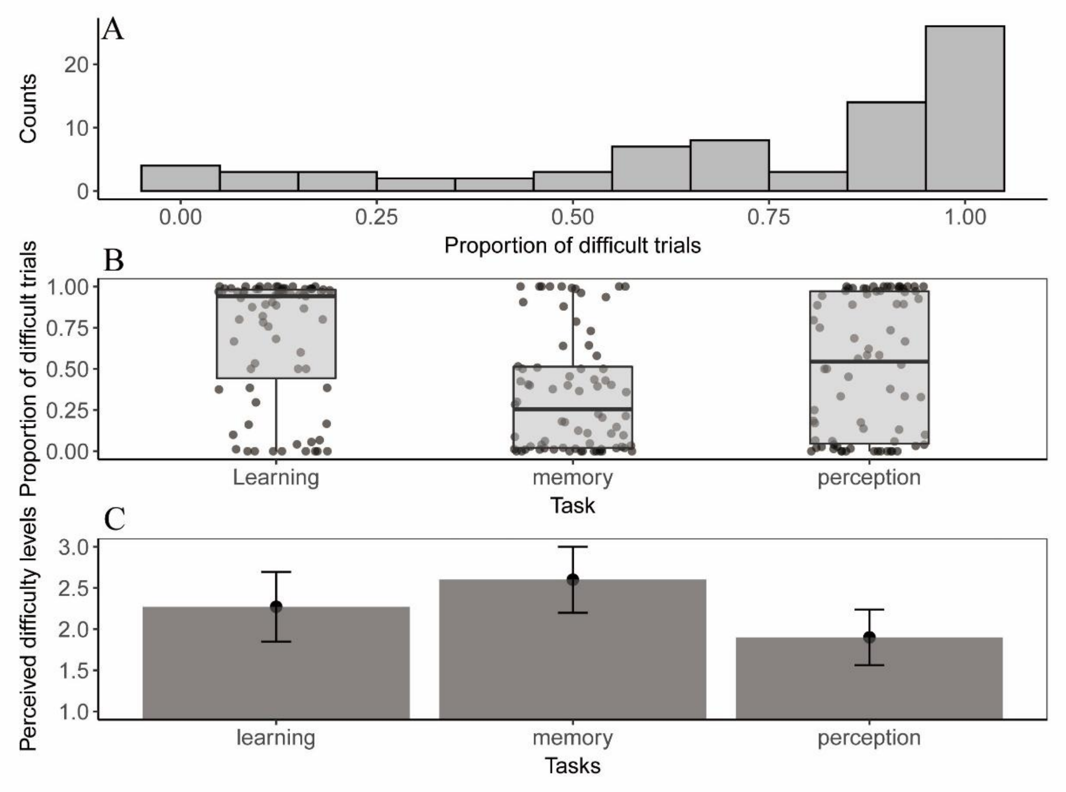


Figure 20. Difficulty levels related results in Experiment 2. (**A**) The distribution of difficulty trials chosen rate in all the participants. (**B**) The difficulty trials chosen rate in the three tasks. (**C**) The perceived task difficulty levels of the three tasks.

The performance of each task was measured with accuracies and RTs. The accuracy and the reaction time of different tasks at different difficulty levels are shown in **Table 6** and **Figure 21**. As it is possible that participants would only choose and switch between two preferred tasks or stick to a certain difficulty level, the number of valid data points varied. Two linear mixed-effect models with random intercepts were used to investigate the effect of tasks and the difficulty levels of the task performance. The model with both task types (Akaike Information Criterion (AIC) = 3642.3) and difficulty levels for the accuracies performed statistically better than the model with only one of the factors (AIC = 3650.8 for the difficulty level only model and AIC = 3663.5 for the task type only model, both *p*s < .001), suggesting both task types and difficulty levels had influence on the accuracy. Similarly, the model with both task types and difficulty levels for the RTs (AIC = 270892) was also better than the model with only one of the factors (AIC =270897, *p* < .001 for the difficulty level only model and AIC = 271019, *p* = .008 for the task type only model), suggesting the effects of both task types and difficulty levels on the RTs. Therefore, the final linear mixed-effect model used for accuracy was

Accuracy ~ task + difficulty levels + (1+ task | subjects)

The final linear mixed-effect model used for RTs was

RT ~ task + difficulty levels + (1+ task | subjects)

In the first model (i.e., the one had accuracy as outcome effects), fixed effect of task has an intercept (i.e., the accuracy of the difficult learning task) of .931± .009 (*p* < .001). The estimated coefficient of the memory task is -.037 ± .013 (*p* = .006), the estimated coefficient of the perception task is -.073 ± .012 (*p* < .001), and the estimated coefficient of the easy task was .025 ± .007 (*p* < .001), suggesting participants on average had higher accuracy in the learning task and in the easy task. In addition, the random effects had a grouping structure of subjects with a random effect term of task types. The intercept (i.e., the learning task) had a variance component of .005 ± .068, the memory task had a component of .008 ± .089, and the perceptual task had a component of .006 ± .080, suggesting relatively low variability of task accuracy among all the participants.

In the second model (i.e., the one that had RT as outcome effects), the fixed effect of the task has an intercept (i.e., the RT of the difficult learning task) of 16061.3 ± 1004.5 (*p* < .001). The estimated coefficient of the memory task is -3805.7 ± 944.4 (*p* < .001), the estimated coefficient of the perception task is -12426.8 ± 1002.3 (*p* < .001), and the estimated coefficient of the easy task was -741.5 ± 272.8 (*p* = .007), suggesting participants on average had higher accuracy in the learning task and easy task. In addition, the random effects had a grouping structure of subjects with a random effect term of task types. The intercept (i.e., learning task) had a variance component of 70789913 ± 8414, the memory task had a component of 57479194 ± 7582, and the perceptual task had a component of 67665285 ± 8226, suggesting a substantial variability in the RT across different participants, way beyond what would be expected due to random variation within each individual.

Table 6. The accuracy and the RTs of three tasks at different difficulty levels

Task	**Accuracy**				**Reaction time (ms)**			
	Easy		Difficult		Easy		Difficult	
	mean	SD	mean	SD	mean	SD	mean	SD
Learning	.83	.034	.90	.029	17953.30	1174.41	17019.04	1199.09
Memory	.92	.018	.80	.031	3134.95	179.42	3519.23	278.57
Perception	.86	.028	.84	.020	9579.71	499.19	14645.69	689.87

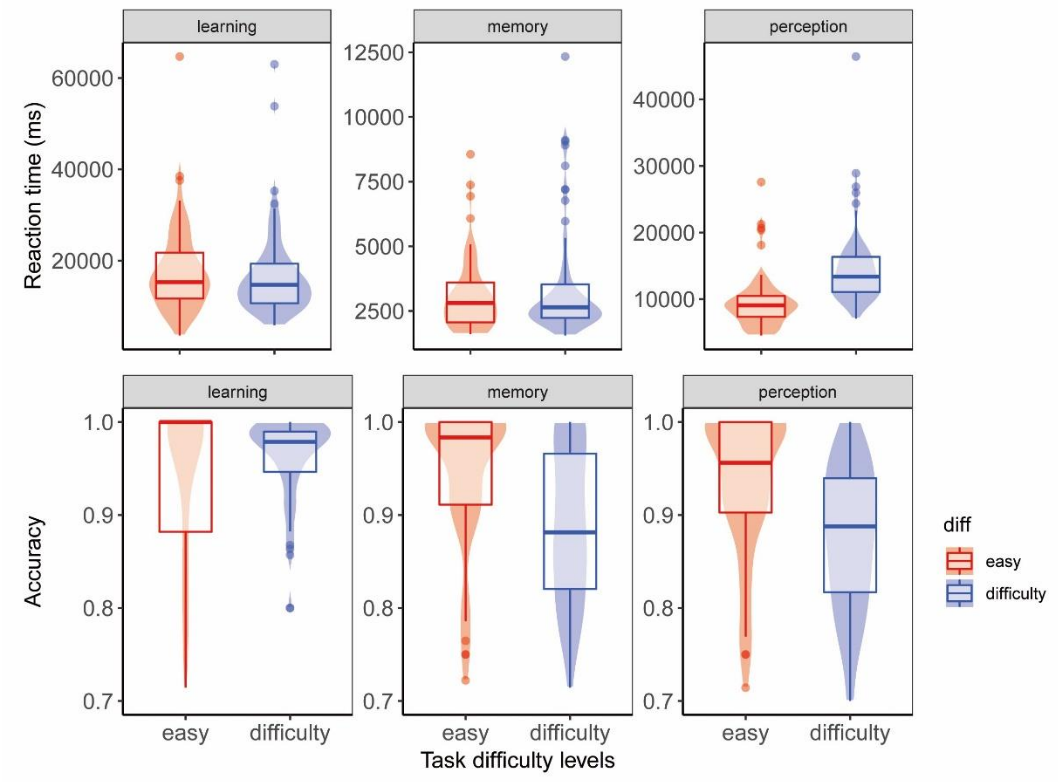


Figure 21. Task performance in Experiment 2. (**A**) The reaction times of the three tasks at different difficulty levels. (**B**) The accuracies of the three tasks at different difficulty levels.

The SVM prediction presented a result similar to that in Experiment 1. Task availability can predict the participant’s next choice with over 80% accuracy. A one-way ANOVA on the prediction accuracies with 4 levels of different numbers of recent histories suggested that adding recent choices to the model did not have a significant influence on the SVM classification accuracy (83% - 85%, $F(3, 296) = 1.410$, $p = .240$) (**Figure 22**).

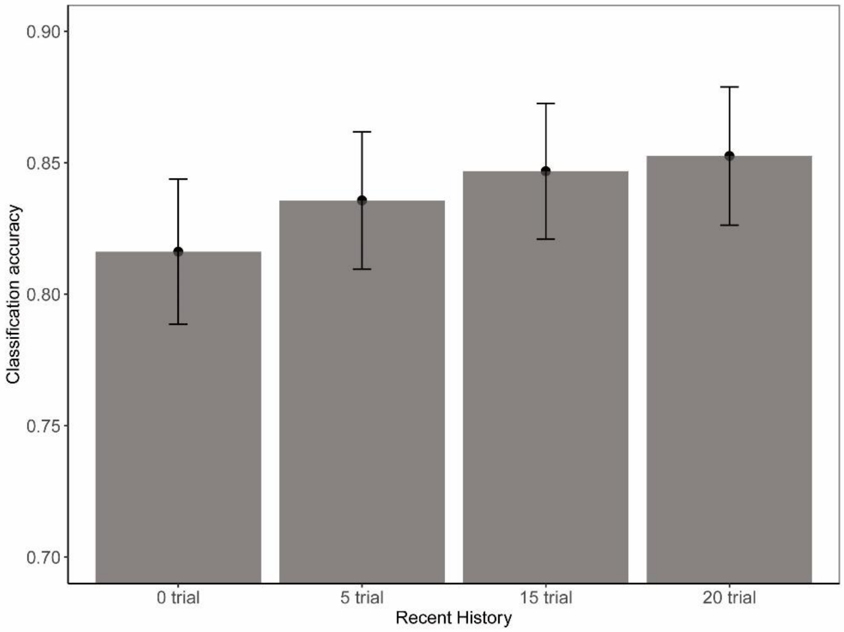


Figure 22. SVM prediction in Experiment 2. The choice prediction accuracy with task availability plus different numbers of history trials in the sample. The error bars indicate the standard error of the decoding accuracies.

The questionnaire scores were calculated and analysed with the behavioural patterns. The scores of the MPI measure ranged from 14 to 59 with a mean score of 26.24 ± 12.52, and the scores of the CSI measure ranged from 20 to 75 with a mean score of 48.33 ± 13.09. The MPI scores were positively correlated with the proportion of difficulty trials chosen by participants ($r = .236$, $p = .049$), indicating that the participants who had high MPI scores tended to choose more difficulty trials. Pearson correlations were conducted between the questionnaire scores and the repetition rates, and 3 task types × 3 transition types ANCOVAs with the questionnaire scores as covariates were conducted for the accuracy and the RT. However, there was no other significant correlation between questionnaire score and behavioural pattern (all *p*s > .05).

4.3.9. Summary of Experiment 2

Experiment 2 introduced two difficulty levels for all the tasks to further investigate how it may affect the intentional decision-making on higher cognitions.

The difficulty level was reflected in the task performance but only for task accuracy rather than the reaction time. This newly introduced variable balanced the perceived difficulty levels of each task as well as the task choice rate at the group level. However, at the same time, Experiment 2 replicated the repetition preference at the group level, suggesting a consistent repetition bias in cognitive intentions. Moreover, participants' choice tendency corresponds with their own ranking, as the task availability itself can still significantly predict the task choice, and adding recent histories would not facilitate the prediction accuracy. The covariations of the perceived task difficulties and task choice rate at both group and individual levels provided supportive evidence for the perceived difficulty levels as an influencing factor on cognitive intentions.

4.4. Discussion

4.4.1. Task performance and switch cost

The general performance in all the tasks was as predicted. First, in Experiment 2, the difficult trials had lower accuracy than the easy trials. Plus, the switch cost was found in the time spent on the choice page, and the RTs of the learning and the perception tasks, but not in the RTs of the memory task or the accuracies of all three tasks.

The switch cost of the time spent on the choice page (i.e., more time is needed when participants choosing to switch to a different task) was possibly a result of relocating the target task by saccades (Hunt & Klein, 2002). Because the repetition choice was preferred by the participants, the targets of the saccades would be (a) to check if the previous task is still available, and if the previous one is not available, (b) to find the new targeted task. Because the task position on the choice page was fixed for a single participant, the first saccade can be prepared before the choice page is shown. However, the task availability is unpredictable for each trial and the second saccade can only be done after the choice page is shown. Before initiating these saccades, the brain needs a while to integrate the visual information, and the integration process costs about 100 ms (Caspi et al., 2004). This has the same order of magnitude as the switch cost of RTs on the choice page in both experiments and thereby increases the credibility of this possibility.

The switch cost in RT of each task (i.e., more time is needed when participants performing the task after switching) can be explained by the reconfiguration of the cognitive set in the task switch (Hsieh & Liu, 2005; Rogers & Monsell, 1995). The learning task and the perception task presented the stimulus and the options on the same page. Therefore, the time spent on the reconfiguration process was included in the RT and thereby would illustrate switch costs. However, the memory task consisted of two successive pages of stimulus (word list) and response options. The cognitive reconfiguration was forced to be done in the fixed duration of stimulus presentation and hence cannot be detected with the RT recorded on the response page.

The unexpected task performance lies with the group difference in Experiment 1. The 210-trial group has an average higher accuracy than the 250-trial group. This was opposite to normal expectation, as more switches should related to more potential switch costs and thereby related to lower accuracy. One possible explanation is that doing more trials means the participants were more prone to fatigue and thereby resulted in lower performance. An electroencephalography study has suggested that with the task duration increasing, the number of errors made will increase and the ERP difference between stay trials and switch trials will diminish, indicating that attention loss is probably the reason for performance decrease (Lorist et al., 2000).

We did not find a significant difference in switch costs for different types of task switches as in classical voluntary switch tasks (Arrington & Logan, 2005). The voluntary and the forced switch showed similar costs compared with the stay trials. This could be attributed to the paradigm used. In the classical voluntary task switch, the stimuli are consistent and the required cognitive processes are similar for different tasks (e.g., digits for magnitude (i.e., less than or greater than five) or parity (i.e., even or odd)) judgments in Arrington & Logan, 2004, 2005). The high similarity between cognitive processes will intensify their mutual interference (Koch et al., 2018), which will increase the switch cost and its difference between different tasks.

4.4.2. Task bias and perceived difficulty levels

In Experiment 1, participants preferred the perception task over the other two tasks. This tendency is consistent with the post-experiment self-reported rating of the perception task as the easiest task.

However, these perceived difficulty levels did not match the difficulty levels evaluated via a more objective index such as accuracy, as the accuracies of the three tasks did not significantly differ. One possible explanation is that the metacognitive process of the participants was affected by some features of the tasks (Livingston, 1997). First, the memory task forced the participants to spend a period of time remembering the items, which may result in a direct sense of time-consuming. Participants were prone to link this with the task being difficult because individuals tend to spend more time on the more difficult tasks and less time on the easier tasks (Liu et al., 2012). Second, judgment confidence is also related to the perceived task difficulty (Chung & Monroe, 2000). Individuals' choice confidence is highly associated with the error detection process as the two processes have a shared computational basis: they depend on evidence accumulated before and after the decision (Charles & Yeung, 2019; Yeung & Summerfield, 2012). An EEG study suggested that monotonic reduction in error positivity amplitude is associated with increasing confidence in the preceding choice (Boldt & Yeung, 2015). Error positivity is a parietal-focused potential and has an established link to subjective error awareness (Steinhauser & Yeung, 2010). In addition, multivariate analyses on error positivity further suggested that the neural markers of error detection are a strong predictor of confidence level in decision-making (Boldt & Yeung, 2015). In our studies, the nature of the memory task and learning task limited the possibility of error detection. Therefore, they would be perceived as more difficult than the perception.

Moreover, the task preference towards perceptual task disappeared at the group level when the additional freedom to choose the difficulty level was introduced in Experiment 2. At the same time, the difference in perceived task difficulty levels also equalised at the group level. On the individual level, the task bias still exists, because inter-subject variations of cognitive abilities and cognitive styles widely exist in behavioural, neural imaging, and molecular studies (Parasuraman & Jiang, 2012).

4.4.3. Repetition bias

The results of both studies suggested when repetition was available, participants preferred to repeat the same task rather than switch to the other tasks. The repetition bias existed for all three tasks but could be further shaped by individual differences, such as perceived task difficulty levels. As shown in Experiment 2, the preference for perception only disappeared at the group level, and there was still an unbalanced task choice at individual levels. When task switching operates as an incentive (i.e., to have fewer trials to complete) in Experiment 1, only half of the participants exhibited a bias towards task repetition when available. When the potential benefit of task switching was removed in Experiment 2, task repetition became a common feature for all the participants.

