Hierarchical control in task switching



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A thesis submitted for the degree of D.Phil.
in Experimental Psychology

Hilary Term 2018

Abstract

Human flexible behaviour is often seen in everyday life tasks. These tasks (e.g., making coffee) are composed of actions (e.g., pouring sugar) that are typically nested within a large task structures made of superordinate components and nested subcomponents. Task switching has been adopted widely as an effective tool to explore the mechanisms of flexible behaviour and can be easily adapted to real-life situations. The core hypothesis explored in this thesis was that there might be another level of control that is responsible for coordinating and scheduling actions in task switching, which I label "meta-control".

My first project aimed to establish robust behavioural evidence of meta-control. To test this hypothesis, switching efficiency was treated as a measure of meta-control influence. In a novel design, participants' beliefs about switch probability were manipulated through explicit instruction, allowing manipulation of meta-level control independent of the specific sequence of tasks required. The first three behavioural experiments demonstrated behaviorally that instructions influenced the efficiency of switching even when low-level (bottom-up) experience was matched, and that this effect was motivation-dependent. In follow-up studies, this meta-control influence was found to bias voluntary task selection. Two EEG studies aimed to characterize the level at which instruction affected processing. Motor and task levels were examined with lateralized motor potentials and oscillatory alpha power, respectively. Effects of instruction only existed on alpha power. Overall, the results suggest that expectancy prompts the adoption of distinct control modes across sequences of trials.

The second project explored meta-control in a task switching paradigm with a hierarchical task structure in very short (2-4 trial) sequences that were preceded by instructions about switch frequency or switch position. The experiments focused on the benefits and costs of sequence structure, based on the hypothesis that trial sequences are treated as coherent units. Three behavioural studies were conducted for testing this hypothesis. The first utilized instructions about switch frequency to test for sequence transition effects and their influence on switching performance at the trial level. In two subsequent experiments, instructions made explicit the position of a task switch. The results confirmed that instructions about switch position helped participants to build useful sequence representations, and that alternating between sequences influenced trial-level switch processes. Generally, sequence representations have a persisting influence across trials and a pronounced impact at the first trial position of sequences.

The experiments in this thesis provide evidence of meta-control in task switching. The first conclusion is that meta-control can be studied with the novel experimental design introduced in this thesis and was found to be reward dependent. The second conclusion is that meta-control acts as a set of parameters that can modulate the mode of control in a sustained way across trials.

Acknowledgements

Firstly, I would like to express my sincere gratitude to my advisor, Nick Yeung, for the continuous support of my PhD study, his patience, inspiration, and immense knowledge. He has been a tremendous mentor and an exemplar of a good supervisor, professor, and researcher. I could not have imagined having a better advisor and mentor for my Ph.D. study.

Second, I would like to thank all members of ACC lab for their help on the data collection and for valuable inspiring discussions. No matter how hard the problems were, people such as Niccolo, Annika, Raluca, Karen, Michael B., Michael C., Naomi, and Marike were able to help me to overcome numerous obstacles I have been facing through my research. In addition, I am also grateful to the examiners of my transfer and confirmation vivas for their constructive suggestions.

A very special gratitude goes out to all down at the Ministry of Education (Taiwan) for helping and providing the funding for my study.

Finally, this thesis also benefited from my parents' love and encouragement. Their support let me know I have two strong supporters in my corner to focus on research. Last but not the least, I could never find enough words to truly express the influence M.C. has had on my life in Oxford.

Thanks for all your encouragement!

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Chapter 1

A literature review and an overview of the thesis

Introduction

Cognitive control is fundamental to goal-directed behaviour. Without the contribution of cognitive control in mediating goals in a constantly changing environment, flexible behaviour would be difficult. People might respond reactively to any external stimulus but be unable to behave in a proactive way to achieve goals and to perform willed actions. This goal-directed behaviour is often seen in everyday life tasks ranging from relatively simple and practiced to more complex and infrequent actions, for example, making a cup of coffee to cooking a three-course meal. To make coffee, not only the individual actions have to be in correct order, but also each precise transition between small steps is necessary to reach the goal. It might be surprising that even simple tasks also require certain degree of involvement of cognitive control. However, control might be recruited both for the current task and also for preparing the next task element or protecting from interference from previous actions. Thus, someone who is preparing coffee might accidently forget to turn on the coffeemaker or forget to put in milk. There errors might occur because irrelevant

distractions attract attention, causing a failure of switching to the next event. Thus, the role of cognitive control in this situation is to ensure that each step is executed correctly and consecutively.

One of the most common and influential ways to study cognitive control is through the task switching paradigm (a review sees Kiesel et al., 2010). In task-switching experiments, participants are required to perform one of two or more simple tasks on each trial. On some trials, the task remains the same (task repetition trials), while on others the task changes to one of the other tasks (task switch trials). Participants are required to classify different elements or attributes of the stimulus according to rules that specify the associations between stimuli and responses. Quite often the stimuli are bivalent, which means that they afford two or more tasks (e.g., number stimuli afford both magnitude and parity categorization tasks). Further, the same responses are often used for both tasks, such as a left key press to indicate that a number is even or smaller than a given reference value, and a right key press to indicate that a number is odd or larger. On each trial, the task can be repeated or switched to another one. Generally, responses take longer to initiate on task switch trials than on repeat trials, often by a substantial amount (e.g. 200 ms relative to a baseline of 500 ms). Also, the error rate is often higher after a task switch.

If a person intends to perform a task, he/she must adopt a corresponding mental

task set. A task set is commonly defined as a set of task processes that are responsible for acting in accordance with task requirements. These processes usually comprise representations of stimuli, required task responses, and the correct associations between them. In general, task sets can be acquired through explicit instructions or trial-and-error learning. The more we practice a task, or the more recently we have practised it, the easier it becomes to re-enable that task-set. For some tasks, the S-R mappings are relatively easy because they are highly overlearned (such as in word reading or object naming), whereas for other tasks, the S-R mappings are more difficult to establish because they are arbitrary (e.g., blue digit 3 to left response key, red digit 3 to right response key) or because they overlap for different possible tasks (e.g., naming the ink color of a color word or reading the word itself as in the Stroop task).

Since this thesis addresses multiple levels of task representation, it is important to specify how the term 'task set' will be used in the current context. In the task-switching literature, the term task set refers broadly to the organization of cognitive processes and mental representations that enable a person to act in accordance to task requirements (a review sees Kiesel et al., 2010). On the other hand, task set at a higher level of behavioural structure could include a representation of several task names in sequences and most importantly a set of parameters that monitor

and ensure the goal and subgoals are both fulfilled. Although task set can be broadly defined, here I use task set to refer to a set of mappings of particular stimuli to particular responses and refer to meta-control (or sequence-level control) as operating at a higher level of abstraction/organisation. Before introducing the idea of high-level task structure and the corresponding idea of multiple levels of control, I will first discuss some basic features about the task switching paradigm and how the paradigm has been designed to investigate cognitive control.