This repetition bias is different from preference in value-based decision-making, as it can vary not only between the subjects but also within a single subject. Preference in value-based decision-making depends on subjective value, which is usually considered to be a common currency and will thereby lead to stable and consistent decisions over time and across contexts (Bartra et al., 2013). For example, behavioural research has shown that individuals tend to stick to one chosen rule (e.g., to make simple and effortless choices) and try to keep the rule throughout their decision-making (Hoyer, 1984; Hoyer & Brown, 1990; Samuelson & Zeckhauser, 1988). Along this line, if repetition (or a certain task) is subjectively valued higher than a switch (or the other tasks), it should be chosen all the time when it is available. However, we showed in the SATs that participants did voluntarily switch to other tasks when repetition was available.

One explanation of this voluntary switch lies with operant conditioning. Animal studies have provided evidence that behavioural diversity can be acquired via operant conditioning. Some of the studies considered the innate behaviour as stochastic and the repetition as learned (Neuringer, 1992; Odum et al., 2006), while some others considered the vice versa (Gutiérrez & Escobar, 2022; Neuringer, 2002). Human behaviours fit the latter view more because repetition can evolutionarily benefit individuals by helping them avoid uncertainty with minimized effort (Buss, 2005). From the random sequence generation task (Baddeley, 1966; Towse & Neil, 1998) to the voluntary switch task (Arrington & Logan, 2004), decades of intentional behavioural studies have proved that repetition is an innate feature in human decision-making. The variability, instead, was a result of the dynamic interaction between reinforcements or extinctions of individual responses (Nergaard & Holth, 2020). On the one hand, repetition was naturally negatively reinforced by incurring no extra switch cost. On the other hand, repetition is also associated with negative feelings such as boredom, which can trigger a variety of novelty seeking behaviour (Fishbach et al., 2011). In both experiments, when the accumulated boredom overwhelms the cost-benefit from repetition, a voluntary task switch may happen.

This speculation is in agreement with the prediction results of SVM. When participants showed the repetition bias (i.e.: the 250-trial group in Experiment 1 and all the participants in Experiment 2), their choices in each trial can be well predicted by the task availability itself, suggesting an independent task bias. Adding the information of recent histories for 5 trials, though not statistically significant, showed a consistent trend in improving the prediction accuracy, possibly indicating the effect of the accumulated boredom.

Furthermore, cognitive intention is also subject to individual differences. With an encouragement to switch by a discount on the total number of trials to complete in Experiment 1, some participants chose to obtain the time benefit from switching, while some others ignored the extra reinforcement and persisted in repetition. The former type of participants presented a stochastic choice pattern as the random computational simulation, implying that variability can be improved with effort.

4.4.4. Cognitive traits and intentional choice

The CSI tests how analytic or intuitive an individual is (Allinson & Hayes, 1996), and the MPI tests how much an individual likes doing multiple tasks at the same time (Poposki & Oswald, 2010). The scores of these two questionnaires in both experiments did not correlate with participants' choice patterns. That is, both CSI and MPI scores were not sensitive to repetition bias, task type preference, or task performance in both experiment. Only the MPI score had a weak correlation with the rate of choosing difficult tasks in Experiment 2. To be exact, people who prefers multitasking were tend to choose more difficulty tasks but they were not necessarily better at them. One of the possible reasons is that individuals who prefer multitasking may seek out more stimulating or challenging tasks because they provide a greater sense of engagement (Salvucci & Taatgen, 2010).

5. The Temporal-Spatial Neural Correlates of Cognitive Intentions: a MEG Study

5.1. Introduction

Because of the highly dynamic environment in which we live, humans are inevitably engaging in toggling between different tasks, making intentional task-switching one of the most important abilities for survival. A substantial amount of knowledge on task-switching has been established via research on *task sets* (Kiesel et al., 2010; Sakai, 2008), the specific stimulus-response association of a task. A common finding is that, compared with task repetition, the change of task set (i.e., task switches) will lead to a switch cost, manifested by longer reaction times, lower accuracies, or both (Vandierendonck et al., 2010). Furthermore, if the switches are self-initiated, participants would repeat the same tasks more frequently than expected on the basis of chance (e.g., Arrington & Logan, 2004, 2005).

However, most of the intentional task-switching or task-selecting paradigms used homogenous processes. As described in Chapter 3, reactive intention is to choose motor actions (e.g., pressing a left or right button), perceptual intention is to choose the features or the appearances of a given stimulus (e.g., finding red or blue patterns), inhibition intention is to choose whether to inhibit an action, and cognitive intention is to choose different facets of a certain process (e.g., doing addition or subtraction). Some of the task-switching research did involve different cognitive processes (e.g., the phonetic or shaped judgements in Liefooghe, 2017), but the task difference was not the main interest and there was no in-depth discussion. The experiments described in Chapter 4 focused on the effect of different cognitive processes on cognitive intentions (Chapter 4). It revealed individual differences in cognitive intentions, which are associated with the perceived difficulty levels of the tasks. Yet, the results remained at the behavioural level. To further understand the underlying brain activities of different cognitive intentions, this chapter reports a MEG experiment that explores the possible temporal-spatial neural correlates.

The paradigm in the previous online experiment was simplified by keeping only two tasks (memory and perception, which are the tasks having the most different perceived difficulty levels in Chapter 4) to boost the statistical power by increasing iterations of each task. Furthermore, the tasks used the same stimulus library of lattice matrices (instead of the words/letters in the previous online experiments) and were modified into more comparable structures to reduce potential confounding variables such as language-related processing, and thereby enhance the interpretability of the electrophysiological signals. A lattice matrix here is a two-dimensional array of dots. Using the same stimulus in different tasks can eliminate the effect caused by different stimuli. This equalization can help to better understand the cognitive intention itself.

The existing neuroimaging studies on voluntary choices suggested self-initiated behaviours are associated with higher activities in a frontoparietal network of pre-SMA, caudal ACC, dlPFC, IPL and AIC when compared with externally instructed behaviours (Schouppe et al., 2014; Si et al., 2021). In addition, traditional task-switching studies (i.e., switching between different stimulus-response associations under the same cognitive process) showed the engagement of a task set is related to the activation of the prefrontal area, including the anterior prefrontal cortex (Sakai & Passingham, 2003b), dlPFC (Sakai & Passingham, 2006), and ventral prefrontal cortex (Bengtsson et al., 2009). Therefore, the frontoparietal intentional decision-making network appears to have an overlap at the dlPFC with the prefrontal task-set-related regions. Nonetheless, direct evidence supporting this conjunction is scarce, primarily due to limited research on voluntary task rule choice, as proposed in this study.

Therefore, this chapter aimed to explore intentional choices on different cognitive tasks on two hypotheses: 1) the cognitive intention can be predicted by the brain activities before the choice onset, and 2) the task choice will influence the stimulus processing. Similar to the previous chapter, the behavioural performances were analysed using RMANOVA for the choice and the transition types. In addition, cluster-based permutations were applied to the MEG event-related fields (ERFs) to detect the sensor-level activity differences, and multivariate pattern analyses (MVPAs) were applied to the MEG source-localized data to investigate the brain-level representations of cognitive intentions.

5.2. Method

5.2.1. Participants

A total of 47 participants (35 females and 12 males) were recruited from the Cardiff University School of Psychology participant panel. Among all the participants, 4 participants withdrew from the experiment after the behavioural session, 1 participant had less than 40% accuracy in memory task and 1 participant had ineligible head digitalization results because of their hairstyle. These 6 participants were excluded from the future data analyses. The remaining 41 participants (29 females and 12 males) were aged 18 to 50 years with an average age of 22.95 ± 6.55 years. All participants had current education levels above secondary education, normal or corrected-to-normal vision, and no history of any significant neurological or psychological disorders. Informed consent was obtained from all participants for all the sessions they took part in respectively, and all participants received momentary compensation for their time accordingly. The study was approved by the Cardiff University School of Psychology Research Ethics Committee.

5.2.2. Experiment paradigm

A voluntary choice paradigm with cognitive intentions was used in the experiment (**Figure 23**). Participants were asked to complete 4 runs of the task in 2 separate MEG sessions. Each run of the task contained 128 trials including 112 choice trials and 16 control trials.

Each trial starts with a choice stage. Two potential choices of cognitive task are presented on the screen for 1.3 seconds. One is a memory task, and the other is a perceptual task. For choice trials, participants voluntarily choose one of the tasks that they intend to perform at any time within the time limit. The chosen task is immediately highlighted and remains onscreen until the 1.3 second presentation period ends. Participants are not able to change the task after it is highlighted. If participants fail to decide within the time limit, a reminder message of “please make a choice” is presented for 0.8 seconds and then followed by a 1.2-second blank screen before the next trial starts. The trials without a chosen task will be discarded. That is, participants need to make their choice within the time limit for 112 times. For control trials, a targeted (i.e., pre-chosen) task is randomly selected and highlighted on the screen from the beginning of the trial.

After the choice stage, there is a stimulus stage. At the start of the stimulus stage, a 0.1-second blank screen is presented, followed by a 2×3 matrix of round dots that lasts for 1.5 seconds. The whole experiment was presented on a middle grey background. The matrix consists of red and blue dots and can appear in one of 16 different patterns. The patterns were selected from all the possible permutations and combinations of red and blue dots with the following criteria: (1) the matrix contains only one or two columns that have the upper and the lower dots in the same colour; (2) if a matrix meets the first criterion with two columns, those two columns need to be next to each other and in a different colour; (3) if a matrix meets the first criterion with one column, the remaining two columns need to have different colours in the same row. With these criteria, 12 matrices have one same-colour column and 8 matrices have two same-colour columns. To match the numbers of the two conditions (i.e., 8 for both), half of the matrices which have their only same-colour column at the side of the matrix were further removed. In a single run, each of the selected patterns appeared 8 times with 7 times in choice trials and once in control trials. A library of all the matrices of a single run is generated and randomized at the beginning of the run, and the task choice only affects the cognitive processes required.

After the stimulus screen, again, a 0.1-second blank screen is presented, followed by the response screen according to the task chosen. For the memory task, the response screen displays one of the four-column patterns in the middle of the screen with two choice boxes ("Y" or "N") underneath. Participants need to decide whether the given one-column pattern appeared in the previous stimulus screen by pressing the corresponding button. For the perceptual task, the response screen shows a column of two white dots in the middle with boxed numbers 1 and 2 on two sides. Participants need to decide the number of columns that have the upper and the lower dots in the same colour for the matrix shown in the previous observation screen. The time limit for the response was 1.5 seconds. Participants can respond at any time within this time limit. After a response is made, the response screen remains for 0.1 seconds before the end of the trial. Late responses after the time limit were discarded.

Finally, there is a 0.4 to 1.2 seconds inter-trial interval (with an average duration of 0.8 seconds) of a blank screen before the next trial starts.

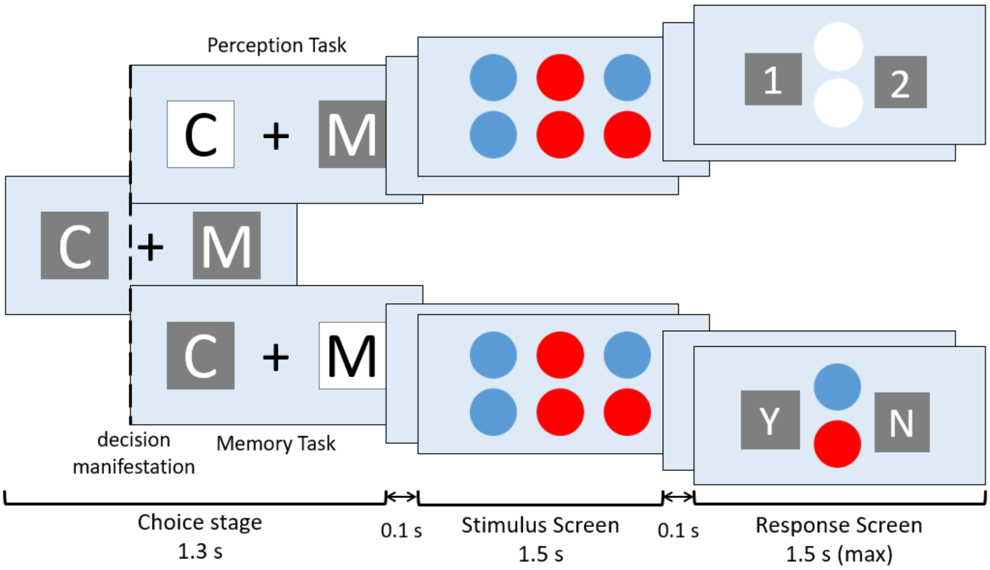


Figure 23. An illustration of a choice trial from choice stage to response screen and the examples of two tasks.

5.2.3. Procedures

Each participant attended four separate sessions including one behavioural session, two MEG sessions and an MR session.

In the behavioural session, a detailed task instruction is demonstrated and orally explained. After the induction, participants were asked to practice a short run with 48 trials (42 choice trials and 6 control trials). The number of memory and count tasks chosen, the average response accuracy and the number of missed responses is presented at the end of the practice run. Participants were asked to repeat a practice run if they met one of the following conditions: (1) having an average response accuracy lower than 0.6 or (2) missing the task response for over 15 trials. Additionally, the participants would be explicitly asked to try to balance their choices and try not to form any regular pattern.

The two MEG sessions are the same. In each MEG session, participants would be asked to complete two blocks of the decision-making experiment. The two blocks were performed approximately 25 minutes apart. Each experiment block contained 128 trials, resulting in a total of 512 trials including 448 voluntary choice trials and 64 control trials in two MEG sessions. The rate of the control trial (i.e., trial of pre-chosen task) in the MEG session was the same as in the behavioural session. The task positions on the choice screen and the option positions on the response screen were randomized across the blocks. All visual stimuli were displayed on a MEG-compatible PROPixx projector (VPixx Technologies Inc., Canada) with a resolution of 1920 × 1080 pixels and a refresh rate of 120 Hz. The screen was located approximately 120 cm in front of the participants.

The MEG data was acquired using a CTF MEG system with 275 axial gradiometer sensors distributed over the whole cortex (CTF MEG Neuro Innovations, Inc., Canada). Before entering the scanner, digitized head data was acquired from each participant using a Fastrak digitizer (Polhemus, Inc., US). The digitized head data includes the location of three fiducial points at the nasion, the left and the right preauricular points, three head position indicators at the same places and at least 200 points of the head shape that are evenly spread on the scalp for spatial co-registration in analyses. Furthermore, three pairs of EOG electrodes were attached to participants to record their eye movements. A pair were placed above and below the right eye for recording the blinks, another pair were placed about 1 cm away from the lateral canthi on each side for recording ocular artefacts and the last pair was placed at both mastoids for reference. During the MEG recording, a chin rest was used to maintain participants' head position to minimize the artefacts generated by head movements. A NATA button box was used to obtain the responses and participants were instructed to choose with their left index and middle fingers for the left and right buttons, respectively.

In the MR session, a T1-weighted structural image was acquired for each participant using a 3T Siemens PRISMA MRI scanner (Siemens, Erlangen, Germany) with TR = 2.1 s, TE = 3.24 ms, flip angle = 8°, acquisition matrix= 256 ×256, voxel size =1mm^3. For the participants who had blurred images due to the head motions during the session, an additional structural image was acquired using a 3T Magnetom Skyra MRI scanner (Siemens, Erlangen, Germany) with TR = 2.3 s, TE = 2 ms, flip angle = 9°, acquisition matrix= 256 ×256, voxel size =1mm^3.

5.2.4. Behavioural data analyses

The choice of cognitive task (memory or perception), the reaction time (RT) of the choices and the task performance (i.e., RT and accuracy) in each trial were recorded. The RT of the choices was quantified as the time between the onset of the choice screen and the onset of the task choice. The RT of the task performance was quantified as the time between the onset of the response screen and the onset of the answer choice. The accuracy of the task performance was quantified as the proportion of trials where participants made correct responses for the task they chose.

The behavioural analyses were based on the task types and the relationship of the tasks compared with the previous trial (i.e., chosen to stay on the same task or switch to another task). The choice frequency of each task and transition type were summarised with a density map, and a chi-squared statistic was used to examine the pattern of task choices. Furthermore, 2×2 RMANOVA analyses on the RT of the choices and the task performance were conducted to reveal the differences between task types and transition types.

5.2.5. MEG data analyses

The MEG data was analysed using the FieldTrip toolbox (Oostenveld et al., 2011, Version 20201203) and custom-made scripts in MATLAB R2015b (Mathworks Inc., USA).

5.2.5.1. Pre-processing

The data were pre-processed with the following steps: (1) band-pass filtered the data from 0.1 to 90 Hz; (2) down-sampled the data to 200Hz. (3) ran independent component analyses (ICA) on the down-sampled data with fixed random seeds. (4) manually identified the independent components with ECG/EOG artefacts. (5) attenuated the artefacts by removing the identified components. Between 3 and 5 components were removed for each subject. The removed components mainly reflected eye movements and cardiac responses. (6) segmented the data into trials. To analyse different periods of the task, three segmentations were made for each trial. One was aligned to the onsets of the choice cue presentation (i.e., the cue epochs), another was aligned to the onsets of choice being made (i.e., the choice epochs), and the last was aligned to the onsets of the stimulus presentation (i.e., the stimulus epochs). The length of the cue epochs was 1.5 seconds, which consisted of 0.2 seconds before the cue presentation and the whole 1.3 seconds of the cue presentation. The length of the choice epochs was 2 seconds, which consisted of 1 second before the choice and 1 second after the choice. The length of the stimulus epochs was 1.5

seconds, which was the presentation time of the whole stimulus screen. (7) did the baseline correction for all the epochs. The signal of the first 0.2 seconds of cue epochs was used as the baseline for all the epochs. The baseline correction was performed for every trial and every sensor respectively.

5.2.5.2. Sensor-level analysis

Because the signal at neighbouring time points and channels are highly correlated, sensor-level analysis was performed through cluster-based Monte Carlo simulation (Maris & Oostenveld, 2007), where the significance probability was calculated for the within-subjects difference between two univariate pairs on the task types (i.e., memory vs. perception) and the transition types (i.e., stay vs. switch), respectively. The family-wise error rate was controlled at 0.05 with 1000 permutations. The statistics were chosen according to the behavioural results that there was no interactive effect between the two pairs and only main effects within each pair (see Behavioural results for details).