Methodology: measuring task switching performance

Instructed task switching

Over decades of research on task switching, there have been various views on the core processes of task switching. This also leads to subtle differences on the ways to instruct task switching. Perhaps the most common method, and the one adopted in all experiments in this thesis, is the task-cueing paradigm, in which the task to perform is signaled by a cue presented with or prior to the target stimulus. In the task-cueing paradigm, the order of the tasks and thus the order of task switches and repetitions is random. For example, in Sudevan and Taylor (1987), participants switched between categorizing a digit as odd/even or as smaller/larger than 5. The tasks were cued by the words ODD/EVEN and LOW/HIGH appearing above/prior to each trial. Other

studies have used task names (e.g., magnitude or parity) or symbols (e.g., a square or a diamond) as task cues. Importantly, the task-cuing paradigm allows varying the interval between the task cue and the target stimulus (cue-stimulus interval, CSI) and the response in the preceding trial and the onset of the next task cue (response-cue interval, RCI). Both CSI and RCI are key parameters in task-cueing paradigm for studying task preparation. Prolonging the CSI results in decreased switching costs (Meiran, 1996). The relationship between CSI and switching cost has been treated as evidence that people can engage in active reconfiguration in preparation for an upcoming task, since increasing preparation time would be beneficial for upcoming task preparation. In contrast, the RCI not only provides time for advance preparation for an upcoming task but also allows passive decay of the previous task, so that switching costs can change due to less interference from previous tasks (Allport, Styles, & Hsieh, 1994). In general, the longer the RCI, the smaller the switching cost that is observed

Even though I only used the task-cueing paradigm, the other methods are also relevant. Jersild's original (1927) method, which is still sometimes used, compares the duration of blocks of trials that mix switching trials and repetition trials with blocks in which just one task is repeated (Jersild, 1927). The contrast of mixed-task and single-task blocks reflects the "global" costs associated with task switching compared

with performance of the same task repeatedly. However, one potential concern is that the alternation blocks impose a greater working memory load – to keep track of the task sequence and maintain two tasks in a state of readiness – and might promote greater effort and arousal. These problems are avoided by the alternating-runs paradigm (Rogers & Monsell, 1995), in which the task alternates every n trials (a run), where n is constant and predictable, so that one can compare task-switch and task-repetition trials within a block. An alternative is to give the participants short sequences of trials with a pre-specified task sequence (e.g. colour–shape–colour). Despite these variations in task settings (Jersild vs. alternating-runs methods), switching costs remain substantial around 100-300 ms.

Finally, in the intermittent-instruction paradigm, the series of trials is interrupted occasionally by an instruction that indicates which task to perform on the trials following the instruction. Even when the instruction specifies continuing with the same task, there is a 'restart' cost after the instruction, but this is larger when the task changes; the difference yields a measure of switching costs (e.g., Pojac, Haan, & Galen, 2006; Yeung, Nystrom, Aronson, and Cohen, 2006). For instance, Gopher, Armony, and Greenshpan (2000) administered short blocks of 15 trials during which only a single-task switch would or would not occur (see also Allport & Wylie, 2000). Task cues indicating the to-be-performed task on the following trials were presented

prior to the first trial and (randomly chosen) prior to one of trials 4–11. Comparing performance in cued-switch trials and performance in cued-repetition trials revealed robust switching costs. In addition, this paradigm showed restart costs, that is, a slowdown of responding in explicitly cued-repetition trials relative to repetition trials that were not immediately preceded by a task cue. A common explanation for the restart cost is that it reflects additional time required to re-activate a task set in order to compensate memory decay over trials (Altmann, 2002). What is relevant here is that the functional role of reactivation might hint that another type of control is needed in particular for situations with sequences of tasks.

Voluntary task switching

Although studying instructed task switching has provided fruitful evidence for understanding cognitive control, this approach appears to be ecologically incomparable to real-life situations, which are usually not guided by instructions. Instead, people rely on their will to perform tasks sequentially according to their changing goals and priorities. As a result, the voluntary task-switching paradigm was proposed, which allows participants to select between tasks randomly according to their own will (Arrington & Logan, 2004). These free choices are made in response to stimuli which are, as in most task-switching procedures, bivalent. The main small

modification is that responses for the two tasks are given on separate, nonoverlapping sets of keys, so that the chosen task can be inferred afterwards. Thus, with this demanding for voluntary selection, the voluntary task-switching procedure was introduced as a valid tool for exploring endogenous control. However, later studies have revealed that voluntary task-switching does not depend on purely internally-based task selection, because selection is not immune to stimulus-driven effects. For example, when the stimulus repeats from the previous trial, voluntary task switches are less likely (Mayr & Bell, 2006; Yeung, 2010). Nevertheless, it has been widely acknowledged that endogenous control is both involved in voluntary and instructed task switching paradigms (Arrington & Logan, 2005; Rogers & Monsell, 1995).

Switching cost as an index of switch efficiency cognitive control

The definition of task-switching cost varies somewhat among studies. Nonetheless, a commonly used definition is that when performance on task-switch trials is compared with that on task-repetition trials, then so-called *switching costs* are observed. These comparisons are usually taken from a block of trials in which both task switches and task repetitions occur (mixed-tasks block). In addition to the above-mentioned contrast (switch vs. repeat, or switching cost), a mixing cost exists when contrasting

between blocks with both switch and repeat trials and trials taken from a block involving one task only (Los, 1996; Rubin & Meiran, 2005). The switching cost reflects dynamic, trial-to-trial effects, whereas the mixed-list cost reflects a more ongoing state of readiness for multiple tasks (e.g., Braver, Reynolds, & Donaldson, 2003). The existence of a mixing cost apparently hints that some control processes are required to alternate between tasks, which prompts two competing theories on the origin of the cost.

In the history of task-switching research, a pendulum swings between two seemingly opposing positions regarding the interpretation of task-switching costs. One side proposes that the cost reflects a unique process of task-set reconfiguration found particularly on task switch trials (Meiran, 1996; Rogers & Monsell, 1995) whereas the other side proposes that the cost stems from memory processes like priming or associative strengthening of tasks (Allport et al., 1994; Meiran, 2000; Philipp, Gade, & Koch, 2007; Schuch & Koch, 2003; Steinhauser & Hubner, 2006). The main discrepancy between these two views is that the latter one treats the cost as indirectly reflecting online control processing. Two specific priming hypotheses have been most influential. Allport et al. (1994) argued that the switching cost does not reflect online control processing but instead reflects the time needed to resolve interference from the previous task. They based their conclusion on the several lines

evidence: First, they found that it was the difficulty of the task in trial n -1 rather than the difficulty of the task required in trial n that affected switching cost in trial n. The second piece of evidence used by Allport et al. (1994) concerned the influence of advance task preparation (inter-trial interval) on the size of the task-switching cost. Presumably, because the task sequence was known in advance in their study, the participants could make use of it and prepare for the task switch. The authors found only a moderate reduction in switching cost in the condition with a long inter-trial interval. This evidence suggested that the switching cost mainly results from the time taken to resolve interference from the previous task instead of preparing the upcoming task.