5.2.5.3. Source-level analysis

Linearly Constrained Minimum Variance (LCMV) beamforming was applied in the time domain to estimate the amount of activity at a given region of interest (ROIs) in the brain (Hillebrand & Barnes, 2005).

The brain was divided into a regular three-dimensional grid of equivalent current dipoles (ECDs). Then the source strength of each grid was calculated by adjusting the filter coefficients to minimize the output signal power while maintaining a certain linear constraint. A linear constraint helps to steer the main lobe of the beamforming array towards a desired direction and null out interference from other directions. This produced a 3D spatial distribution of the power of the neuronal sources and the distribution was then overlaid on a structural image of the subject’s brain. The automated anatomical labelling (AAL) atlas (Tzourio-Mazoyer et al., 2002) was further employed to define the regions of interest (ROIs) for decoding processes.

A time-resolved MVPA was conducted on source-localized MEG data, as the analysis is sensitive in decoding information representation from human electrophysiological data (Dima, 2018). Two MVPA decoding analyses were performed to identify the latency and spatial distribution of the MEG multivariate information. The first was to decode task choices (i.e., the perceptual task vs. the memory task). The other was to decode transition types (i.e., staying at the same task or switching to the other task). In each analysis, a discriminant analysis classifier was trained with the MEG source-level time courses of each ROI. Source data was smoothed by averaging the signals of four random trials in a given condition. A 5-fold cross-validation was applied to the decoding process using the signals of all the ECDs for each ROI.

In each validation, 80% of the data was issued as a training set, and the remaining 20% as a test set. To address the inherent imbalance in the distribution of trials across the two classes within the training dataset, an under-sampling methodology is employed, involving the random selection of a number of trials from the majority class to align with the count in the minority class. In the interest of reducing data dimensionality, a principal component analysis (PCA) is conducted on the training dataset, and the number of principal components is determined to capture over 99% of the variance within the training data. Subsequently, the test dataset is projected onto the same reduced-dimensional space through the application of the eigenvectors corresponding to the selected principal components. The ensuing step involves the training of a Linear Discriminant Analysis (LDA) model to discern between the two classes, and the classification accuracy is assessed utilizing the test dataset. This entire process is iterated five times, employing distinct training and test datasets in each iteration, and the resultant classification accuracies are averaged to derive a comprehensive assessment. These procedures are executed utilizing the LDA implementation within the MATLAB Machine Learning and Statistics Toolbox.

Decoding accuracies were averaged across the folds to generate a matrix of all the

ROIs at all the time points for each participant. The results were smoothed by 50 milliseconds time steps and the group results of each ROI were then compared with a 50% chance level using a two-tailed one-sample t-test to reveal whether they played a role in the given processes. To account for the number of statistical tests across ROIs and at multiple time points, the alpha levels were corrected using the Bonferroni method.

5.3. Results

5.3.1. Behavioural results

In this experiment, participants voluntarily choose between a memory task and a perceptual task in each trial. The chi-squared statistic suggested that the participants had a biased choice pattern for both task types and transition types with $\chi^2(1, N = 444) = 436.37$, p = 2.92e-94 (**Figure 24**). Participants presented a tendency to select the memory task (i.e., memory > perception) and to repeat the previous choice (i.e., stay at > switch to). A density map in **Figure 25** shows a detailed distribution of the task and transition choices.

A 2 task types (i.e., memory and perception) x 2 transition types (i.e., stay at and switch to) RMANOVA on choice RTs did not show a significant interaction between the task types and the transition types on the RT of the choices (F(1, 40) = .241, p = .626). There was also no interaction between task type and transition type in the RT (F(1, 40) = 1.789, p = .189) or the accuracy (F(1, 40) = 1.038, p = .314) of the task execution.

There was a main effect on task types of the RT of the task choice, the accuracy of the task, and the RT of the task performance. Participants spent less time choosing the memory task than choosing the perception task (MD = -13.0 ms, p = .007, **Figure 26A**). Executing the perception task yielded faster RT (MD = -416 ms, p = 2.27e-30, **Figure 26B**) and higher accuracy (MD = -70.0 ms, p = 2.28e-10, **Figure 26C**) than the memory task. For the memory tasks, participants took on average 557 ±86.0 milliseconds to make the decision, and 855 ±98.0 milliseconds to respond with an accuracy of .883 ± .081; while for the perception tasks, participants averagely took 570 ± 87 milliseconds to make the decision, and 439 ± 102 milliseconds to respond with an accuracy of .952 ± .055. Moreover, main effects were also found on the transition types for the RT in task performance. Participants made quicker responses in the stay trials than in the switch trial (MD = 12.0 ms, *p* = .005, **Figure 26B**). The average RT was 641 ± 98.0 milliseconds for the stay trials and 653 ± 102 milliseconds for the switch trials. Therefore, participants exhibit a switch cost in RT in the binary choice of cognitive intention.

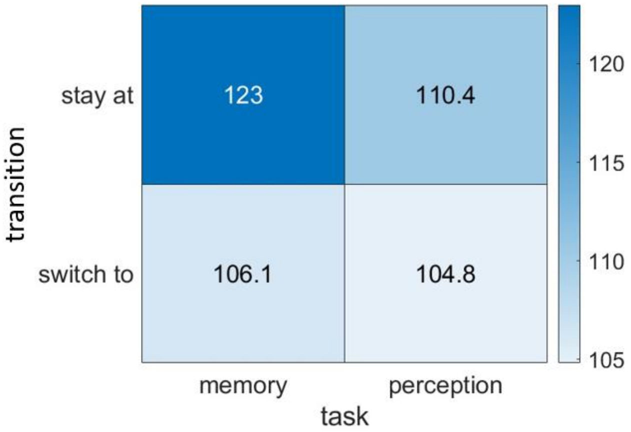


Figure 24. The heat map of the chosen trial numbers on the task and transition types. The vertical comparison showed the choice difference between the transition types, while the horizontal comparison showed the difference between the task types.

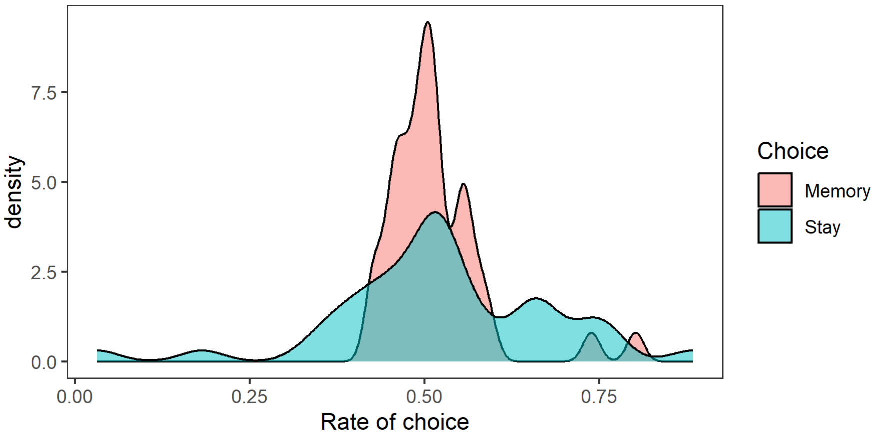


Figure 25. The density map of the choice rate for memory tasks in task types and staying on the same task in transition types. The X-axis shows the rate of choice, the Y-axis shows the density scale (i.e., the number of participants that had

this choice rate), and the colour indicates the two aspects of the task choices (i.e., types and transitions).

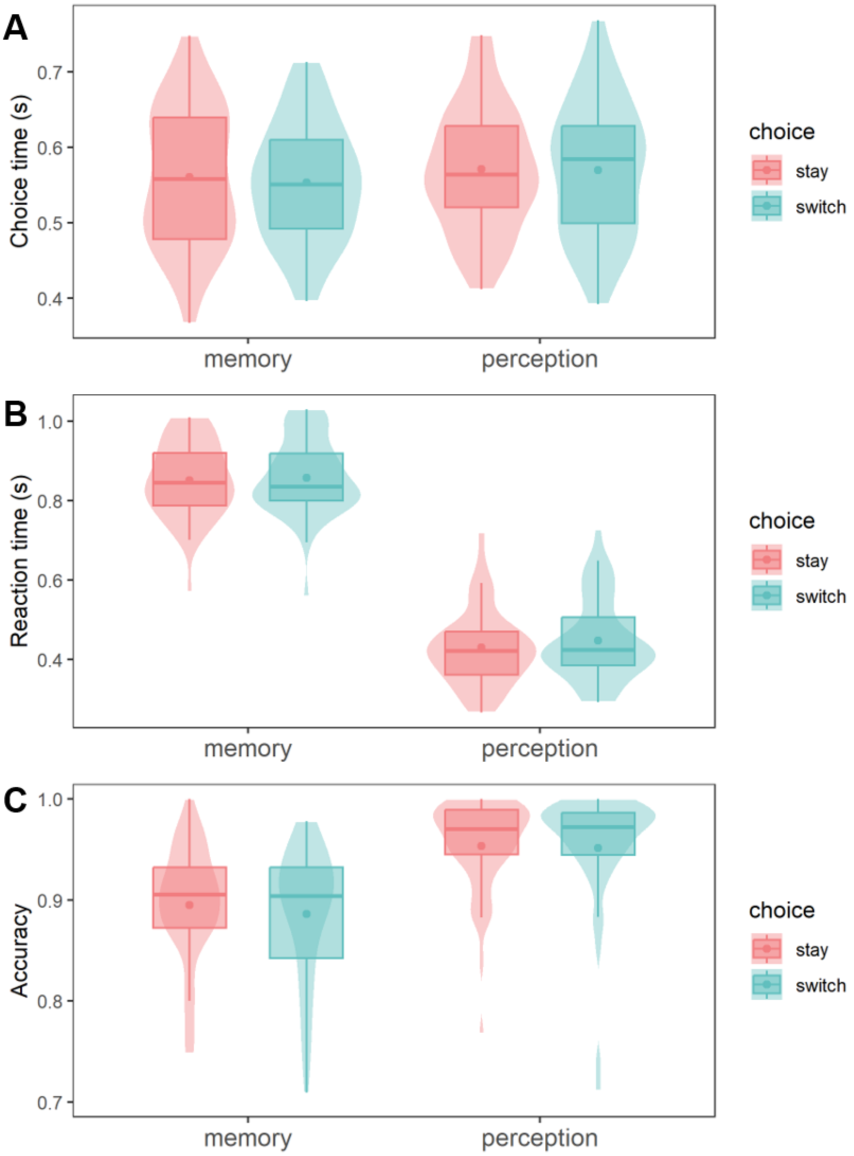


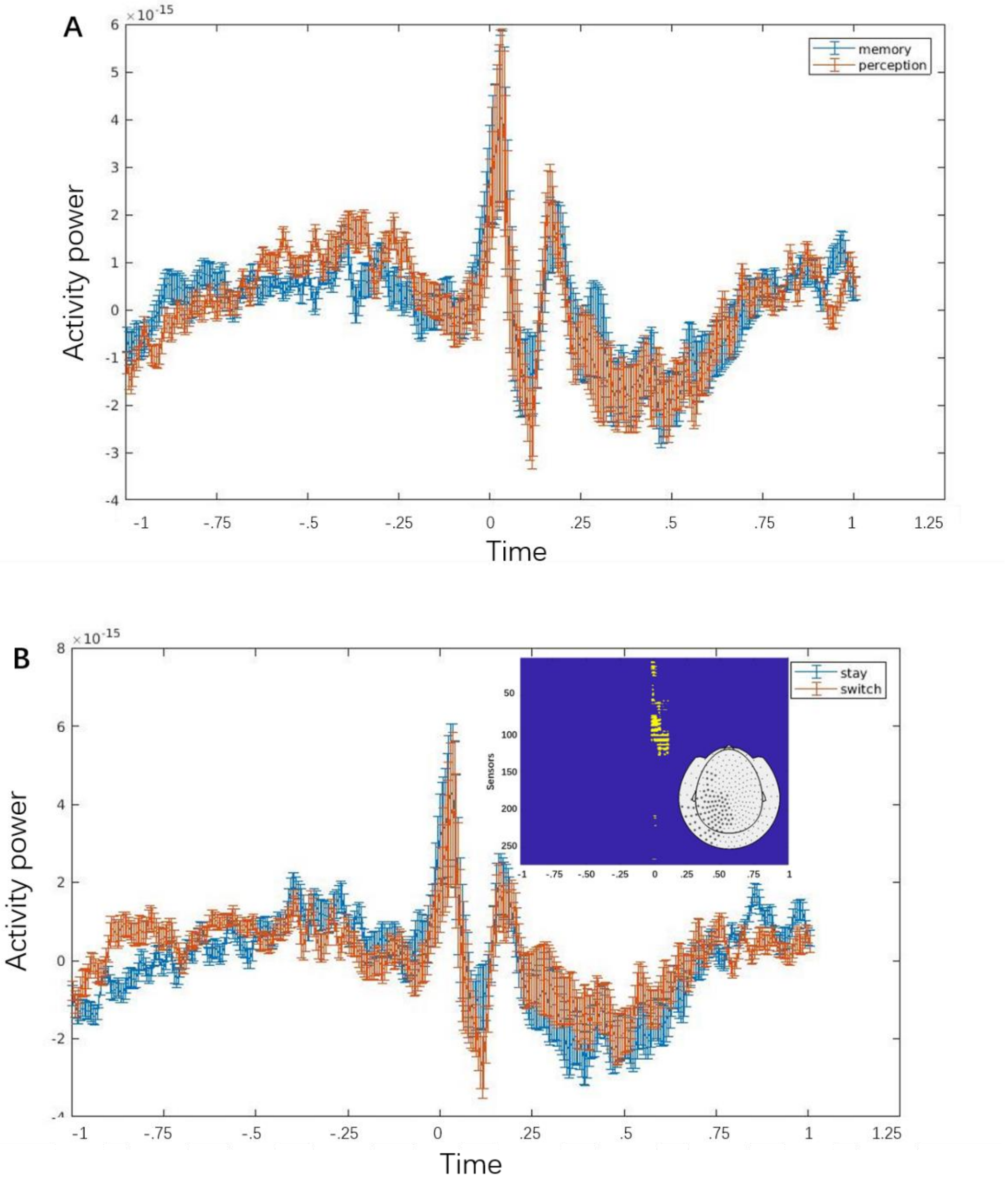
Figure 26. The RT of task choices, the RT of the tasks and the accuracy of the tasks in different task types and transition types. The X-axes showed the comparison between different task types, while the colour showed the comparison between the transition types.

5.3.2. MEG results

5.3.2.1. Sensor-level analysis

Cluster-based permutation suggested that 87 sensors detected transition difference in choice epochs at the choice onset and their significance lasted between 5 to 140 ms (p = .008). These significances were at 950 to 1090 ms period relative to the start of the epoch. However, there was no significant results at the sensor level for the other comparisons (all ps> .063 for task types in choice epochs, all ps> .137 for task types in stimulus epochs, and all ps > .790 for transition types in stimulus epochs).

The all-channel averaged event-related activities for the task types and the transition types are shown in **Figure 27**. An auxiliary chart was attached to the panel that contains significant results to clarify specific channels and time-course.



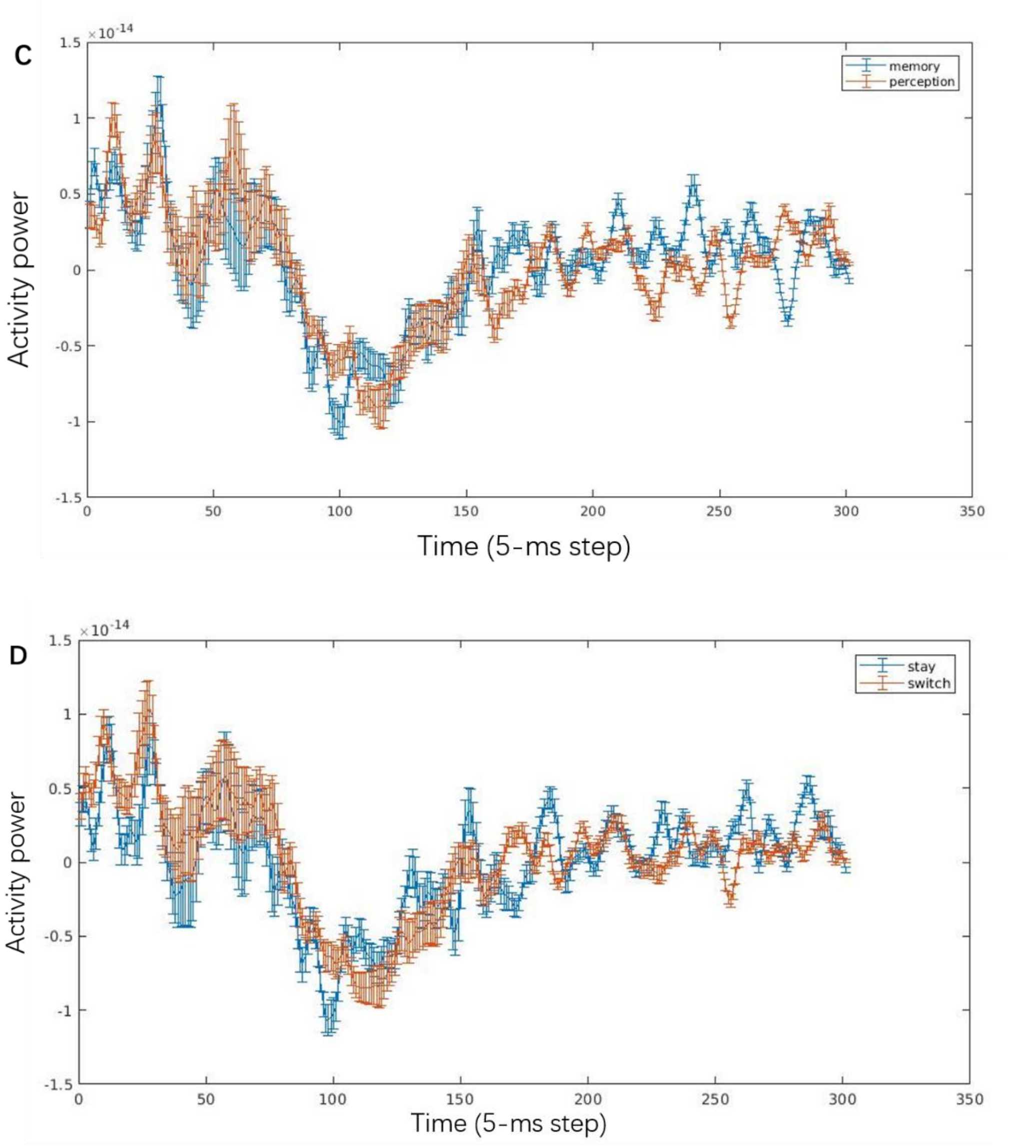


Figure 27. The all-channel averaged event-related activities of different task and transition types during different periods. The error bar indicates the standard error across participants. **A.** The ERP of task types (memory vs. perception) in the choice epoch. **B.** The ERP of transition types (stay vs. switch) in the choice epoch. An auxiliary chart was attached to this panel to specify the channels (and their locations) and the time courses that captured significant information of transition types. **C.** The ERP of task types (memory vs. perception) in the stimulus epoch. **D.** The ERP of transition types (stay vs. switch) in the stimulus epoch.