Rogers and Monsell (1995) varied the inter-trial interval in a manner similar to that of Allport et al. (1994). Critically, they showed that whether or not advance preparation reduced switching cost depended on the blocking of the preparatory interval. This indicates that the reduction of switching cost was due to strategic factors. Under the for task switching setting, control does not solely concern the influence from past tasks, advance preparation certainly also plays a role.

Reconfiguration theories (Mayr & Kliegl, 2000; Meiran, 1996; Rogers & Monsell, 1995) propose that the switching cost reflects switch-specific preparation, or reconfiguration process that configures an appropriate set of processes linking sensory

input to motor output. In contrast to the priming view, the cost is assumed to reflect additional time needed to perform these control processes. Nonetheless, these theories typically also assume some form of priming—that is, they assume that the system has a memory for the preceding trial. For example, Rogers and Monsell (1995) used a railroad metaphor for reconfiguration, according to which the role of control is analogous to that of the signalman who heaves the heavy lever that is used to operate the switch between railroad tracks so that the next train will run onto a different line. This metaphor assumes that switching would not be required if the task repeats because the line remains unchanged. In other words, the system "remembers" its state from the preceding trial. Although this assumption concerning system memory was not articulated in terms of priming, it reflects some form of priming nonetheless. Similarly, Meiran (2000) explicitly assumed that the system retains its configuration from one trial to the next. Even though the reconfiguration view successfully adopts the notion of task set to describe how control should be deployed, it does not specify how a sequence of actions can be encompassed into the notion of task set and how control is retained and monitored over trials. Therefore, next I will introduce theories, which relatively focus on the decision process between tasks.

Another variant version of the priming theory emphasizes the role of general, nonspecific preparation rather than switch-specific preparation in generating the

switching cost (Meiran & Daichman, 2005). In task cueing experiments, a task sequence is not known to participants, and hence a task decision needs to be made on every trial, even in repeat trials. Also, such decision variables typically impact both switch and repeat trials and the effects are additive. For instance, if a sequence is learnt by participants implicitly, an RT benefit can still be seen on both types of trials (Gotler, Meiran, & Tzelgov, 2003). Moreover, explicit task expectancies can be manipulated, and their effects are found to be additive with the task-switching effects (Dreisbach, Haider, & Kluwe, 2002; Ruthruff, Remington, & Johnston, 2001; Sohn & Carlson, 2000). The switching cost results, in the general preparation point of view, from the fact that the task executed in repeat trials has been more recently practiced or primed. The idea is that task preparation affects task switch trials more strongly than task repeat trials because on switch trials the task set is weaker (e.g., less activated because it has not been recently used) and is therefore more sensitive to top-down assistance. This idea is further supported by a study from Dreisbach et al. (2002) using probabilistic task cues, in which expected task switch trials were found to perform much faster than unexpected task repeat trials. That is, the expectation benefit for task repeat trials will cause an overestimation of switching costs whereas an expectation benefit for task switches will underestimate the switching costs. This indicates that expectancies will distort the switching cost if task switches and repetitions are not equally frequent or

expected. Potentially, these theories suggest a common task decision process affecting task switch and task repetition trials, which might relate to control parameters in situations with sequences of tasks.

Overall, the priming and reconfiguration views uncover a variety of effects in task control. Nevertheless, the effect that receives most of attention probably is the switching cost. As will be clear later, some results discussed above imply that switch efficiency may also sensitive to the context of sequence. Thus, from the next section onwards, I will discuss examples and research that indicate effects of broader task context on task switching that could prompt the hypothesis that there is an additional level of control which modulates switching processes at the individual trial level.

Meta-control in task switching

Though task-switching experiments have been very informative in fostering theoretical development and discussion in the field of cognitive control (e.g., for a review see Kiesel et al., 2010), they lack a critical feature that characterises most naturalistic settings: that there is high-level structure to the tasks being switched between. Similarly, as Monsell (2003) suggested, goals and tasks can be described at multiple grains or levels of abstraction: The same action can be described as both 'pouring milk into a cup' and 'making a cup of coffee'. This suggests that everyday

life requires frequent shifts between cognitive tasks and most of our daily life tasks are made up of multiple steps that may be represented at different levels. Following the previous example, the structure of each small step for making a coffee can be seen as a parcellation of the main goal into smaller sub-goals. The whole sequence of behavioral actions (e.g., pour water - add coffee powder - add milk or sugar) may be organized into distinct subtasks, corresponding to achievement of goals at lower levels (e.g., Cooper & Shallice, 2006). On the relatively microscopic level a 'task' is defined as an appropriate action (e.g. put milk to a cup) in response to a stimulus (e.g. milk in a particular context). At a more macroscopic level, a 'task' may be defined as preparing a meal. From this perspective, the events making up a task goal structure can be conceptualized as comprising a hierarchy of differing levels of goals they complete. Importantly, it is difficult to indicate whether the act of heating water on the stove is a "boiling water task" or an even broader "making coffee task." Actions can be nested within a large task structures made of superordinate components and nested subcomponents. In other words, one can view finishing boiling water is not only completion of sub-component but also a transition of one-step forwards a goal. Thus, control processes responsible for each level should have some relationship with each other.

Hierarchical control vs. meta-control

As illustrated above, most simple everyday tasks have complex structure and one aspect of this structure is in terms of hierarchical goal/subgoal organisations. There is now much research in understanding this kind of hierarchical structure and its neural basis. In this thesis, control relating to explicit hierarchical structure of goals and subgoals will be termed "hierarchical control". The focus of this thesis, however, is on a related but distinct form of adaptive higher-level control, which involves setting various "meta-control parameters" relating to how tasks should be performed and scheduled – e.g., whether there is time pressure (so that individual steps should be executed quickly, and optional steps skipped), or whether the task must be combined with others or performed alone. This thesis is primarily concerned with this type of meta-control parameter setting. Within this perspective, the control parameters that regulate the order of actions might be slightly different in different contexts, which results in an updating of meta-control. Importantly, though a task or an action can be related to different tasks, the meaning of such associations can be different depending context. To protect associations but allow preparation to switch flexibly in accordance with context, meta-control is needed. Effective cognition requires a delicate, 'just enough' calibration of endogenous control that is sufficient to protect an ongoing task from disruption (e.g. not looking up at every movement in the visual field) but does not

compromise the flexibility that allows the rapid execution of other tasks when appropriate.

Meta-control specifically focuses on planning and control rather than the control over a sequence of movements, which is also different from theories in motor sequence control. Specifically, the number of steps towards a task goal is similar, but the order of motor actions is allowed to have some variability in meta-control. This suggests that task goal information is coded in a representation but not in a specific sequence of movements or actions, which implies that a set of control parameters may be necessary rather than storage space for individual actions in order. Second, sequences of actions are often executed with few external cues whereas motor control theories often assume motor feedback or sensory input is necessary for the next movement (Diedrichsen, Shadmehr, & Ivry, 2010). Moreover, in contrast to the subcortical regions involved in motor sequence control (e.g., striatum, Jin & Costa, 2010), prefrontal cortex has been associated with goal-directed behaviour. Patients with prefrontal lobe dysfunction often exhibit selective deficits in their higher-order planning and sequencing capabilities (e.g., preparing meals for friends), but they retain relatively normal standard performance on simple tests of executive function such as alternation tasks (e.g., Shallice & Burgess, 1991).

Finally, as has been illustrated in the example above (making coffee) the role of

cognitive control is critical in mediating constantly shifting goals (at either low or high levels). This example illustrates the importance of high-level representations on maintaining task goals. In particular, in novel situations when errors or unexpected events are likely, to some extreme cases requiring a change of a task goal, high-level representations are needed to cope with the adjustment. Apparently, apart from transmitting the signals detailing the low-level task, a certain degree of flexibility is required for high-level representation. At this point, the two ideas of goal maintenance and flexibility might sound contradictory, but in real life examples people are able to strike a good balance between the two ends. This constant adjustment between flexibility and stability according to different situations hints at the need for a specific set of parameters to maintain balance between low level tasks. This idea is reminiscent of control dilemma theory (Goschke & Bolte, 2014), which will be discussed in detail later.

In addition to adjustment of meta-control parameters, another critical feature of meta-control is that the control signal itself can have several levels that map to different levels of task structure, from the lowest level of action control to the highest level of goal switching. Goal switching control involves a set of parameters that optimize the switching efficiency for trials of the same context. For example, Dreisbach, Goschke, and Haider (2007) demonstrated that actions that are represented

as tasks are subject to switching costs while the same actions, when represented as individual S–R associations, are not. They had participants learn to respond to stimuli either with or without knowledge of the underlying task rules that dictated the assignment of stimuli to responses. Though all participants were exposed to this same learning environment, only participants informed about task rules represented the actions within a task structure and exhibited impaired performance when they switched between those tasks. In the context of meta-control, if people can treat a sequence of actions as a "task-set", then a set of control parameters would be required too.

Hierarchy has psychological reality

Evidence of the psychological reality of hierarchical control and meta-control can be seen in some common everyday errors in our planned actions that imply hierarchical organization of behaviour. These errors could be a result of a failure at one of multiple levels of control. For instance, when adding several spoons of sugar into a cup of coffee, one might forget how many teaspoons had been put in. This type of error occurs when a person faces some well-practiced or habitual sequence of actions while their attention has been directed to other irrelevant thoughts. Apparently, the intention of the goal of making a cup of coffee might be contaminated and this

implies their mind has been pre-occupied by unrelated mental activity. We often assume action control will execute quite smoothly and accurately if we are paying enough attention to individual tasks. However, these errors sometime cannot be eliminated completely, because our mind is regularly preoccupied with other thoughts. Corrections of these errors or unexpected responses to novel events will uncover the existence of control at upper levels.

Even though the evidence of hierarchy is rich, most studies published recently concerning hierarchy have focused on the nature of hierarchical representations and how these relate to the organization of the brain. In a computational model by Botvinick and Plaut (2004), they claimed a model without explicit representation of mental control structure (without a supervisory unit for controlling activation of sequences) could still produce complex behaviour. Moreover, the issue of reality status has regained attention partially stimulated from the development of simulation work in cognitive functions. When building a simulated model, researchers are often forced to decide whether systems operate either on hierarchical or on non-hierarchical principles to best capture the characteristics of human performance (Botvinick, 2007). Mental hierarchies involve multiple levels of control processes that involve planning, monitoring, and decision-making, and these necessarily involve higher-level processes controlling lower level actions. The higher-level processes are similar to

some forms of control systems. In the Supervisory Attentional System (SAS; Shallice & Burgess, 1996), the key role of SAS is to modulate routine behaviour by providing strong top-down activations. This high-level system is concerned with forming strategies for novel tasks using processes of abstraction and generalisation, and monitoring the implementation of these processes. Indeed, there is corresponding neurological evidence for the reality of a high-level control system. Patients with lesions of the prefrontal cortex typically exhibit what has been called "dysexecutive syndrome", with prominent deficits in many aspects of the control of non-routine behaviour. To make a cup of coffee, these patients might pour salt in place of sugar as long as this irrelevant ingredient is in their sight. The pattern of deficit exhibited by these patients indicates that different levels of the control of behaviour are differentially vulnerable.

In the last two decades, studies have tried to segment supervisory control into different levels (Koechlin & Summerfield, 2007) and link this to the organization of prefrontal cortex, especially along the anterior-posterior axis (for a review see Badre & D'Esposito, 2007). In this context, the focus has extended to the exact content being signaled in each region and their relationships in terms of functional hierarchies. There are plenty of studies investigating functional organisation of frontal lobe (e.g., as reviewed by Badre & D'Esposito, 2009). Assuming that control can be decomposed

into selecting and maintaining task goals at multiple levels of abstraction (e.g., temporal abstraction: action goals become more abstract as the timescale of actions govern by the goal increases), from the lowest level of concrete motor response to the highest level of maintaining general task goal. The key notion is that this hierarchy of action control is represented along the axis with frontal regions holding a dominant relationship with posterior regions. For example, anterior regions of the lateral surface exhibit tonic variations in respond to the complexity of the current block, whereas relatively posterior regions again reflect task complexity but only for individual trials (Koechlin, Ody, & Kouneiher, 2003). In addition, another hierarchy relating to states of motivation has been found along the medial surface, with more-anterior portions reflecting changes in reward value in block-wise comparisons while more-posterior regions detect changes on a trial-to-trial basis (Kouneiher, Charron, & Koechlin, 2009). In short, these studies have linked hierarchical task control to the organization of prefrontal cortex (Badre & D'Esposito, 2007; Christoff, Keramatian, Gordon, Smith, & Madler, 2009; Koechlin et al., 2003).

The idea of hierarchy has been recognised for decades, but it has recently gained practical significance both in developing theories and simulation work. Recent advances in neuroimaging and computational techniques have allowed the idea of hierarchy proposed in the past to further flourish. To date, the idea of hierarchy is

sufficient to explain and simulate many complex behaviour such as problem solving and complex decision-making (e.g., Cooper & Shallice, 2006). Therefore, it is not surprising that the notion of hierarchy has regained research attention in recent years. Some early work began to try to connect cognitive control and task structure in the field of psychology (Broadbent, 1977; Lashley, 1951). Lashley (1951) had already stressed that simple associations between perceptual inputs and actions might be inadequate for explaining human sequential behaviour. Since the meaning of such associations can only be inferred from the final results of these activities, the meaning of behaviour is complete only when the background of the interaction between stimulus input and action is taken into consideration. This internal representation of 'background' in terms of task structure can sufficiently indicate the association of actions. For instance, in language, no single letter follows another letter with certainty; the association between them depends upon a larger unit of action, the word.