5.3.2.2. Source-level analysis

MVPAs were performed on the source-localized activity to identify cortical ROIs that contain significant information on choices on task types and task transitions around the decision-making and during the following stimulus processing. **Figure 28** shows the classification accuracy of the four univariate pairs. The bordered yellow patterns in each panel indicated the time and ROIs with significant decoding results. The alpha was set at 1.38e-6 (i.e., 0.05/(90*401)) for the choice epochs and 1.84e-6 (i.e., 0.05/(90*301)) for the stimulus epochs after being Bonferroni corrected for ROI number and time points number.

For the choice epochs, the data were aligned to the onset of decision manifestation (i.e., time of button pressing for the corresponding task), and contained a second before the choice and a second after the choice. The classification results on task types (**Figure 28A, Figure 29A**) suggested that different cognitive intentions can be detected ~200 ms before the decision in areas related to visuospatial attention (e.g., calcarine and cuneus), visual recognition (lingual area and middle occipital gyrus), self-awareness (e.g., precuneus and inferior parietal lobe), cognitive control (e.g., superior frontal area and inferior parietal lobe), and voluntary motor control (e.g., precentral and postcentral area). These regions continuously reflected the intentional differences till about 600 ms after the intentional decision (**Figure 29C**). Furthermore, ~200 ms after the intentional decision, the brain areas related to motor planning (e.g., thalamus, inferior frontal lobe and middle frontal lobe), memory formation (e.g., temporal lobe) and updating (e.g., orbitofrontal cortex, OFC) started to play a role in distinguishing different cognitive intentions. These activations lasted for about 300 ms which is the average duration of the continuous presentation period of the choice screen after decision manifestation.

The classification results on the transition types (**Figure 28B, Figure 29B**) showed the repeating and the switching intentions can be detected ~200 ms before the decision in the superior and the middle occipital area. In addition, the classification accuracy for the two transition types was significantly higher than chance level after the decision manifestation in the precentral area, the postcentral area, the paracentral area, the supramarginal area and the precuneus (**Figure 29D**). 200 ms after the decision manifestation, the basal ganglia (i.e., caudate, putamen, pallidum and thalamus), the temporal lobe, and the supplementary motor area (SMA) started to reflect the choice difference. All these aforementioned differences lasted till the end of the choice stage. Moreover, it is worth noting that the middle cingulate area showed significant classification accuracy for two transition types (i.e., stay with the same task and switch to the different task) around the decision manifestation, but the effect was temporary and only lasted for about 50 ms.

For the stimulus epoch, the data were aligned to the onset of stimulus presentation and contained the whole stimulus stage. The decoding results of the stimulus epoch (**Figure 28C**) suggested that the two tasks could also be distinguished in multiple ROIs at various time points. There were mainly four distinct time points. The earliest distinctions were shown in the supplementary motor area, the calcarine, the precentral area, the middle frontal area and the middle cingulate cortex within 250 ms after stimulus presentation. Then multiple regions in the parietal and frontal lobes presented differences from about 500 ms after stimulus presentation. Next, the insula, the temporal and occipital areas started to reflect the differences since about 700 ms after stimulus presentation. Finally, the medial orbitofrontal cortex, the parahippocampal area and the hippocampus began to show classification significance since about a second after the stimulus presentation. The decoding results on the transition types (**Figure 28D**) did not show any stable significance during the stimulus stage for all the ROIs.

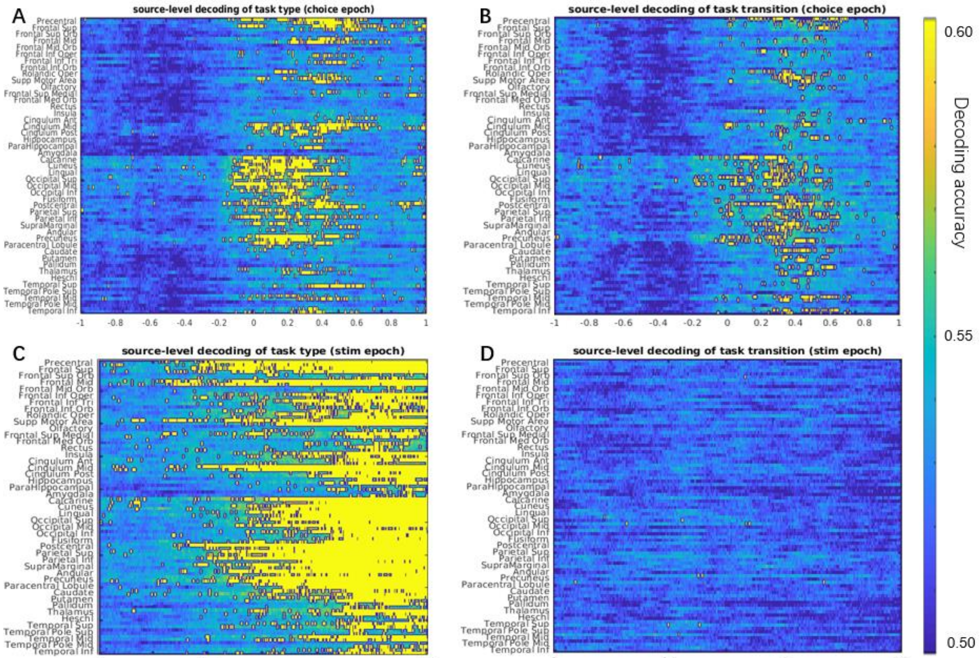


Figure 28. The decoding results of source-localized MEG data for types of tasks and transitions. In all the panels, the bordered yellow pattern indicates the statistically significant ROIs and periods. **A.** The decoding results of the choice epochs for memory task versus perception task. **B.** The decoding results of the choice epochs for staying at the same task versus switching to the other task. **C.** The decoding results of the stimulus epochs for memory task versus perception task. **D.** The decoding results of the stimulus epochs for staying at the same task versus switching to the other task. The colour bar indicates the decoding accuracy. The dark blue colour indicates that the decoding accuracy was not higher than chance level (i.e., 0.5), and the bright yellow colour indicates the decoding accuracy was not less than 0.6.

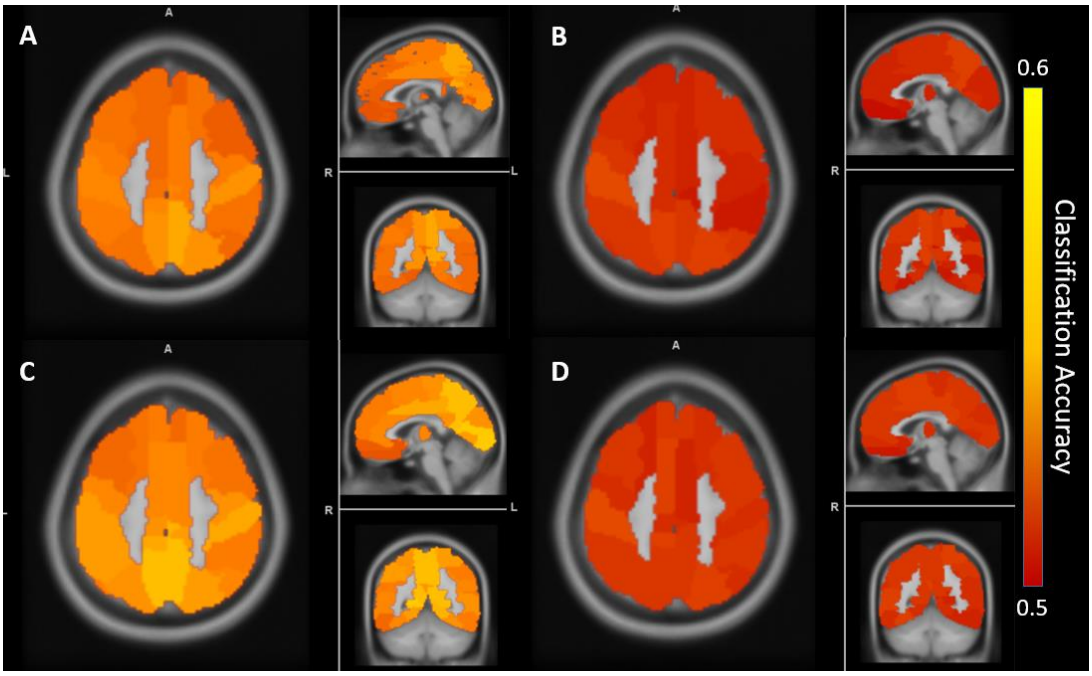


Figure 29. Visualized decoding results of source-localized MEG data for task and transition types before and after the decision manifestation. All the panels presented the results at X = -2, Y = -54, Z = 52 in standard MNI space. **A.** Average classification accuracy of task types (i.e., memory task and perception task) during the 200-ms period preceding decision manifestation. **B.** Average classification accuracy of transition types (i.e., stay trials and switch trials) during the 200-ms period preceding decision manifestation. **C.** Average classification accuracy of task types during the 200-ms period after decision manifestation. **D.** Average classification accuracy of transition types during the 200-ms period after decision manifestation.

5.4. Discussion

This study replicated and extended the behavioural results of previous online experiments (Chapter 4). As expected, participants had lower performance in memory tasks than in perception tasks for both RTs and accuracies, and they responded quicker in the stay trials than in the switch trials.

Surprisingly, participants spent less time selecting the memory task than the perception task, but staying with the same task or switching to the other task did not show any RT difference during intentional choices. There are two possible explanations for this phenomenon. First, participants could prefer the memory task more thereby leading to the cognitive intention being confounded by value-based decision-making. People make faster decisions when the option they choose has a higher value (Pirrone et al., 2018; Teodorescu et al., 2016), which refers to individuals' preferences (Glimcher & Rustichini, 2010). This internal preference is stable during an experiment (O'Doherty, 2014), and thus results in a systematic difference between the two tasks. The decoding results for the task types suggested that OFC showed significance after the decision manifestation and before the stimulus presentation. Because OFC is one of the classical brain areas related to affective value (i.e., rewards or reinforcers) (Rolls, 2004; Rolls & Grabenhorst, 2008), this might imply the participants' preference being different towards the two tasks.

On the other hand, it is also possible that participants were always more "prepared" for selecting a memory task. During the behavioural session, the participants were instructed to balance their choices but try not to form regular patterns if they had very biased responses on task types. This instruction might affect participants' performance (Guseva et al., 2023). As most biased participants were inclined to the perception task, they need to be more engaged in selecting memory tasks and thus result in better performance (i.e., shorter RTs) in task choosing (Engelmann et al., 2009; Zapata-Phelan et al., 2009). The decoding results of the MEG data on task type during the task-choosing periods suggested that before decision manifestations, the brain areas related to visuospatial attention (Hopfinger et al., 2001; Pollmann & Von Cramon, 2000), motor planning (Inagaki et al., 2022) and voluntary motor control (Cavanna, 2007; Scott, 2012) would present significance for the tasks, implying different cognitive efforts for memorial and perceptual intentions. The decoding results of transition types during the choice stage further supported the hypothesis, because there were less ROIs that showed significant decoding performance between stay and switch trials. When decoding the transition types, the influence of task types was averaged across all transition types. Essentially, this decoding outcome highlighted ROIs containing substantial information about transition types regardless of the specific task involved. Notably, only the ROIs linked to visual recognition displayed significant information preceding decision manifestations, indirectly suggesting distinct cognitive processes for the two task types beyond mere voluntary choices.

In either case, it is worth highlighting that the task types can be detected at ~200 ms before the decision. The sources of this significance lay in not only the brain region related to motor actions but also the areas involving in cognitive processes, suggesting the formation of a task set in advance of task selection. The result might provide insights into the temporal dynamics of intentional decision-making in line with the *readiness potentials* (Libet, 1985).

After decision manifestations, the task types can also be decoded from the thalamus, inferior frontal lobe and middle temporal lobe, while the transition types can be decoded from the basal ganglia, middle temporal lobe and SMA. The middle temporal lobe is widely accepted to be a region related to declarative and recognition memories (Eichenbaum et al., 2007; Squire & Zola-Morgan, 1991). This implied a recall process after both memory and perceptual intentions, most possibly related to the task rules, and the recall process was task-specific. The basal ganglia (including the thalamus), the SMA and the inferior frontal lobe are associated with motor control and planned behaviours (Aron et al., 2014; Cameron et al., 2009; François-Brosseau et al., 2009; Inagaki et al., 2022; Nachev et al., 2008), indicating the time point that participants start to prepare the stimulus processing.

In addition, the transition onset, which was the only time course that contained sensor-level significances, can be successfully decoded in the SMA and the middle cingulate area. These regions are closely associated with task rules (Sakai & Passingham, 2003a, 2006), probably hinting that participants might also conceptualize staying and switching as two separate tasks during the experiment. In this case, a layer of complexity is added to our understanding of the neural processes involved in intentional decision-making, as the transition types will become elements of task types and lead to a univariate design of the task types.

Finally, during the stimulus processing, only the task types had a significant influence on the brain activities. The earliest distinctions were shown in areas related to task rules including the SMA, the middle frontal area and the middle cingulate cortex (Miller et al., 2002; Sakai, 2008) within 250 ms after stimulus presentation, suggesting the information processing of the same stimuli relies on the specific task-rule. Then multiple regions in the parietal and frontal lobes started to play roles in distinguishing task types since ~500 ms after stimulus presentation. The regions belong to the neural network of intentional decision-making (Chapter 3), possibly reflecting the time point that participants got their answers for the perception task, as the options for the perception task were fixed. Next, the insula, the temporal lobe and the occipital areas began to reflect the task types from ~700 ms after stimulus presentation. Those regions are closely related to visual attention and working memory (Jeneson & Squire, 2012; Menon & Uddin, 2010; Namkung et al., 2017; Ungerleider, 2000). Finally, the medial orbitofrontal cortex, the parahippocampal area and the hippocampus began to show classification significance from about a second after the stimulus presentation. It is widely acknowledged that those regions all play important roles in declarative memory encoding and consolidation (Petrides, 2007; Van Strien et al., 2009). All the components after 500 ms post to the stimulus presentations were memory-related, which corresponds to the different memory loads of the two tasks.

5.5. Conclusion

To sum up, this study modified the experimental paradigm in Chapter 4 and investigated the temporal-spatial neural correlates underlying cognitive intention and their following stimulus processing. Most of the behavioural results replicated the findings in Chapter 4, and the MEG results verified the hypothesis that cognitive intention can be predicted by the brain activities before the choice onset and the task choice will influence the stimulus processing.

However, there were also unexpected findings. On the behavioural aspect, we found that participants spent less time choosing the memory task, which is different from the results in previous online studies. Two possible reasons were proposed. One is related to the preference and the other is associated with the motivations for the task. MEG results provided supportive classification evidence for both hypotheses, leaving an inquiry for future studies. On the imaging aspect, the transition types can be distinguished by the activities of the task-rule-related ROIs at the choice manifestation time. This raised the possibility of the transition type being elements of the task type rather than an independent variable from it. Further studies on staying and switching intentions are recommended to test this speculation.

6. Neural Correlates of Heuristic-Based Strategic Decision-Making in Humans: an fMRI Study on Pac-Man

6.1. Introduction

Decision-making is a fundamental cognitive process that plays a critical role in both human and animal behaviour (Chittka et al., 2009; Edwards, 1954; Kaplan & Frosch, 2005; McFarland, 1977). The ability to make effective decisions is crucial for adapting to changing environments and achieving goals and thereby is extensively studied in psychology and neuroscience (e.g., Frydman & Camerer, 2016; Gärling et al., 2009; Johnson & Busemeyer, 2010; Mishra, 2014).

From behavioural patterns to neurological correlates, existing research has revealed abundant possible factors that can influence decision-making with the underlying mechanisms behind them, such as emotion (Lerner et al., 2015), stress (Starcke & Brand, 2012), judgement (Mellers et al., 1998), culture (Yates & de Oliveira, 2016), and learning (O'Doherty et al., 2017). However, these experiments were usually conducted under simplified scenarios with most of the variables being controlled experimentally, which differs from the complex and dynamic decision-making situations in real life. A common approach in studying voluntary decision-making involves presenting participants with multiple equally viable options in a trial, which they must choose from repeatedly across hundreds of trials (e.g., Zhang et al., 2012). However, in real-world scenarios, individuals rarely encounter such simplified and repetitive situations. Therefore, in order to facilitate the application of fundamental research, an increasing number of researchers started to use more naturalistic decision-making paradigms (Cross et al., 2021; Hunt et al., 2021; Klein, 2008; Macquet & Fleurance, 2007). Video games are one of the examples. As a human-designed interactive electronic media based on simplified real-world scenarios that can amplify selected features according to the needs of their specific genre, video games are gradually being employed in a wide range of decision-making studies, including but not limited to the decisions related to risk-taking behaviours (Fischer et al., 2007; Mather et al., 2009), morality (Holl et al., 2020), cooperation and competition (e.g., Decety et al., 2004; Gallagher et al., 2002).

A recent monkey study elicited the possibility of using the classic arcade game Pac-Man as a natural paradigm for strategic decision-making (Yang et al., 2022). The Pac-Man game requires the player to navigate through a maze, collect pellets, and avoid ghosts, which provides a highly dynamic and complex situation with fixed elements. The study highlights that trained monkeys rely on a set of intuitive strategies in game playing and are able to constantly adapt to particular game situations. This presents supportive evidence for monkeys having a similar ability as humans to use take-the-best heuristics by only focusing on a subset of game aspects when confronted with intricate environments (Hutchinson & Gigerenzer, 2005; Marsh, 2002a). This ability facilitates quick decision-making in a complex environment, and can actually lead to better choices than taking all possibly related information into account (Gigerenzer, 2008; Gigerenzer & Gaissmaier, 2011). However, it remains unclear if the heuristics adopted by humans are the same as those used by non-human primates. In the case of the Pac-Man game, the difference potentially lies in two aspects: the types of intuitive strategies and the choice of the strategy under specific situations.

Additionally, despite a range of decision-making studies in cognitive neuroscience, not many of them focus on strategic decision-making (e.g., Lee & Seo, 2016). The neural mechanism of strategic decision-making is yet to be clarified. The main question is whether strategic decision-making shares the same brain functional pattern with the other kinds of decision-making that may have shared features, such as value-based decision-making (Bartra et al., 2013) or intentional decision-making (Si et al., 2021).

Therefore, by modifying the Pac-Man game and replicating it in humans, we aimed to investigate two questions. One is whether the adoption of heuristic strategy varies between the humans and the non-human primates. The other is the functional localization of strategic decision-making in humans, and whether the model-derived strategies are associated with different BOLD responses across the brain.

6.2. Materials & Method

6.2.1. Participant

This study recruited 34 healthy participants (19 females, 14 males and 1 prefers not to say). The participants were aged from 18 to 40 with average age of 24.79 ± 5.45 years. All the participants attended both eye tracking and the imaging sessions. However, only the data from 32 participants (19 females, 12 males and 1 prefers not to say, with an average age of 24.31 ± 4.91 years) were used in the final analysis. The exclusion of participants was based on the data quality of their functional fMRI scans (please see Quality control for the details).

None of the participants had a previous history of neurological or psychiatric disorders. All participants gave written informed consents for the sessions they attended separately and received monetary compensation for their time. The study was approved by the Cardiff University School of Psychology Research Ethics Committee.

6.2.2. Game paradigm

The Pac-Man game used in the study was an adjusted version of the game used in a previous study using non-human primates (please see Yang et al., 2022 for a monkey version of Pac-Man), which was adapted from the original game by Namco. The game was built and run using MATLAB 2018b with the Psychophysics Toolbox extensions (Brainard, 1997; Kleiner et al., n.d.; Pelli, 1997).

The game contains five main elements including the Pac-Man, the maze, the pellets, the energizers, and the ghosts (**Figure 30**), replicating all key features of the original game. Participants were asked to navigate the Pac-Man using four direction buttons through the maze to collect all the pellets and gain as high a score as possible.

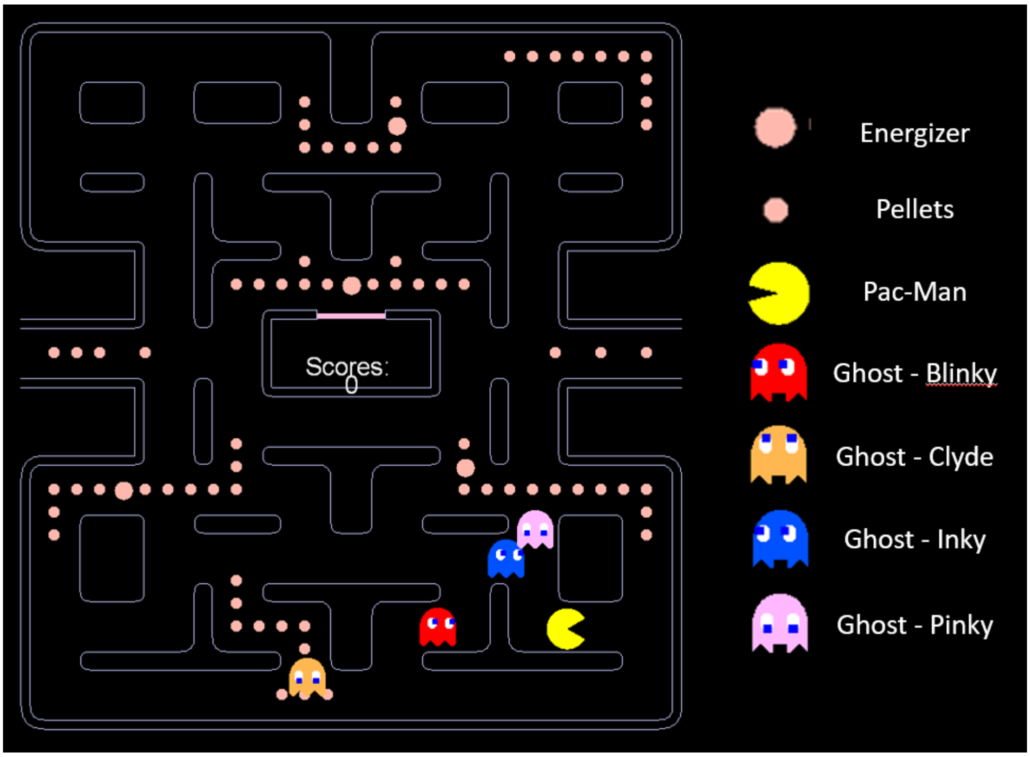


Figure 30. Game panel and all the game elements. This example illustrates the four-ghost game.

The maze is 29 × 36 square tiles in size. The tile size depends on the resolution of the screen. The side length of a square tile is 1/43.2 of the screen height (e.g., 25 pixels for a screen resolution of 1920 × 1080 pixels). The maze contains two tunnels at the 18th row that can teleport Pac-Man to the opposite side of the maze.

A pellet is always placed at the centre of a tile and will be consumed when Pac-Man moves into the tile. Not all the accessible tiles contain a pellet or energizer. There were 9 unconnected patches in the maze. Each patch has 9 to 13 square tiles and pellets will only fill 7 random patches for a game resulting in 76 to 83 pellets on the map. From all the pellets' locations, four will be randomly selected to be replaced with an energizer. Plus, those four locations will be scattered at the upper-left, upper-right, lower-left, and lower-right areas of the maze. Collecting a pellet and an energizer will gain 2 and 4 points of score, respectively.

The ghosts will be released from the centre box of the maze at the beginning of the game and will move automatically during the game based on pre-set algorithms. They have two different action modes: normal mode and scared mode. In the normal mode, ghosts have the same speed as the Pac-Man and will chase the Pac-Man. When Pac-Man is caught by a ghost, a 2-second colliding animation will be played. Then the current game round ends and 30 points of score will be deducted from the total score as a penalty. If the player still has a round, Pac-Man and ghosts will all return to their start locations and the new round will start. The scared mode is triggered by collecting an energizer. In this mode, ghosts become slower than Pac-Man and will move randomly in the maze. Pac-Man can catch scared ghosts. Each scared ghost will provide 10 points of score. The caught ghosts will return to the centre box and return to the normal mode. If not caught, the scared model will last 14 seconds, and the ghosts will flash 5 times in 0.5 seconds before they return to the normal mode.

A single game can have either 2 or 4 ghosts. If the game has 2 ghosts, the ghosts will always be Blinky and Clyde. Blinky is red. It will always head to Pac-Man’s location. Clyde is yellow. It will only head toward Pac-Man when it is more than eight tiles away from Pac-Man. Otherwise, it will move toward the lower-left corner of the maze. If the game has 4 ghosts, Pinky and Inky will be added. These two ghosts have a better optimised rule set for catching Pac-man. They will try to predict Pac-Man’s movement and intersect it. Pinky is pink. It will target 4 tiles ahead of Pac-Man. Inky is blue. It will head towards a point at the extended line of the Blinky and Pac-Man. The distance between the target point and the Pac-Man will be the same as the distance between the Blinky and Pac-Man. Ghosts can also use the tunnel to teleport but their speed in the tunnel will be 1/3 of the normal speed.

At the very beginning of every round, there will be a 2-second pause phase when all the game elements are presented but the Pac-Man and the ghosts are not able to move. This phase is designed to be a baseline for the gameplay. A single game will have a maximum of two rounds. If successfully collecting all the pellets in two rounds, participants win the game, and a win page will be presented. Otherwise, they lose the game. In other words, for a single game, Pac-Man can only be caught by the ghosts once. At the second time, the game ends. After each game, a result screen will be presented for 1.5 seconds with the game outcome (i.e.: win or lose) and game score. Finally, there will be a 6- to 10-second inter-game interval of a black screen before the next game starts.

6.2.3. Procedure

Participants were asked to attend two sessions for the study. One is the eye tracking session outside of the scanner, and the other is the brain imaging session.

For the eye tracking session, all the participants were introduced to the Pac-Man game including the game panel, all the elements, conditions for winning or losing the game, and the personalities of each ghost. The game was displayed at the resolution of 1920 × 1080 on a 24-inch ASUS VG248 monitor placed 63 cm away from the participants. The four direction keys on an English keyboard were used to play the game. Participants could choose to play the game using either both hands or just one hand according to their preference. They were also explicitly instructed to try to win all the games first and then get as high a score as they could. During the session, an eye tracker (Eyelink 1000 Plus) was used to record participants' eye movements and pupil size with a sample rate of 500 Hz.

The MRI session was conducted 1 to 14 days after the eye tracking session depending on participants' availability. The game with a resolution of 1920 × 1080 was projected by a PROPixx DLP LED projector on a matched MR-compatible screen. A RESPONSEPixx handheld 4-button fibre-optic response box was used to play the game. Participants were instructed to hold the response box with both hands and press the buttons with their thumbs only.

The rest of the game settings were exactly the same for the two sessions. The eye tracking or functional MRI record will end when the continuous gameplay reaches 42 minutes and participants finish the current game (i.e., until a result screen is presented), resulting in the total recording time varying from 42 to 44 minutes. Additionally, the total number of games played depends on the participants' performance. On average, participants played 36.00 ± 6.31 games with a total of 48.47 ± 6.59 rounds in the eye tracking session, and 36.35 ± 5.66 games with a total of 51.08 ± 7.58 rounds in the imaging session.

6.2.4. Behavioural modelling

The behavioural modelling was adjusted and modified from the monkey version which assumed the moving direction is based on the weighted sum of several basic strategies, and the relative strategy weights remain unchanged in a set interval.

In the original study, five intuitive basic strategies, namely global, local, evade, approach, and energizer, were used for behavioural modelling (Yang et al., 2022). Under the global strategy, Pac-Man will head in the direction that has the highest score in general. Under the local strategy, Pac-Man will head in the direction that has the highest score in 10 steps. Under the evade strategy, Pac-Man will escape from the ghost(s). Under the approach strategy, Pac-Man will move toward the ghost(s). Under the energizer strategy, Pac-Man will head to the closest energizer.

The utility value of each strategy was calculated via the averaged sum of the scores of corresponding game elements on all possible trajectories. A softmax policy was then employed to linearly combine the utility values of each basic strategy with the strategy weights as model parameters. A softmax policy is a mathematical function used in reinforcement learning and decision-making to select actions based on their probabilities (Sutton & Barto, 2018). Each game trial was divided into segments where participants' moving direction was unchanged and the strategy weights were calculated with maximum likelihood estimation (MLE) according to each segment. The accuracy of the moving directions under the strategy with the largest strategy weight was then calculated for labelling each time segment with a discrete strategy. If the prediction accuracy is larger than 80%, the strategy with the largest strategy weight was used for the label. Otherwise, the segment was labelled as "vague".

This method was adjusted to fit human behaviours in the current study. There were four major modifications. First, six intuitive basic strategies were used for model fitting (**Figure 31**). A new intuitive strategy named "no-energizer" was added into the model, because human players had an exclusive behaviour of avoiding collecting energizers during certain periods of the game. The strategy was decided post-test as an intuitive strategy can only been decided after observing participants' behaviours. Second, the utility algorithm of the global strategy was adjusted to take the availability of nearby resources into account by using the score difference between the whole area and the area within 10 steps of each potential direction. Third, an L1 penalty term was introduced to prevent the overfitting of strategy weights. An L1 penalty term is a regularization technique used in machine learning to prevent overfitting by adding a penalty term to the loss function. Fourth, the optimization algorithm was changed from SLSQP (Sequential Least Squares Programming) to the genetic algorithm (GA) to further avoid the local optimums. The GA used was implemented in the *scikit-opt* Python library. Its parameters were set with a population size of 100, mutation probability of 0.1, crossover probability of 0.8, and a maximum iteration number of 500. Finally, the strategy label for the time segments was further corrected based on the game events according to the following rules: (1) the strategy with the second largest weight will be used to replace the "vague" label if its prediction accuracy is higher than 50%; (2) the "energizer" will be used to replace the other labels if the time segment is right before collecting an energizer and its prediction accuracy is over 80% of the strategy with the largest weight; (3) the "approach" will be used to replace the other labels if the time segment is right after collecting an energizer and its prediction accuracy is over 80% of the strategy with the largest weight; (4) the “approach” will be used to replace the other labels if the time segment is in between of two “approach” segments after the same “energizer” segment.

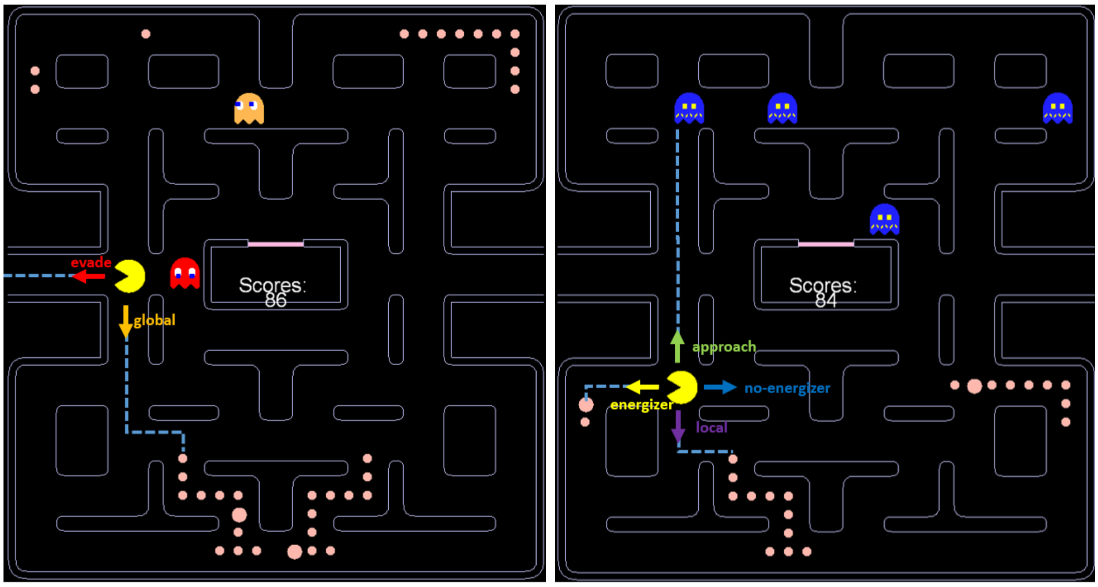


Figure 31. The conceptual illustration of the six basic strategies. The coloured arrows indicate the potential moving directions for different strategies and the cyan dot lines indicate the possible trajectories to the target. The red, orange, yellow, green, blue, and purple arrows illustrate the typical situations for evade, global, energizer, approach, no-energizer, and local, respectively.

6.2.5. Eye tracking data

The pupil size and the saccades from the eye-tracking records were extracted and analysed for the basic strategies in the behavioural models.

The pupil size data that is marked invalid by the original record or 3 standard deviations from the individual mean was cleaned before analysis. The eye with more valid data was then used for further analysis. Averagely, 5.66% ± 4.86% of the raw pupil size data in each participant was removed after this step.

The saccade data was filtered with a duration longer than or equal to 100 ms to remove consistent eye movement because human saccade is defined as rapid ballistic eye movements shorter than 100 ms (Fischer & Weber, 1993). Similar to the pupil size, the eye with more valid data remained was then used for further analysis. On average, 30% ± 9.72% of the raw saccade data across participants was removed after this step. The RMANOVA was conducted to test the saccade number differences among strategies using the *ranova* function implemented in MATLAB 2018a (MathWorks Inc.).

6.2.6. MRI data acquisition

Brain images were obtained using a 3T MRI scanner (Siemens PRISMA, Siemens, Erlangen, Germany) at Cardiff University Brain Research Imaging Centre (CUBRIC). Head motions were minimized with comfortable paddings around the participant's head. Functional images (at least 2105 volumes for each scan) sensitive to blood oxygen level-dependent (BOLD) contrasts were acquired by a multiband echo-planar imaging (EPI) sequence (TR = 1.2 s, TE = 30 ms, multiband factor = 4, flip angle = 70°, acquisition matrix = 80 × 80, number of slice per volume = 52, voxel size = 2.5 × 2.5 × 3 mm^3). After the functional scans, structural images were collected for all participants (MPRAGE, TR = 2.1 s, TE = 3.24 ms, flip angle = 8°, acquisition matrix = 256 × 256, voxel size = 1 mm^3).

6.2.7. fMRI data analyses

6.2.7.1. Quality control

The image qualities were assessed using MRIQC (Esteban et al., 2017) which extracts no-reference image quality metrics (IQMs) from MR scans. We mainly referred to the temporal derivative of the variance of the signal (DVARS) and the frame-wise displacement (FD) for potential motion artefacts. Due to the long-time continuous recording method used in this study, the exclusion standard was set based on the group performance. The group DVARS was 32.49 ± 3.80 and the group FD was .208 ± .088 mm. Participants who had DVARS or the mean FD at 75-100 percentile of the group data and exceeding 3 standard deviations from the group mean were excluded from further analyses. Two participants were excluded after the quality control and all further imaging analyses were done with the remaining 32 participants.

6.2.7.2. Pre-processing

The MRI data was pre-processed with an SPM-based analysis pipeline called automatic analysis (Cusack et al., 2015).