Evidence of hierarchical control from past studies

There is fruitful evidence of hierarchical control from animal neurophysiological and human neuroimaging studies. It is commonly hypothesised that spatially distinct portions of the prefrontal cortex (PFC) support qualitatively distinct cognitive control functions. Recent neuroimaging experiments have provided evidence of a functional

organizing principle along the anterior-posterior axis of the frontal lobes that reflects a hierarchy of action control. Since the seminal experiments by Koechlin et al. (2003) and other groups (Badre & D'Esposito, 2009; Collins, Cavanagh, & Frank, 2014), numerous studies have indicated that the PFC is organized along a rostral-caudal gradient with more anterior regions being involved in increasingly higher-order control functions (cf., Duncan, 2010). Across different domains and paradigms these studies revealed two vital features that are characterised as hierarchy – temporal abstraction and policy abstraction.

Despite the differences among the models of PFC mentioned, it is relatively natural to consider timescale as the key parameter governing the layout of cortical representations: moving anteriorly over the cerebral cortex, and within the DLPFC, representations that guide behaviour over progressively longer temporal spans are encountered. From this point of view, the prefrontal hierarchy is understood as involving levels of increasing temporal abstraction.

Although this is consistent with much empirical evidence, there is also data indicating that the prefrontal hierarchy might also align with the abstractness of rules. For example, Badre and D'Esposito (2007) have found that frontal activation shifts rostrally as successive layers of conditional dependency are added to a behavioural task. For instance, learning that a red square means presses a right key while a blue

circle indicates press a left key would be a first-order rule. An additional rule can further specify whether the colour or shape is relevant to the current task. Thus, this additional rule that associates the context and first-order rules can be treated as second-order rule. Here, it is not temporal abstraction that seems to be most relevant but, rather, policy abstraction – the representation of a task, at any given moment of performance, as a set of choices over lower-level tasks. Thus, a higher-order task (or 'policy') does not specify a specific action but a class of action rules. The general conclusion is that more rostral regions of PFC are capable of representing abstract rules (e.g., Badre & D'Esposito, 2007).

All in all, several theories agree that there is a hierarchical representation in PFC. Some argue that this hierarchy reflects temporal abstraction. Others argue that it reflects policy abstraction. There is evidence on each side. However, for the present purposes, the crucial point is that the theories agree that hierarchical structure in control is explicitly reflected in neural architecture. Since the current thesis more relates to temporal abstraction, the evidence from the policy abstraction will be briefly mentioned below and but the focus will be on evidence of temporal abstraction.

In addition to the evidence from neuroimaging studies on policy abstraction, evidence has revealed hierarchical structure during task switching in temporal abstraction, which is naturally and frequently experienced in our daily life. In general,

a goal hierarchy can be layered based on its functional operation over a short or longer time frame. When a higher-level task goal has to be maintained over a relatively longer period, an additional process may be required to maintain this goal. The finding in general is very similar to policy abstraction in which the frontal pole region is capable of maintaining and monitoring higher-order task goals (e.g., Koechlin et al., 2003). To investigate brain activities in different time frames (e.g., event vs. sequence that contains several events) that might serve corresponding levels of control signals, Braver, Reynolds, and Donaldson (2003) adopted a combination of blocked and event-related designs to dissociate different cognitive components in task switching. With the advantage of this hybrid design, they decomposed brain activity into sustained and transient components and related these activities to specific behavioural indexes. Their participants were tested in blocks that varied between mixed and single-task blocks. Given that anterior PFC (aPFC) is likely to reflect a high demand for active goal maintenance (Sakai & Passingham, 2003) and lateral PFC (lPFC) has been frequently associated with transient components of task switching (e.g., task reconfiguration by Sohn & Carlson, 2000), the authors hypothesized that discrete brain regions will support two types of control signals in task switching: one for the longer time-frame of blocks and another one for the shorter time-frame of individual trials. They found that lPFC activates for transient aspects of

task-switching cognitive control via the event-related contrast of task-switch to task-repeat trials, in line with findings from the task switching literature suggesting that this region represents the current task-set and supports response preparation (Hyafil, Summerfield & Koecklin, 2009). Conversely, right aPFC showed stronger activation in a sustained fashion in mixed blocks compared to single-task blocks, suggesting a role in maintaining a heightened level of cognitive control for rapidly alternating between different tasks. This double dissociation implies the existence of multiple levels of control signals, with one concerning current task set information and the other concerning contextual task-set information.

At roughly the same time, partly inspired by evidence that foreknowledge of next task to be performed reduces RTs for both switch and the repeat trials (Sohn & Carlson, 2000), Dreher, Koechlin, Ali, and Grafman (2002) studied the parameters of a sequence (such as predictability of sequences and task timing) in task switching. They aimed to demonstrate that timing and task order predictability/unpredictability are mediated by different regions of PFC along anterior-posterior axis. In particular, they hypothesized that anterior parts of PFC will show stronger activation as the task becomes more endogenously guided (predicable in terms of timing and task order). A sequence with foreknowledge of task order should be relatively dependent on control that can be applied in advance, whereas in sequences without any knowledge of task

order participants can only apply the stimulus–response mapping after stimulus presentation or task cue in a reactive fashion. Their results revealed that anterior medial PFC (as well as right hippocampus and the posterior cingulate gyrus) activated when task order was predictable. This effect was not specific to switch trials, which implied the function of this region is mainly concerned with general preparatory processes. Activity in lPFC was present with the combination of unpredictable task order and random timing. In contrast, when both task order and timing were predictable, a pronounced activation was found in left frontopolar cortex. Together, these findings led them to conclude the aPFC was more related to internally driven control processes, being related to knowing task order within sequences, whereas the lPFC was recruited to tackle external events. These findings again suggest a hierarchical organization of the prefrontal cortex along a posterior-anterior axis as the task gradually relies more on proactive control. More importantly, this evidence is also consistent with the view that frontopolar cortex is associated with 'meta-level' control processing when two or more ongoing tasks need to be coordinated and maintained (Braver & Bongiolatti, 2002).

In addition to lateral prefrontal regions, emerging evidence has started to indicate that medial frontal cortex might be also sensitive to high-level control signals and could also form another parallel hierarchical organization from anterior to posterior

(Kouneiher, Charron & Koechlin, 2009). The ACC and PFC are often observed to coactivate during task switching (e.g., Braver et al., 2003), but their unique contributions to task switching have started to emerge. In an fMRI study by Hyafil, Summerfield, and Koechlin (2009) the ACC and PFC were shown to be uniquely associated with different levels of task control during task switching. Their participants were asked to move a joystick in response to a word (e.g., up) superimposed on a directional-pointing triangle that could either be incongruent or congruent. A task cue (the colour of the triangle) indicated whether the word or triangle was task relevant on any given trial. They hypothesized that ACC and PFC contribute, respectively, to assigning task priorities and resolving the interference from a competing task. Then, the authors adopted a Stroop-task switching paradigm, sorting trials as a function of the current task transition (for a test of assigning task set) and current and previous trial congruency (for a test of resolving interference). ACC activity was mainly driven by task switching irrespective of the demands of previous and current congruency. This indicated that ACC engagement was associated with assigning priority of task sets. On the other hand, these patterns were not observed in the dorsal lPFC. Instead this region was only sensitive to two consecutive incongruent events. The activity of lPFC here was associated with representing the relevant context to resolve recent competing task sets. The role lPFC seems to mainly deal

with the task at hand whereas ACC is capable of scheduling tasks across times. Such differences in terms of control required implies a functional hierarchy between lPFC and ACC, although here the organisation in PFC is on the axis of medial to lateral. These findings clearly support the idea of temporal abstraction in that medial PFC regions tend to be involved in representing temporally extended events whereas lateral regions are mainly concerned with short period events.

One relevant proposal about hierarchical organisation ACC and PFC can also be found in Holroyd and Yeung (2012). The proposal is formalised in terms of an extended version of reinforcement learning (RL) – hierarchical reinforcement learning (HRL). In short, RL aims to characterise the learning process of agents in a complex environment by a simple algorithm that assesses the difference between the actual and predicted results of actions to guide future action selection. However, this algorithm becomes increasingly inefficient as the environment becomes more complex, due to the exponential increase in possible associations between stimuli, responses, and sequences of actions. HRL addresses this problem by grouping associations that could relate to each other into temporally-extended action sequences that together comprise high-level plans. These plans (sometimes called 'options') can be learnt about and selected as coherent units according to standard RL principles. With HRL, the authors claim that ACC is responsible for maintaining and selecting the plans, while lPFC

executes the plans selected by ACC. Even though the hierarchical organisation differs from the past theories that propose aPFC as highest control agent, this view does converge with the notion of hierarchy in brain organisation.

In conclusion, this part of the literature review reveals evidence of hierarchical organization of brain from human neuroimaging. There are various approaches to understanding the neural correlates of hierarchy: rostral-caudal axis vs. medial-lateral axis. Moreover, there are still opposing views in the literature on whether a hierarchical organisation is represented specifically in the PFC. For instance, Duncan's group instead proposes a generalized and distributed network of frontal-parietal regions, which they formalised as adaptive coding model, based on evidence that multiple studies find the same regions to be co-activated during various tasks (Cole & Schneider, 2007; Duncan, 2010). Their main claim is that neurons of prefrontal cortex are tuned to code information that is relevant to the current task, given a widely accepted view that frontal regions control task-relevant processing in other regions. Increasing the complexity of the stimulus–response mapping, from their perspective, increases the task space or the number of stimulus–response alternatives, which in turn creates a confound with task difficulty that might explain the differing patterns of neuroimaging activity reported. Currently, it remains unclear how to resolve the debate. However, for purpose of the literature review here, these two

views to certain degree still agree that PFC is capable of delivering a high-level control signal and is required to coordinate with other brain regions.

Evidence of meta-control

The previous section reviewed neuroimaging studies of hierarchical control that adopted a strict assumption of hierarchy of task structure in terms of temporal or policy abstraction. In contrast, this section will focus on how tasks are organised and controlled during task switching according to certain parameters that do not imply adopting a rigid and strict rule or time abstraction. The general finding is that the switching cost is modulated by the meta-control parameters, such as the probability of task changes (Dreisbach & Haider, 2006), frequency of switches (Mayr, 2006), and even by the frequency of voluntary switches (Arrington & Reiman, 2015), as reviewed below.

Switch expectancy

As the reconfiguration model emphasized the role of task preparation, some early studies turned their attention to the relationship between preparation effects and the context of expectation (e.g., Dreisbach et al., 2002). An early study by Dreisbach and her colleagues (2002) investigated the relative contributions of task preparation and

task expectation in repeat and switch trials. The core hypothesis was that task repeats and task switches will benefit differently from task expectation. They tested this hypothesis by assigning cues that announced respective tasks with probabilities of 1.00, .75, .50, or .25 individually prior to each trial. The results showed increased latencies with decreasing probability for both task repeats and switches, and importantly the probability effect was additive with the effect of switching. Their results suggest that the efficiency of task performance and task switching are affected by expectations, which might suggest the existence of a meta-control parameters that affect all trial types. Expectancies can be altered in advance and can be tuned across trials flexibly, which implies the involvement of strategic control.

Monsell and Mizon (2006) investigated the influence of the probability of task switching in a cued switching paradigm, in which the sequence of tasks was unpredictable and the frequency with which the task changed (25%, 50%, or 75%) was manipulated between participants. They found that switching costs decreased with increasing switch frequency. Their interpretation for such modulation was that when switch trials are likely, it is efficient to tend to reconfigure away from the task that has just performed. This strategy adjustment mainly depends on people's expectancy of task transition type.

To further emphasize the idea that the switch frequency is used to coordinate tasks internally and thus could be treated as an important meta-control parameter, one study has directly investigated the impact of self-generated task predictions on switching costs in conditions with different switch frequencies (Duthoo, De Baene, Wühr, & Notebaert, 2012). Their participants were required to try to predict the upcoming task on a trial-by-trial basis in conditions with varying switch rates (30, 50, and 70%). Irrespective of a strong repetition expectancy across different switch rate conditions, this study also replicated previous evidence (e.g., Monsell & Mizon, 2006) that the switching cost is attenuated as the switch rate increases. Importantly, the self-generated expectancy did interact with context. The switching cost vanished following a task switch prediction, while a prediction of repetition was followed by a larger switching cost. Such a change of switching cost in relation to the expectancy of task might result from a strategy adjustment. This study highlights the importance of internal predictions in the context-sensitive adjustment of task switching performance.

Switch frequency has also been suggested to affect cognitive control in a sustained and preparatory fashion. Dreisbach and Haider (2006) suggest that in addition to a control process that is responsible for transient task switching, there may be another tonic control process operating at a contextual level. Similar to previous studies that manipulated the probability of a change of task within participants, they

compared two expectancy conditions: (1) a global condition, in which the participants were informed at the beginning of each block about the ratio of task switch to task repeat trials; and (2) a local condition, in which the participants were given a preparatory task-cue before stimulus onset. Their results showed that both task switch and task repeat trials were affected by task-switch frequency in the local expectancy condition, but with a more pronounced effect for task repeat trials than task switch trials. This implies that the repetition benefit cannot be avoided. Similar patterns were found in the global condition, however, the differences between the two frequencies were less pronounced on task repeats and even absent on task switches. Based on the results from local and global conditions, their findings suggest preparatory adjustments are not only triggered by explicit cues but also can be dynamically altered by global information that is sustained over trials. The finding of a less pronounced preparation effect was interpreted as that in the global condition people could not prepare as effectively as they did in the local condition.