The main steps of functional pre-processing in AA included (1) signal equilibration by removing the first 5 volumes of each scan, (2) field map-based EPI distortion correction, (3) slice timing correction, (4) 3D motion correction, (5) Application of the transformation derived from co-registering the structural to a standard-space template to the EPIs, (6) Fine-tuning the registration of the EPI to the structural, (7) spatial smoothing with a Gaussian Kernel of FWHM = 5 mm.

6.2.7.3. fMRI data analyses

Activity estimates were computed for the pre-processed functional time series from each run using an event-related general linear model (GLM) implemented in SPM12 (http://www.fil.ion.ucl.ac.uk/spm/). The basic strategies generated from behavioural modelling, baseline periods, colliding events, and result screens were used as predictors, and head motions were used as nuisance regressors. They were convoluted with a hemodynamic response function (HRF) to generate the main model regressors. Plus, temporal derivative terms derived from each predictor were added to the GLM to compensate for slice-timing variability in the HRF delay across regions.

For each decision strategy, 0-duration onsets (i.e., events that occur at a single point in time, without a duration) were used to capture the peak response of the neural activity (Dale, 1999). Additionally, a fixed delay of 2 seconds was introduced to all the onsets of the strategies. This 2-second delay was determined by the pupillometry analysis: it approximates the average latency from the onsets of the pupil size change to the onsets of a new strategy (see section 6.3.2.1 for details). It is worth noting that pupil dilation can be used as an indirect index of effort in cognitive control such as task switching (van der Wel & van Steenbergen, 2018).

The baseline periods were the 2-second paused phase at the beginning of every game round. It serves as a baseline period where the perceptual demands are presented but the cognitive demands are minimal, leading to more accurate and reliable estimates of the neural processes underlying task performance.

Both colliding events and the result screen were modelled separately as nuisance events.

6.2.7.4. Region of interest (ROI) analysis

Seven selected peaks on the whole brain activation map of all the strategy onsets versus the baseline period were used to create ROIs (**Table 7**, **Figure 35B**). Those peaks were either in the frontal-parietal intentional decision-making network (Si et al., 2021) or the reward-related brain areas (Sescousse et al., 2013), because we consider playing the Pac-Man game as a reward-based, successive intentional decision-making process. To have a better understanding of the ROIs, we projected all the ROIs to the human connectome project atlas (HCP360, Glasser et al., 2016) to get the detailed labels.

All the ROIs were created using an SPM-based region of interest toolbox MarsBaR (Brett et al., 2002) via the following steps: (1) build a sphere of 10-mm radius with a centre at the selected peak; (2) flip the sphere by the middle sagittal axis, producing a the hemispherical symmetric ROI; (3) extract the conjunction of the two spheres and the activation map of all the strategies as the final ROI.

The ROI data were extracted for seven basic strategies from participants' individual scans. The multivariable RMANOVA was conducted to test the interaction effect of the ROIs and the strategies using the *ranova* function implemented in MATLAB 2018a.

6.2.7.5. Whole brain analyses

To explore the other possible brain activation differences, further whole-brain voxel-wise analyses were conducted for the four-ghost vs. two-ghost contrast and three between-strategy contrasts, including global versus local, evade versus approach, and energizer versus no-energizer. The differences were calculated at the individual level and then statistically tested with a one-sample t-test at the group level. Threshold-free cluster enhancement (TFCE) was applied to all the contrasts for multiple comparison correction (Nichols & Holmes, 2003; Smith & Nichols, 2009).

6.3. Results

6.3.1. Behavioural modelling

The average duration and proportion of the six basic strategies and the vague periods are shown in **Figure 32**. The paired t-test results suggested that the average duration and proportion of strategies used in the eye tracking session and the MRI imaging session did not differ significantly ($t(6) = -1.33$, $p = .232$ and $t(6) = .002$, $p = .998$, respectively).

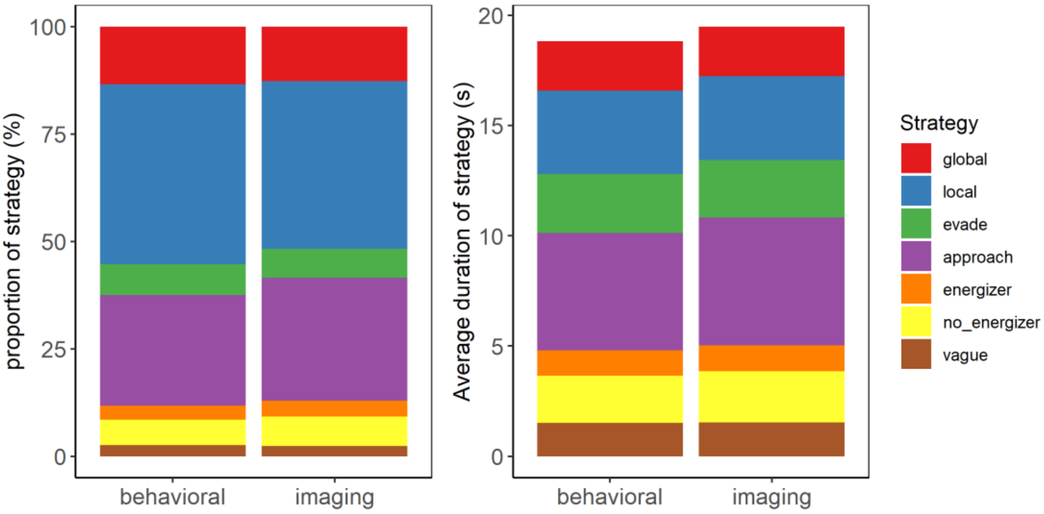


Figure 32. Behavioural comparison between the two sessions. Right: the comparison of the average duration of each strategy in the two sessions; **Left**: the comparison of the proportion of each strategy in the two sessions.

6.3.2. Eye-tracking

6.3.2.1. Pupillometry

The dilation starts at around 2 seconds before the behavioural strategy change, reaches the peak at 200 ms after the switch onset, and then drops back to a relatively steady baseline state at 4.5 seconds after the switch onset (**Figure 33**). Paired t-test for the pupil diameter at the steady peak (200 – 1200 ms) and the baseline (4500 – 5500 ms) suggested that pupil size had a significant increase during the strategies transition period ($t(31) = -12.30, p < .001$).

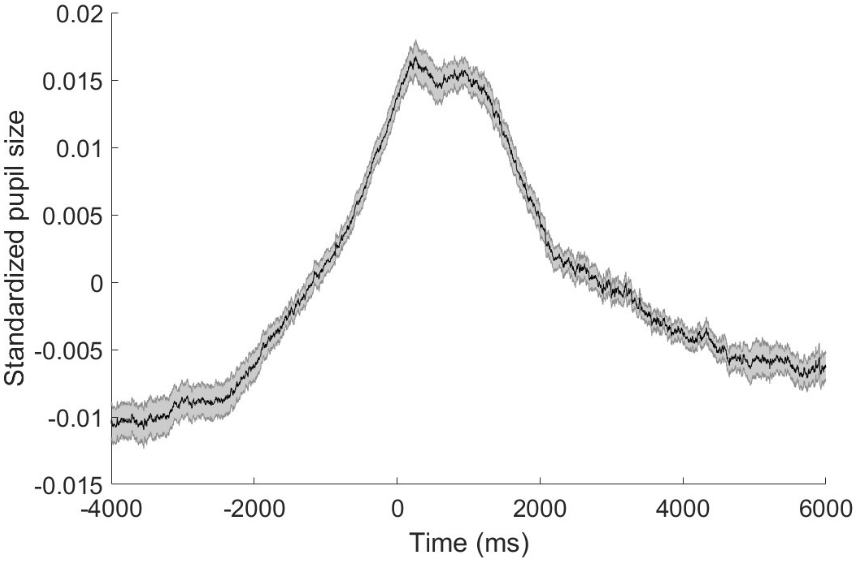


Figure 33. The pupil size changes over time. 0 on the X-axis is the time point for the behavioural strategy switch. The shaded error is the standard error of mean (SEM) across participants.

6.3.2.2. Saccades

We summed the saccade numbers in different strategies and found significant differences between strategies ($F(5, 155) = 25.19, p < .001$). Further pair-wise analyses suggested differences in the strategy contrast of global vs. local (MD = .173 ± .021), evade vs. approach (MD = .251 ± .025) and energizer vs. no-energizer (MD = -.195 ± .057) with Tukey's multiple comparisons corrected $p < .001$ (**Figure 34**). Most of the other comparisons were also significant with Tukey's corrected $p < .001$. Only the comparisons between global and evade, local and evade, local and no-energizer as well as approach and energizer did not show significant differences.

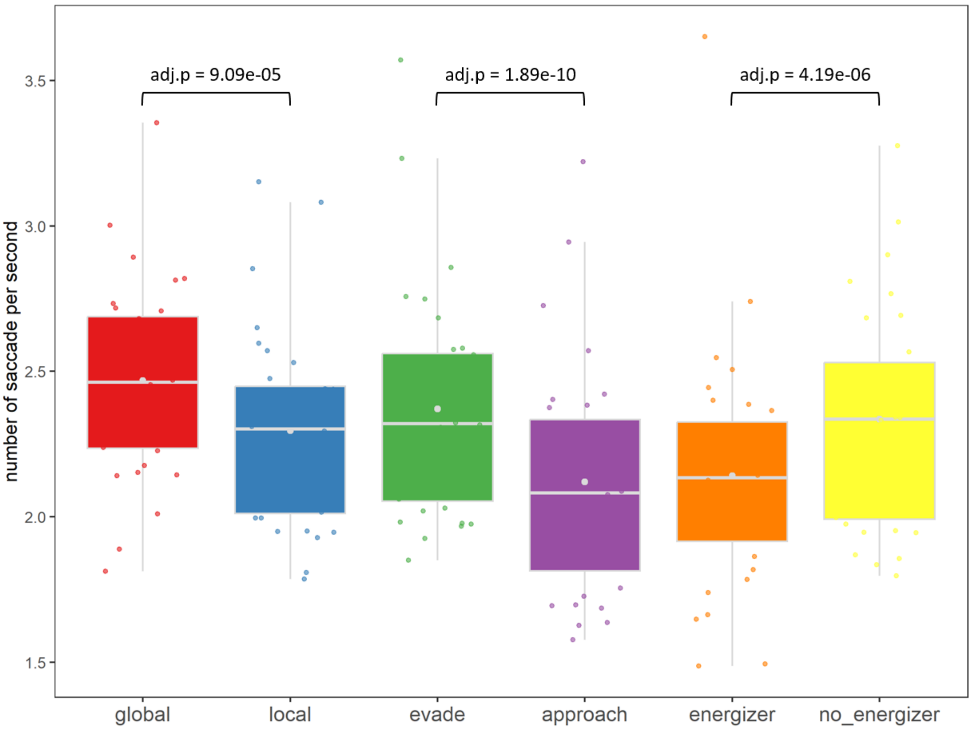


Figure 34. Number of saccades per second for each strategy. Significant differences were shown in the three main strategy contrasts of global vs. local, evade vs. approach and energizer vs. no-energizer.

Note that there were 13.88% ± 3.19% of the saccades on average that happened in the baseline period, colliding events or result screens, and were not included in this strategic analysis.

6.3.3. ROI analysis

For all the strategy change events in general, a front-parietal-occipital brain network was more activated compared to the baseline period (**Figure 35A**). This activation map was used to generate the ROIs for subsequent orthogonal analyses (section 6.2.7.4). A detailed list of all the peaks used to generate the ROIs can be found in **Table 7**.

Table 7. Selected peaks for the ROIs

Name of selected ROI	MNI coordinates of the peak		
	X	Y	Z
Cingulate cortex (CC)	0	12	50
Basal ganglia (BG)	16	-2	0

Frontal lobe (FT)	33	33	40
Insula	33	18	8
Lateral occipital cortex (LO)	43	-67	15
Superior frontal cortex (SF)	26	-4	62
Superior parietal cortex (SP)	16	-54	60

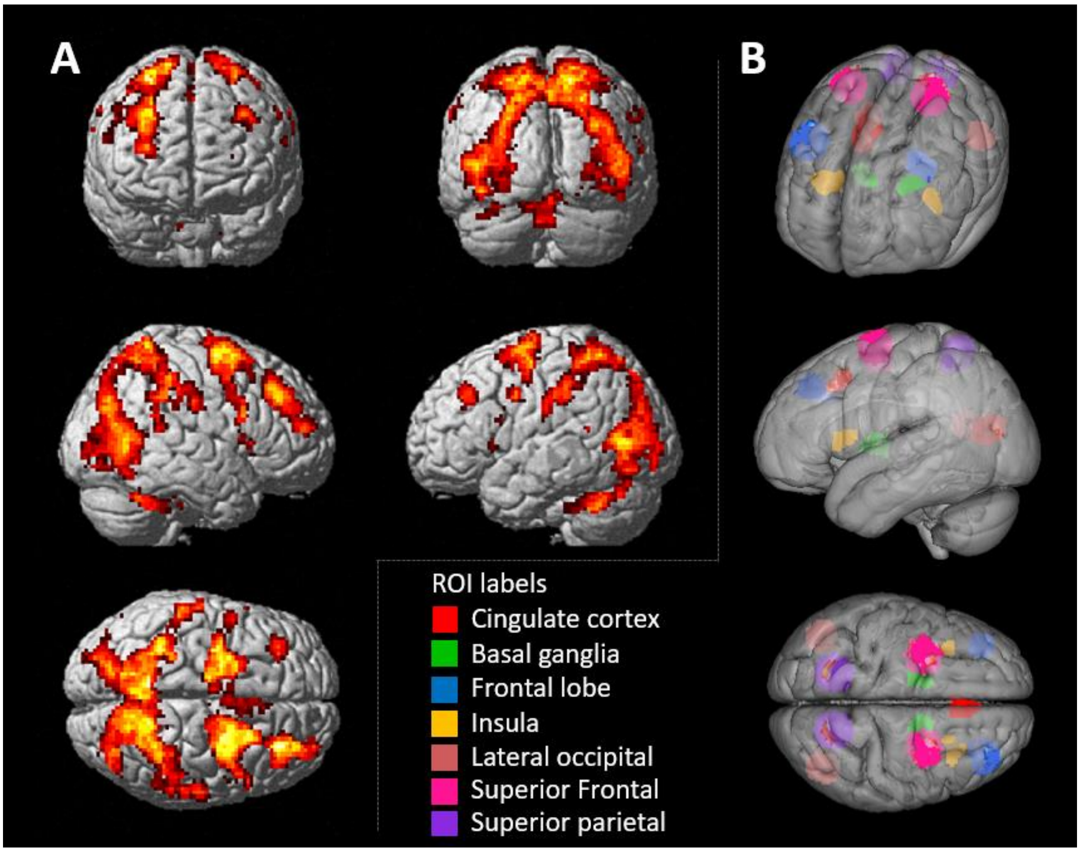


Figure 35. The contrast results of the whole brain activation differences between all the strategies and the baseline period. The FWE corrected results of positive contrast (i.e.: all strategies - baseline) presented on a single subject render template provided by SPM.

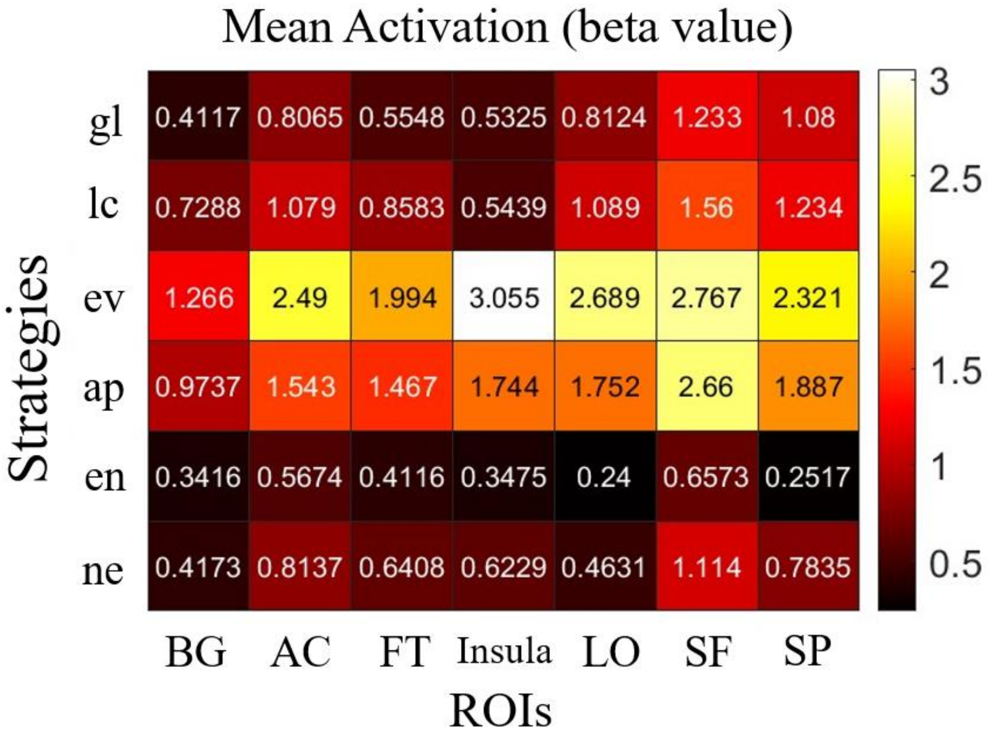
The RMANOVA result suggested an interaction effect between the ROIs and the six unambiguous strategies ($F(30, 930) = 5.89, p < .001$). Among the three contrasts of our main interest (i.e.: global vs. local, evade vs. approach and energizer vs. no-energizer), only evade vs. approach showed significantly different activation in the ROI of insula. The full list of significant results of the simple effect analysis on the strategies by the ROIs were shown in **Table 8**, and the mean activations of each strategy in each ROI was shown by a heat map in **Figure 36**

Table 8. The full table for corrected P value for all the significant contrasts in

ROI analysis. The ROI contains significant result of any main contrasts (i.e.: global vs. local, evade vs. approach or energizer vs. no-energizer) are marked with stars (*).