Taken together, these findings indicate that switching costs vary according to global switch expectancy context. The results converge on the conclusion that preparation is dynamically modulated by the expected task requirements (e.g., Dreisbach & Haider, 2006). Moreover, adjustment of activations for the two tasks in different switch probability contexts suggests that the activation can be initiated

intentionally and underlies strategic control. From the results of voluntary switch procedure, it becomes clear that this adjustment is voluntary. Overall, these studies demonstrate the possibility that meta-control affects switching processes in different contexts with switch frequencies. Nevertheless, in addition to switch frequency, other switch-related parameters (e.g., RSI) have also been suggested to form part of hierarchical task organization, which could relate to meta-control. The details are evident in another line of studies focusing on hierarchical task structure.

Task sequences promote application of meta-control

It has been illustrated in the task switching literature that foreknowledge of the next task to be performed can improve performance (Sohn & Carlson, 2000). As in the studies concerning switch frequency, the overall structure of the task sequence itself could serve a clue for participants to adopt different strategies according to the predictability of the experimental condition (Gopher et al., 2000). This implies that predictability of sequential parameters (cues, tasks, stimuli, responses) and knowledge about the probability of particular sequences (e.g., sequence repetitions) affect performance in task switching.

A group of tasks could prompt people to form a hierarchical representation if the tasks serve as subcomponents that are part of a superordinate representation. There

has been fruitful evidence that high-level representations exert an influence and can even overwrite the effect of task switching. For example, in the alternating runs paradigm, in which participants perform tasks in a repeated sequence (e.g., AABB) with time gaps demarcating separate sequences, performance on the first trial always incurs a large performance cost that is even larger than the magnitude of switching costs found on switch trials within a run (e.g., de Jong, 1995; Koch, Philipp, & Gade, 2006; Lien & Ruthruff, 2004; Koch, Philipp, & Gade, 2006; Lien & Ruthruff, 2004; Schneider & Logan, 2006, 2007). Similarly, temporal overlap in stimulus presentation within the psychological-refractory-period (PRP) paradigm can lead the two tasks to be represented as a chunk (Luria & Meiran, 2003). This is evidenced by the results from Luria & Meiran (2003) that advance preparation can modulate an order-switching cost effect. The 'order' here refers to task order where the response of the first trial could overlap with the stimulus processing of the second trial. The order-switching cost is measured by comparing RTs of the first trials in which the order is the same as previous trials with trials in which the order changed. The cost indicates an involvement of order control. Based on such findings influences above task-level control, more and more studies have started to address this issue directly.

Lien and Ruthruff (2004) have shown how temporal and spatial overlap between stimuli can prompt spontaneous adoption of hierarchical representations. In this study,

they gradually added the spatial information (by presenting stimuli for two tasks close together in the display) and temporal grouping information (by shortening the time interval between trials) in order to prompt short sequences of tasks being treated as a chunk. They used two types of alternating runs sequences: AB–AB–AB sequences in which a task switch always occurred at the sequence boundary, but the sequences repeated, and AB–BA–AB sequences, in which task repetitions always occurred at sequence boundaries but the sequences themselves keep switching. The effect of hierarchical structure was assessed by comparing performance of the first trials in each chunk (e.g., BB - AB vs. BB - BA). As the hierarchical structure became more and more apparent, the switching cost on the first trials of sequences decreased accordingly, suggesting that one cannot gain a repetition benefit if that repetition spans two different hierarchically represented task sequences. These findings show that regularities in a series of simple representation are sufficient to elicit a chunk-level of influence on switch performance.

The modulation of switching cost at first positions cannot be simply explained by traditional theories of task switching (Allport et al., 1994; Rogers & Monsell, 1995), which do not take hierarchical task structure into consideration. As a result, Lien and Ruthruff (2004) proposed a dual-route model of control in which response selection relies on two main routes. Task-level processing relies on simple reapplication of the

mental state carried over from the previous trial, explaining the task-level switching cost. However, at boundary points when chunk-level processing is required, automatic and simple reapplication of a mental state (task set) is not possible. Instead, a more controlled processing route replaces it, which is able to maintain several task elements at the same time to set up performance of the whole sequence. This controlled processing is similar to the meta-control proposed here, in that both of them involve planning and maintaining several tasks across trials.

Besides hierarchical task representations formed through temporal and spatial contingency, similar findings can also be found in an explicit memorized procedure as well. In a sequence cuing procedure, in which sequences were produced as a "task" unit, Schneider and Logan (2006) directly investigated control of coordinated sequences. Based on the study by Lien and Ruthruff (2004), Schneider and Logan (2006) focused on the transition effect at the sequence level. Their participants were asked to memorize sequences of four tasks, such as AABB and ABBA (e.g., with colour and shape tasks denoted as A and B, respectively), which had to be applied repeatedly during the testing later. Although a within-sequence switching cost (standard switching cost) was detected, they consistently found the slowest RTs on the first positions of each sequence, reflecting the time needed to initiate a sequence. Moreover, the RTs slowed even more as the trials were presented in longer (6 tasks)

and more difficult sequences (more task switches). On a more aggregated sequence, in which sequences were combined into super sequences (e.g., a larger sequence consists of AABB and ABBA sub-sequences), they also found that the initiation time of these super-sequences was longer when super-sequence included sequence alternation (e.g., AABB - ABBA) than sequence repetition (e.g., AABB - AABB). This finding suggests that a sequence of several tasks can be represented as an overarching sequence representation. Finally, trial-level switching costs were not found at first serial position of each sequence. Consistent with previous related work (e.g., Lien & Ruthruff, 2004), alternating between sequences seems to eliminate the benefit of repetitions at the task level.

Following the modulation effect of switching cost at the first position, Schneider and Logan (2014) further hypothesized that such effects are restricted to points when the sequence representation updates. Their participants were asked to perform task sequences with different chunking instructions that induced chunk points at various positions within the sequences, e.g., such that a task sequence ABAABA can be broken into two sub-chunks ABAA - BA. In this case, another chunking instruction was ABA – ABA. Then the same sequence can have different chinking points (position 4 & 5 in former case while position 3 & 4 in the latter case) according to the instructions. Schneider and Logan (2014) further created another type of sequence to

calculate switching performance as a function of chunking points, task transition, and sequence type. The results showed that modulation of the task-level switching cost only occurred at chunk points but not at non-chunk points. As in the previous example, the switching cost modulation became apparent at chunk points (chunked into sets of four and two tasks: ABA**A-B**A vs. BAB**A-A**B) rather than the first trial (chunked into either set of three tasks: AB**A-A**BA vs. BA**B-A**AB). These results suggest sequence-level modulation of switching costs does not always occur at first trials, but instead this effect is more associated with the chunk retrieval process, which again suggests the involvement of sequence-level control.