ROI	Strategy 1	Strategy 2	Corrected P value
CC	global	evade	3.50E-03
CC	evade	energizer	1.78E-03
CC	evade	no-energizer	1.15E-02
BG	global	evade	3.64E-02
BG	global	approach	3.28E-02
BG	evade	energizer	2.07E-02
BG	evade	no-energizer	5.49E-03
FT	global	evade	7.99E-03
FT	global	approach	2.40E-02
FT	local	evade	1.57E-02
FT	evade	energizer	1.25E-03
FT	evade	no-energizer	9.37E-03
FT	approach	energizer	5.22E-03
Insula	global	evade	1.11E-04
Insula	global	approach	4.43E-03
Insula	local	evade	1.54E-05
Insula	local	approach	8.49E-03
Insula*	evade	approach	2.80E-02
Insula	evade	energizer	2.86E-05
Insula	evade	no-energizer	5.43E-05
Insula	approach	energizer	1.27E-03
Insula	approach	no-energizer	2.12E-02
LO	global	evade	7.29E-05
LO	global	approach	8.36E-03
LO	global	energizer	2.78E-02
LO	local	evade	1.31E-04
LO	local	energizer	5.05E-04
LO	evade	energizer	5.18E-07
LO	evade	no-energizer	1.03E-06
LO	approach	energizer	4.42E-05
LO	approach	no-energizer	1.87E-03
SF	global	evade	4.86E-03
SF	global	approach	2.76E-03

SF	local	evade	8.24E-03
SF	local	approach	1.34E-02
SF	local	energizer	7.14E-03
SF	evade	energizer	3.01E-04
SF	evade	no-energizer	3.28E-04
SF	approach	energizer	7.98E-05
SF	approach	no-energizer	2.86E-03
SP	global	evade	5.79E-03
SP	global	approach	1.47E-02
SP	global	energizer	2.36E-03
SP	local	evade	3.86E-03
SP	local	energizer	2.44E-04
SP	evade	energizer	6.65E-06
SP	evade	no-energizer	8.07E-06
SP	approach	energizer	1.87E-05
SP	approach	no-energizer	4.97E-03



	BG	AC	FT	Insula	LO	SF	SP
gl	0.4117	0.8065	0.5548	0.5325	0.8124	1.233	1.08
lc	0.7288	1.079	0.8583	0.5439	1.089	1.56	1.234
ev	1.266	2.49	1.994	3.055	2.689	2.767	2.321
ap	0.9737	1.543	1.467	1.744	1.752	2.66	1.887
en	0.3416	0.5674	0.4116	0.3475	0.24	0.6573	0.2517
ne	0.4173	0.8137	0.6408	0.6229	0.4631	1.114	0.7835

Figure 36. The heat map for the mean ROI activations (beta value) of each strategy. The gl, lc, ev, ap, en, and ne on the y-axis represent global strategy, local strategy, evade strategy, approach strategy, energizer strategy, and no-energizer strategy respectively.

To better understand the ROIs, we projected all the ROIs except the BG to the

HCP-MMP atlas (Glasser et al., 2016) to get their detailed labels, as the BG is not included in the HCP surface parcellation.

The ROI of CC includes a part of the anterior cingulate cortex (8BM) and the pre-supplementary motor areas (SCEF). The ROI of FT is located in dlPFC (8Av, 8Ad, 8C, p9-46v, 46 and 9-46d). The ROI of insula contains the frontal opercula areas 4 & 5, the middle insular area, anterior ventral insular area. The ROI of LO contains the medial superior temporal area, middle temporal area, MT+ complex (TPOJ2 and TPOJ3), posterior inferior parietal cortex (PGp, PGi, and PGs), and extra-striate area hOC4la. The ROI of SF contains the supplementary motor area (SMA, including 6ma and 6mp), the primary motor cortex (M1, 6a, and 6d), and part of the dorsolateral prefrontal cortex (i6-8). The ROI of SP contains 7AL, 7Am, LIPv/VIP complex, and a part of subdivisions of area 5 (5mv and 5L).

6.3.4. Whole brain exploratory analysis

The contrast between global strategy and local strategy exhibited differences for both positive and negative contrasts (TFCE corrected $p < .05$, **Figure 37**, **Table 9**). The results of the positive contrast (i.e., global-local) were mainly located in the visual area extended from V1 to V3. The results of the negative contrast (i.e.: local - global) were mainly located in the bilateral primary somatosensory cortex (Area 1, 2 & 3b) and bilateral superior parietal area (7PC & LIPv/VIP complex).

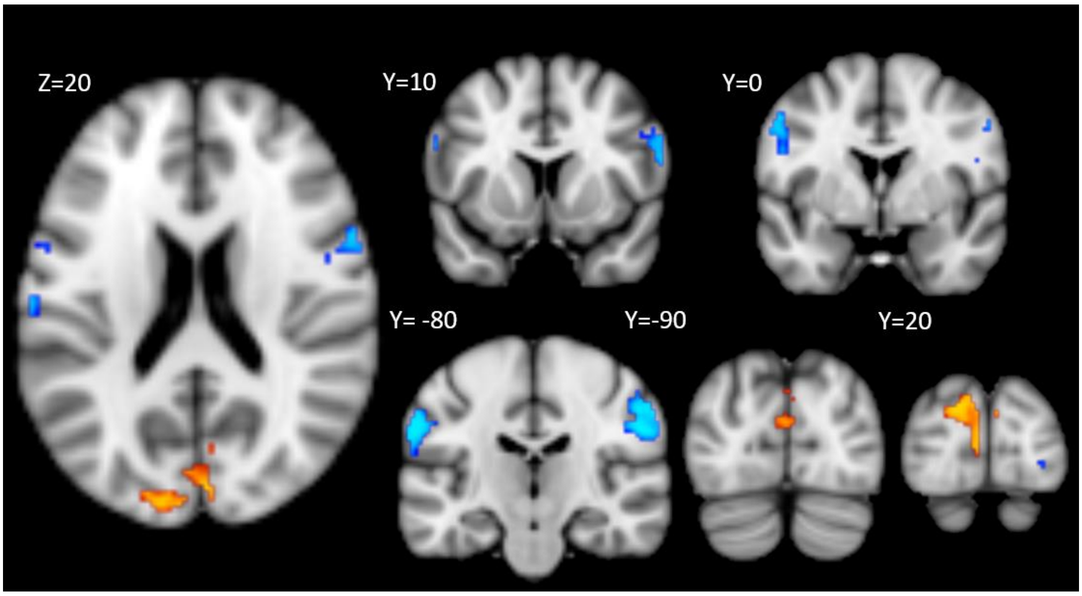


Figure 37. The contrast results of the whole brain activation differences between global strategy and local strategy. The red-yellow area indicates the results of the positive contrast (i.e.: global - local), while the blue-cyan area indicates the results of the negative contrast (i.e.: local - global). All results were corrected with TFCE *p* < .05.

Table 9. The contrast results of the whole brain activation differences between global strategy and local strategy. The voxel size is 2.5 × 2.5 × 3 mm^3. The peaks are presented in standard MNI space.

Cluster	No. of voxels	Minimum p value	Peak coordinates X	Y	Z
Positive contrast					
1	400	0.0068	5.7	-99.0	62.0
2	34	0.0368	17.1	-76.3	30.0
Negative contrast					
1	1064	0.0014	-48.6	-27.9	114.0
2	851	0.0010	42.9	-39.3	118.0
3	212	0.0060	68.6	14.7	98.0
4	187	0.0010	-62.9	11.8	102.0
5	37	0.0020	-25.7	-101.8	42.0
6	13	0.0457	-48.6	-62.1	30.0

The contrast between evade strategy and approach strategy also exhibited differences for both positive and negative contrasts (TFCE corrected $p < .05$, **Figure 38**, **Table 10**). The results of the positive contrast (i.e.: evade – approach) were mainly located in the visual area (V1 to V6), the posterior cingulate cortex (POS1, POS2, ProS, DVT, V23ab & 31pd), and a part of the inferior frontal cortex (IFSa). The results of the negative contrast (i.e.: approach - evade) were mainly located in the somatosensory and motor cortex (area 1 to 4), SP, prefrontal cortex, and frontal and parietal opercula area.

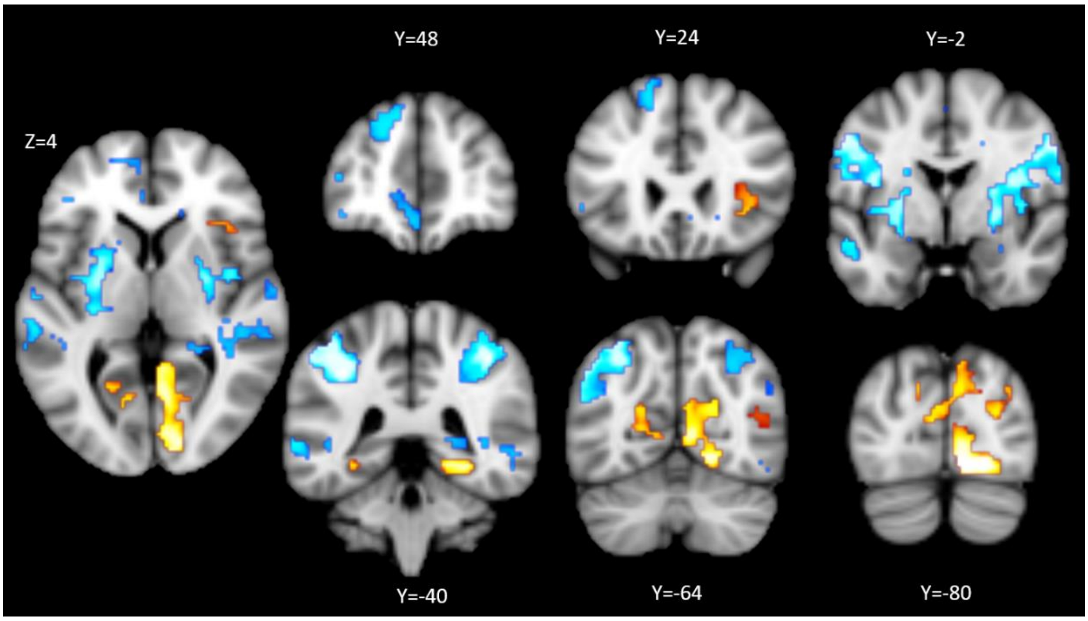


Figure 38. The contrast results of the whole brain activation differences between evade strategy and approach strategy. The red-yellow area indicates the results of the positive contrast (i.e.: evade - approach), while the blue-cyan area indicates the results of the negative contrast (i.e.: approach - evade). All results were corrected with TFCE $p < .05$.

Table 10. The contrast results of the whole brain activation differences between global strategy and local strategy. The voxel size is 2.5 × 2.5 × 3 mm^3. The peaks are presented in standard MNI space.

Cluster	No. of voxels	Minimum p value	Peak coordinates		
			X	Y	Z
		Positive contrast			
1	3189	0.0001	-8.6	-81.9	26.0

2	96	0.0160	-5.7	-25.1	34.0
3	90	0.0089	-37.1	31.7	42.0
4	46	0.0287	-8.6	11.8	62.0
5	5	0.0472	-8.6	-2.37	58.0
Negative contrast					
1	12285	0.0001	71.4	-10.9	74
2	41	0.0252	-51.4	54.5	62
3	21	0.0435	-40	14.7	30

However, no significant difference was detected when comparing the energizer strategy and the no-energizer strategy.

6.4. Discussion

6.4.1. Behavioural modelling

The behavioural modelling results illustrate the behavioural contrasts between the monkeys and the humans during the Pac-Man game. On the one hand, the five basic strategies proposed by the previous monkey study are also applicable in humans, implying a degree of translatability from the primate studies to humans. On the other hand, humans also showed some differences in heuristic choices from non-human primates. The most significant discrepancy is that humans have a common behaviour of not consuming the energizer in certain game phases. Though the rationale behind the no-energizer strategy can be different, either to extend the advantaged time and avoid the colliding penalty or to lure the ghosts together and catch them for higher scores, this strategy is unique to humans. One possible explanation is that monkeys and humans had different motivations for playing the game. Monkeys were externally motivated by the juice drops and thereby only relied on the strategies that led to a maximum number of juice drops per unit of time; whereas humans had intrinsic motivation to win the game and focused on higher scores per game.

In addition, the participants had comparable proportions and average duration of each strategy in the eye tracking session and the imaging session. This allows us to infer the cognitive states from the pupil dilations and apply it to the imaging analysis based on the corresponding behavioural pattern.

6.4.2. Eye-tracking

We mainly analysed two parts of the eye-tracking data. One is the saccade and the other is the pupil dilation.

Saccades have been widely proven to have a close relationship with attention shifts in both behavioural and imaging studies (Kowler et al., 1995; Perry & Zeki, 2000). As we found a variance in the number of saccades per second in different strategies, we presumed that the frequency of attention shifts among game elements is also different for each strategy. Further pair-wise comparisons supported this presumption. Notably, higher saccade frequencies were found in the three main contrasts including global strategy vs. local strategy, evade strategy vs. approach strategy and no-energizer strategy vs. energizer strategy. This was as expected because of the following reasons. First, the global strategy requires more attention shifts than the local strategy as it needs continuous monitoring of the Pac-Man location and the target area in distance. Second, the evade and approach strategy both require the attention of both Pac-Man and ghost(s). However, human players, in most cases, only employed the approach strategy after consuming an energizer to chase the scared ghost(s). Ghost(s) in the scared mode moved slower and thereby led to lower attention requirements. Last, the no-energizer strategy was usually employed when the ghosts were in the distance while the energizer strategy was usually employed when the ghosts were getting closer, resulting in a similar attention need to the global and local contrast. These results were consistent with the result of recent research which suggested that the gaze dynamics including the saccades during challenging visuospatial behaviours fulfil a crucial position in action selection and can potentially reveal the change of the subject's internal beliefs (Lakshminarasimhan et al., 2020).

Pupil dilation, on the other hand, is usually considered a sign of effortful cognitive control (van der Wel & van Steenbergen, 2018), especially for decision-making (De Gee et al., 2014; Laeng et al., 2012; Murphy et al., 2014). In this study, our finding fits this expectation. The participants showed a significant increase in pupil size when switching to another strategy. Moreover, it is notable that the dilation reaches a relatively steady peak at the behavioural switch points but starts happening before the behavioural change. According to Katidioti et al. (2014), in a forced switch task, pupil dilation begins at the moment of the switch onset, indicating a sudden shift in cognitive demands. However, in a voluntary switch task, pupil dilation starts before the actual behavioural switch occurs and typically reaches its peak at the switch onset. This suggests that the cognitive processes underlying the voluntary switch are initiated before the actual switch itself, likely indicating a preparatory phase where the participant is planning the upcoming switch. Therefore, it is reasonable to presume that the onset of pupil dilation can serve as an indicator of when the participant's voluntary switch intention is formed. In our case, the onset of pupil dilation is approximately 2 seconds before the behavioural change and we applied this delay to our fMRI data analysis to adjust the time stamps of the switch onsets.

6.4.3. Brain activation pattern

The whole brain analysis showed that a front-parietal-occipital network together with the subcortical areas was activated for executing all the strategies compared to the active baseline period. The results exhibit similarities to the brain activations during other games that require high-level cognition, such as chess (Atherton et al., 2003) or Go (Chen et al., 2003). This fits the nature of the Pac-Man game being a highly dynamic and complex game that requires multiple cognitive processes.

Based on the contrast between all the strategies and the baseline period, we selected activation peaks and created ROIs via the conjunctions between the spherical clusters centred at the peaks and the activation map to investigate the ROI-specific activation difference.

With the levels of activation of each ROI varying among different strategies, we mainly focused on the three contrary strategy pairs (global vs. local, evade vs. approach, and energizer vs. no-energizer).

The global strategy vs. local strategy contrast showed no activation differences in all the ROIs. However, further whole-brain exploratory analysis suggested that the activation discrepancy for the global against the local strategies lies in the early visual area from V1 to V3. The early visual area plays a key role in conscious visual perception for integrating retinal information (Nasr et al., 2016; Salminen-Vaparanta et al., 2019; Tong, 2003; Willmore et al., 2010). This is consistent with the higher frequency of saccades in global strategy, as the primary visual cortex is found to have post-saccadic increases in activation (Ibbotson & Krekelberg, 2011). Moreover, a reversed contrast illustrates that the local strategy had higher activation than the global strategy in the bilateral primary somatosensory cortex and intraparietal sulcus posterior parietal (LIPv/VIP complex, a part of the superior parietal) cortex. On the one hand, the increased activities in the LIPv/VIP complex suggested that participants had quicker updates in spatial representation in the local strategy than in the global strategy (Rolls et al., 2022). This corresponds with the execution scenarios of the local strategy where players are successively targeting the next close pellets. The primary somatosensory cortex, on the other hand, is closely associated with tactile sense (Tamè et al., 2016). Its enhanced activation could be a result of more frequent button pressing in the local strategy than in the global strategy. However, because the frequency of button presses was not recorded during the experiment, this hypothesis was not testable using the current dataset. In general, the global strategy is associated more with the ventral medial visual cortical stream as it requires a spatial combination of all the game elements, whereas the local strategy is associated more with the dorsal visual cortical stream as it requires rapid refreshes for where the next pellet is.

The evade strategy vs. approach strategy contrast only had an activation difference at the insula in the ROI analysis. The insula serves as a linchpin in a range of functions including sensory, emotional, motivational, and high-level cognition such as decision-making (Uddin et al., 2017). Here we considered the activation difference between evade and approach in insula as a result of different emotional responses for chasing and being chased. On the behavioural side, evading is the only strategy that follows the intuition of avoiding penalties and can be regarded as an anxious scenario. On the imaging aspect, the insula ROI is limited to the middle insular area and anterior ventral insular area, which are both related to emotion processes or emotion-related physiological changes (Duerden et al., 2013; Mutschler et al., 2009). The whole brain exploratory revealed more distinctions between the two ghost-related strategies. The evade strategy had higher activation at the visual area and posterior cingulate cortex (PCC) than the approach strategy, while the approach strategy showed higher activation at the somatosensory and motor cortex (areas 1 to 4), a part of the superior parietal cortex and prefrontal cortex. The higher activation of the PCC in the evade strategy than in the approach strategy implies increased attention controls and adapting behaviours (Leech et al., 2012; Leech & Sharp, 2014; Pearson et al., 2011). This aligns with the evade strategy, which requires players to react according to the locations of the ghosts. In contrast, the approach strategy seems to involve more planning-related prefrontal activity, as the strategy expects players to complete the behaviour in a limited time period to maximize their revenue (Koechlin et al., 2000; Tanji & Hoshi, 2001). Apart from this, the relationship between the evade strategy and the approach strategy is similar to the global and local, where the evade strategy requires a comprehensive spatial representation of all ghosts in the maze, but the approach focuses on the spatial location of one next ghost. This matches the similar activation discrepancy in the visual area, somatosensory/motor area, and the superior parietal area.

However, the contrast between the energizer strategy and the no-energizer strategy did not show any difference in both ROI analyses and the whole brain exploratory experience. The possible reasons are (a) the proportion of these two strategies was small during the whole game period and (b) their average durations in one execution were short. The former feature resulted in the relatively small sample size for these two strategies, and the latter feature made them susceptible to timestamp change as the fixed delay used in the imaging analysis is longer than their average durations.

6.4.4. Limitation and next step

As mentioned, this study used pupil dilations to calibrate the timing of the model-derived mental states (i.e., a 2-second delay to the behavioural model) in the imaging sessions according to their comparable behavioural patterns. However, the temporal accuracy of this deduction is relatively low. At the same time, because of the delay in pupil change itself, it is also difficult to capture those short-duration strategies, such as energizer and no-energizer. Therefore, methods with higher temporal resolutions such as electrophysiology recordings (e.g. EEG or MEG) are recommended for future studies.

In addition, this study did not record the button responses. This limited our ability to test various motor-related hypotheses and explain the activation difference in motor-related areas. For example, a potential explanation for the activation difference of the primary somatosensory cortex between global strategy and local strategy was the frequency of button presses across the strategies. However, this hypothesis is not testable without knowing the frequency of button responses in both strategies. The absence of continuous button press recording is in line with the original Pac-Man game. For example, when the Pac-Man moves up along a continuous path, left or right turns do not affect the Pac-Man’s movement, unless it is at a junction that allows a change in direction.

It is worth noting that this study was conceptualised from behavioural modelling on a non-human primate study, and our goal was to examine whether model-driven strategies correlate with BOLD responses in the human brain. Therefore, we constrained our imaging analyses to the contrasts between model-derived strategies. Such analyses cannot directly infer how individual strategies were implemented in the brain, because each strategy is associated with a number of factors such as motor execution and variabilities in visual stimulus. Nevertheless, our results suggested that model-derived strategies did associate with changes in the BOLD response, consistent with the implication that those strategies represent different mental states during gameplay. This assessment can further help us to develop higher-level models. For example, based on this study, we built a Language of Problem-Solving (LoPS) model to further explain how the different strategies are connected to each other (Yang et al., 2024).

6.5. Conclusion

Our study adjusted and optimized the strategy-based behavioural model of Pac-Man originated from non-human primates and investigated the possible biological and neural supports for the heuristic strategies in humans.

Through duplication, we tended to recreate and validate the monkey behaviours in humans to test the robustness of the strategy-based heuristic model in Pac-Man play. We found that, though both can use heuristics and there are shared basic strategies, humans still have their uniqueness from the monkeys which is potentially related to the motivation system. This gave valuable insights into understanding the similarities and differences between the behaviours of non-human primates and humans.

Besides, we displayed both eye movement and neuroimaging evidence for the discrepancy and reasonableness of different basic heuristic strategies. With eye tracking, we identified the pupil dilation change during strategy switch and observed saccade frequency change among different strategies. The results from the event-related fMRI supported those findings, and further illustrate the dissociated functional localization of different heuristic strategies.

Finally, the study yielded the possibility of applying behavioural modelling results in the imaging study to explore the highly dynamic and complex paradigms and using the imaging methods to test the validity of behavioural models by looking for related features of the potential neural mechanism.

7. Summary

This Chapter provides a summary of the thesis in section 7.1 and discusses the limitations of the research in this thesis and potential directions for future studies in section 7.2, which might give a more comprehensive overview of my current works on intentional decision-making.

7.1. Contribution

The inception of the thesis involved a literature review of the theoretical basis of intentional decision-making. The review began with the definition of intentional behaviours, which highlighted the significance of self-initiation and purposefulness. A widely accepted WWW model (Brass & Haggard, 2008) of intentional actions was discussed. The three eponymous components of the WWW model were outlined with both specific experimental paradigms and neuroimaging evidence. Next, as an extension of the original WWW model, the literature on intentional behaviour based on higher-level cognitions and the sequential feature of intentional decision-making were reviewed. The sequential feature was explained via both random sequence generation tasks and task-switching paradigms. Correspondent behavioural and neurological research were reviewed, showing the effects of recent choice history on decisions. Moreover, to bridge the trial-based results with real-life sensory-cognitive-motor chains, the demands on a continuous decision-making paradigm were highlighted. For example, Pac-Man was presented as an example of such a continuous paradigm, with additional features such as gamification to engage participants. Last, we evaluated the multiple modalities that were later employed in this thesis, including fMRI, MEG and eye tracking.

The main contributions of the thesis were reported in Chapters 3-6, where four studies were presented on different aspects of intentional decision-making. These chapters are interconnected. Chapter 3 is a meta-analysis of existing fMRI/PET studies of intentional decision-making, highlighting a research gap in studies on cognitive intention, particularly cognitive intentions with heterogeneous cognitive processes. Responding to this gap, a novel paradigm was formulated and subjected to behavioural testing in Chapter 4. Following that, based on the behavioural outcomes, the paradigm was refined for a subsequent MEG study in Chapter 5, aiming to uncover potential neural correlates associated with the identified characteristics of cognitive intentions. Finally, in Chapter 6, the potential of using Pac-Man as a continuous paradigm to understand more dynamic and complex cognitive intentions was demonstrated.

7.1.1. Categorization and functional localization of intentional decision-making

Chapter 3 considered 38 independent experiments in 36 studies on the functional localization of *free-choice* paradigms where participants need to make intentional decisions among multiple equally appropriate alternatives.

Behaviourally, all the experiments were categorized into four subsets according to the features of available options, namely reactive intention (RI), perceptual intention (PI), inhibitory intention (II) and cognitive intention (CI). The initial three subsets are intricately tied to motor actions. RI exclusively encompasses the most basic cue-action mapping. PI comprises successive mappings involving cue-target and target-action relationships. II permits a flexible choice between cue-action and cue-inhibition mappings. Meanwhile, CI refers to choices in high-level cognitive processes. The categorization disclosed the *status quo* of the intentional decision-making paradigms that the majority of the research only focuses on motor actions, and more CI studies are needed. The coordinates-based activation likelihood estimation (ALE) meta-analysis (Eickhoff et al., 2012) was conducted over all the experiments as well as the experiments in each paradigm category respectively. Apart from confirming the commonly reported frontoparietal network for voluntary choices, the

ALE results also validated and confirmed the role of the insula in intentional decision-making. Furthermore, a meta-analytic decoding was performed on the ALE activation maps based on a database of over 11,000 brain imaging studies (Poldrack et al., 2012; Yarkoni et al., 2011), which unveiled the cognitive and computational processes involved in intentional decision-making.

7.1.2. Experiment with paradigm on cognitive intentions

Chapter 4 developed an experimental paradigm on cognitive intention in response to the research demand raised in Chapter 3. The study contains two experiments where participants were asked to make intentional decisions among different cognitive tasks on perception, memory, and learning. The perception task required participants to observe a letter matrix and count the number of columns that have the same letter occurring twice. The memory task required participants to remember a word list in a given time and to identify the new word in the following testing phase. The learning task required participants to observe three pairs of letter combinations, find the pairing pattern, and select the correct match for a new letter combination. In every single trial, one of the three tasks would be unavailable, and participants needed to choose from the remained two tasks, which can prevent participants from sticking to one task and set the stage for comparisons across tasks. This was further ensured with an additional setting that only half of the trials allowed participants to stay at the same task. The design balanced the task bias and the voluntariness of the choice, permitting investigations on both aspects.

Experiment 1 replicated the repetition bias in cognitive intention as in previous action-related intentions. The repetition bias presented a large individual variability among participants. Moreover, there was also a bias on the preference of task type. The more preferred task was associated with lower perceived task difficulty, and this perceived difficulty was not necessarily related to the objective task performance. To further understand this phenomenon, the paradigm was revised by adding an independent difficulty dimension to each task in Experiment 2. This newly induced independent variable balanced the perceived difficulty levels of each task and diminished the bias on task type as expected, suggesting the perceived difficulty levels as an influencing factor on intentional choices among tasks.

Moreover, this paradigm was revised in Chapter 5. The task was simplified to binary task choice and two tasks were unified in terms of their trial structures to promote its feasibility under MEG settings. The modified paradigm contained three stages for both tasks, including the choice stage, stimulus stage and response stage. Participants were instructed to make intentional decisions between a memory task and a perception task in the choice stage, and the two tasks shared an identical set of visual stimuli of 3×2 red and blue lattice matrices in the stimulus stage. In the perceptual task, participants were required to count the number of columns that the dots are in the same colour, and choose the answer in the response stage; while in the (visual) memory task, participants were required to remember all the columns, and judging if the column appear on the response page belongs to the previously showed matrix. The design diminished confounding variables during the whole trial and allowed analyses of the different intentional cognitive processes *per se*.

7.1.3. Spatiotemporal neural correlates of cognitive intentions

Chapter 5 presented an MEG experiment using the abovementioned paradigm that aims to reveal the spatiotemporal neural correlates of different cognitive intentions, specifically the intentions on perception and memory. The behavioural data was analysed using the same RMANOVA method as in Chapter 4. As there was no interaction effect for the task types and the transition type for the behavioural results, the MEG data was only analysed for the main effect of the task type (i.e., memory task vs. perceptual task) and transition type (i.e., stay at the same task vs. switch to the different task). The sensor-level analysis was conducted using cluster-based Monte Carlo simulation and did not reveal any difference for either type. The source-localized data went through time-resolved MVPAs to detect the brain areas that contain significant information representation of task types and transition types.

Most of the behavioural results replicated the findings in Chapter 4. Only the time spent on task choice showed an unexpected difference between tasks. Participants made choices quicker when targeting the memory task than the perception task, which might be a result of higher task preference or motivation in choosing. The sensor-level analysis did not show many significant results as the effects were spatially distributed. Source localization, on the other hand, reduced the impact of noise from other sources and enhanced the signal-to-noise ratio. Therefore, it revealed the significant roles of task-rule-related areas in both task choices and stimulus processing. Furthermore, those areas also presented notable relevance to the transition types. This suggested a possibility that participants might regard the transition types as task differences, leaving a potential direction for future research.

7.1.4. Towards dynamic and complex intentions

Chapter 6 provided an example of using the video game as a continuous paradigm to explore cognitive intentions under more dynamic and complex circumstances. The classical arcade game Pac-Man (Namco) was adapted and employed in this study. Participants were asked to navigate the character Pac-Man through a maze to collect the pellets and energizers and avoid the ghosts. Six intuitive strategies (i.e., local, global, evade, approach, energizer and no-energizer) were modelled according to the locations of all the game elements and the moving direction of the Pac-Man to describe the periodical cognitive intentions of participants during the gameplay, resulting in a sole strategy label at each time point. The six strategies were examined under three contrasts. Local vs. global strategies focused on pellet collection, reflecting the intention of direct rewards vs. long-term goals. Evade vs. approach was related to strategies towards the ghosts, indicating the intention of risk avoidance or elimination. Energizer and no-energizer strategies were about shifting the game status, implying the possible planning behaviours.

The study consisted of two separate experiment sessions. The first session employed the eye tracker to record the eye movements, and the second session used fMRI to localize the brain areas associated with strategic intentions.

The eye-tracking session confirmed the discriminant validity of strategies, as the transition between strategies was associated with pupil dilation which implies effortful cognitive control (van der Wel & van Steenbergen, 2018). At the same time, the strategies that require continuous monitoring of more game elements had relatively higher saccade frequency which is usually regarded as an index of attention shift frequency. The gameplay activated a frontal-parietal-occipital network as well as some subcortical areas, reflecting the dynamic and complex nature of the paradigm. Moreover, the brain areas related to the features of different strategies can be detected by the BOLD contrasts, validating the feasibility of using video games as a continuous paradigm in studying cognitive intentions.

7.2. Limitation & Future Direction

7.2.1. Confounded motor components in cognitive intentions

Although the main focus of this thesis is cognitive intentions, it is hard to separate them completely from motor actions. The choices on cognitive processes need to be manifested by motor actions such as pressing buttons in Chapters 5 and 6, or clicking the mouse in Chapter 4. This is an inevitable issue in decision-making research. Changing the experiment designs might be able to detach the motor actions from the cognitive intentions. For example, in Chapter 5, we can instruct participants to choose a task without button-pressing and just carry on the stimulus processing and responding with the chosen task rule. However, the method will result in a new issue of losing track of the decision-making time, as there are no overt signs of their task choice. Another way to alleviate the effect of motor actions is to employ multiple response modalities within a single study, such as eye movement control, manual control and voice control. In this way, a conjunction result of all modalities can be achieved, which should be able to minimize the influence of those motor actions.

7.2.2. Online experiment method

The studies presented in Chapter 4 were based on an online experiment. Though internet-based studies have its advantages of large and diverse sample populations, low cost and high efficiency, they also face a number of technical and scientific challenges (Berinsky et al., 2012; Birnbaum, 2004; Reips & Birnbaum, 2011).

7.2.2.1. Attrition Rate

One of the most important challenges of online experiments is the attrition rate. Participants are more like to drop out before completing the experiment in online studies compared with the physical laboratory experiments. There are two kinds of dropouts. One is attributed to external reasons, such as technical issues or environmental disturbances. The other is condition-dependent, and usually associated with decreased motivation. The first kind of dropout can be considered as systematic attrition that can be compensated with a larger sample size (Arechar et al., 2018), while the second kind can be detrimental to the validity of the research (Zhou & Fishbach, 2016). It is difficult to distinguish the two types of dropouts due to the lack of supervision during experiment conduction and the ethical regulations on participants' withdrawals.

7.2.2.2. Data quality

Another potential problem of the online experiment is the reliability of the data.

7.2.2.2.1. Lack of monitoring of engagement

Conducting and performing the experiments online diminished the interaction between participants and experimenters, leading participants to have a higher possibility of misunderstanding instructions and distracting from the tasks. In this thesis, a continuous attention check was employed in the online experiments to supervise the participants to some extent. When the response accuracy of the recent 30 trials is under .40 (the chance level accuracy is .25 and the average accuracy of all tasks and subjects is over .80), the experiment will terminate prematurely and the data from this participant will not be incorporated in future analysis. This attention check would not fully address the issue but can improve the data quality partly.

7.2.2.2.2. Technical issues

While benefiting from its high accessibility, the online experiments also unavoidably weakened experimenters' control over the hardware factors, introducing the nuisances caused by equipment differences. For example, the screen size and the browser types might influence the presentation of the experiment. Also, the computer and the internet speed might have an effect on the data recording or transition. A slow computer may compromise the reaction time, and an unstable internet connection may result in a higher packet loss rate. In this thesis, the problem is attenuated by instructing the participants to complete the experiments using personal computers (rather than smartphones or tablets) and constraining the participants to use tested valid browsers.

7.2.2.2.3. Possibly biased sample

The participant pool of online experiments is generally considered to be comparable with traditional data sources such as college students and other similar convenience samples (Paolacci & Chandler, 2014). However, because the internet participants are relatively freer in study selection, different online studies usually end up sampling different subpopulations in the pool (Paolacci & Chandler, 2014). This also raises concerns about cross-contamination, as the participants tend to sign up the studies similar to the experiments they completed before (Horton et al., 2011). These issues can be alleviated via pre-screening the participants (Paolacci & Chandler, 2014). The online experiments in this thesis did the screening via the demographic information and the participation histories provided by the participant platform (i.e., the *Prolific*). All the participants had their education levels at or above secondary education and had no previously rejected responses in other experiments.

7.2.3. Temporal resolution of fMRI study

Chapter 6 used fMRI scans to locate the brain areas related to intentional strategic decision-making. The method is employed because of its high spatial resolution and ability to detect subcortical activities. However, the temporal resolution of fMRI scans was constrained at second level because of the metabolic nature of the BOLD response. Therefore, further time-resolved studies are recommended to provide temporal characteristics of strategic decision-making. Electrophysiological records can be one of the appropriate methods. Though some fMRI results lay in subcortical brain areas, the application of the MEG or the simultaneous EEG-fMRI (Huster et al., 2012) would compensate for the limited depth penetration of electrophysiological signals.

7.3. Conclusion

In conclusion, this thesis provided a series of studies on the topic of human intentional decision-making progressively. Chapter 2 reviewed the theoretical basis and pointed out the significance of carrying forward the researches in this field. The functional localization and categorization results in Chapter 3 then revealed the brain network underlying intentional decision-making and a limited number and format of studies on cognitive intention. Responding to this shortage, Chapter 4 proposed a new paradigm for cognitive intentions and conducted internet-based experiments using the paradigm. The results suggested that participants had a repetition bias and a task bias when choosing cognitive tasks, and the task bias is closely associated with the participants' perceived difficulty levels of the tasks. Chapter 5 then employed MEG to investigate the spatiotemporal neural correlates underlying the cognitive intentions and their follow-up stimulus processes. The MVPAs on the source-localized data found the brain areas associated with the task rules, such as the middle cingulate area and the middle frontal area, were engaged in both task choices and stimulus processing, highlighting the criticality of rule-relevant information in cognitive intentions. Finally, Chapter 6 explored the cognitive intentions in a more dynamic and complex environment using the Pac-Man game. With proper behavioural modelling, both eye tracking and fMRI contrasts can reflect the strategic intentions during the gameplay, validating the feasibility of using video games as a continuous paradigm in studying cognitive intentions. Combining all the studies, this thesis contributes to the research of intentional decision-making, especially cognitive intentions, by synthesizing the theoretical backgrounds, the innovative experimental paradigms and the multi-modal measurements of the cognitive processes.

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