Overall, these findings suggest that preparation for upcoming sequences that are either explicitly instructed or implicitly learnt might require a unique control signal at the sequence level. Moreover, sequence-level processing can affect task-level transition processes, resulting in a reduced switching cost. It is therefore possible to distinguish between two hierarchically-related levels of control (task and sequence-level) and to examine how these levels interact. For example, task interference from the previous trial on the task level could be disrupted or neutralized by a need to update a sequence representation (Logan, 2007; Schneider & Logan, 2006). In addition, this line of work has some important theoretical implications. First, sequence-level control not only exists in hierarchical task structure obtained through

implicit learning but also tends to be more effective when such control is induced through instruction. Second, knowledge about what is likely to happen next (expectancy, metacognition) may facilitate the reconfiguration process (Kleinsorge & Gajewski, 2008). To date, however, the interaction of these sequential parameters and cognitive control is still not clear, in particular whether or not they lead to particular decisions or even to the adoption of particular strategies, possibly by mediation of higher-level executive control processes such as task planning.

The functions of meta-control and relevant theories

From the above studies, it becomes clear that the notion of hierarchy is not just useful but may be necessary functionally, but its functions and implications has not been discussed. Next, I will summarize three of the crucial functions of meta-control from a cognitive control perspective.

In the early development of the notion of hierarchy, it was utilized as a framework to explain complex actions, in particular for generating a sequence of actions (Norman, 1981; Vallacher & Wegner, 1987). These researchers argued that before actions are executed, some form of representations must be constructed and serve to guide actions within the sequence. Additionally, these representations may also be built after the completion of actions to explain and justify what has been done.

Apparently, to achieve a goal-directed behaviour, a clear intention must be achieved for correct actions to be performed.

Another role of meta-control is to suppress potentially distracting information. More specifically, at lower levels, hierarchical representations prevent bias during action selection by constraining the tasks that stimuli can activate (Mayr & Keele, 2000) and directing attention only to those actions that are part of one's current goal. This function is similar to the task-set shielding proposed by Dreisbach and her colleagues (Dreisbach & Haider, 2008; 2009). Dreisbach and Haider (2008, 2009) proposed that a key function of task sets is to focus attention and prevent processing of irrelevant stimulus information that could interfere with performance. In one of their later studies, they further extended the notion of task shielding to argue that is context-specific (Fischer, Gottschalk, & Dreisbach, 2014). Just as task sets at the single-trial level can prevent irrelevant stimulus information from influencing task performance, context-sensitive shielding can be useful for maintaining task-set that needs to preserve for consecutive trials. Specifically, hierarchical representations might constrain task choice toward tasks within a given context. For example, when one is preparing the goal of making coffee, context shielding would ensure that after performing one task element, such as boiling water, the next task elements remained in the same context, such as preparing coffee grinds but not tea bags. The task of

preparing coffee grinds would be prioritized for selection over other tasks as compared to no context situation that all possible tasks afforded by the stimulus environment are equally likely. That is, the function of the hierarchical task representations is to ensure that every task sharing the same goal in the same context can be accomplished. Finally, without the maintenance of task goal, in extreme cases attention may lose its focus on task-relevant features while being attracted to other salient stimuli or afforded actions, thus losing the high-level goal (i.e., goal neglect, Duncan et al., 2008).

All in all, this section summarizes three vital functions of meta-control. First, task structure provides a useful tool to represent complex task goals and has been successfully applied to motor control and goal-directed behaviour. Second, high-level representations might also equip the system with a context-specific task-set shield. Finally, meta-control could preserve a balance between sustaining a task-set while preserving flexibility in cases of novel or unexpected situations.

The theoretical implications of meta-control

In some hierarchical control models, relating to hierarchical neural correlates (e.g., Holroyd & Yeung, 2012), the highest level of the hierarchy is often suggested to provide a sustained signal for maintaining an abstract task plan while lower levels

implement individual task-sets or rules. These ideas relate to the dual mechanisms of control theory proposed by Braver (2012). This model postulates that cognitive control constantly shifts between two distinct modes. First, in reactive control, task representations are only activated (or retrieved) at the time when they are required. In contrast, proactive control reflects the sustained and anticipatory maintenance of goal-relevant information. Whereas reactive control frees up mental resources, proactive control is more important when moving to tasks involving a task structure or chunks, as the task-set can include task elements and their order information within the sequence.

The cognitive attributes of abstract and sustained features are generally in agreement with some recent cognitive control theories that emphasize control as a change of modes. For instance, Goschke and his colleagues (a review in 2014) propose complementary control modes for goal-directed actions that balance the dilemma that of rapidly reconfiguring the current task-set in response to changing intentions vs. maintaining goals in the face of competing impulsive responses. Strong goal shielding status supports cognitive stability but inevitably incurs a cost when adapting to changing environment. Conversely, weak goal shielding facilitates swift switching between task sets but at the cost of distractibility. Task-set control therefore involves a dynamic, context-dependent balance between stability and flexibility

(Goschke, 2003), such that the probability of needing to change task should be crucial for internal control setting. There is some evidence suggesting an affective effect could bias the balance between stability and flexibility (Dreisbach & Goschke, 2004). In an example study by Dreisbach (2006), the author found that positive affect weakens maintenance capability and promotes flexibility. In this thesis, I investigate the relationship between high-level control and this stability-flexibility control dilemma. When changes of task are frequent, it should be advantageous to maintain different task-sets active to add switch efficiency (promoting flexibility).

Meta-control might also relate to the idea that there are multiple levels of learning in control, as a way to reconcile various theories of the congruency sequence effect (Egner, 2014). This effect is observed when interference from distracters on the processing of target tends to be smaller on trials that follow an incongruent trial compared to those that follow a congruent trial. Egner (2014) suggested that this effect has many causes that differ according to the abstractness of features of distractors being associated with target. At the low level of physical features, associative accounts propose that co-occurring stimulus and response features form an event compound (e.g., Hommel, 2004). When one of more features from the event file are re-encountered, the entire event file will be recollected providing a shortcut to the correct response, but cause interference if a different response is required.

Simultaneously, at an abstract level, expectations about upcoming trials will facilitate a strategic enhancement (following incongruent trials) or a decrease (following congruent trials) in attentional focusing on the target stimulus feature (Gratton, Coles, & Donchin, 1992). Egner (2014) suggested this strategic status shift not only encompasses associations between specific stimulus and response features, but also could apply to more abstract, categorical stimulus features, such as linking of these features to internal cognitive states (e.g., controlling attentional state).

Overall, the theories reviewed above in this section not only imply multiple levels of task representations but also suggest that updating higher-level representations could be regulated by some parameters (e.g., context, affect, feature abstraction). These theories address several core phenomena of cognitive control from task switching, congruency effect, to emotional effects on cognitive control.

Rationale for the research in this thesis

The core hypothesis explored in this thesis is that the efficiency of task-set control in task switching depends on a higher-level representation of overall goals/context, such as the likelihood and timing of task switches. The method used is to modulate that higher-level (meta-control) representation through explicit instruction. According to this theory of meta-control, whenever a local task is

prepared (e.g., following a task cue prior to each trial), its specific content (i.e., task set) of relevance will be determined in a high-level representation that must be retained across a sequence of trials. On each trial, a revision of control will be needed (e.g., switch probability updating). Thus, in contrast to past studies focusing on temporal or policy abstraction, meta-control is defined here as a set of parameters that modulate rather than specify psychological processes at the trial level.

Project 1

In my first series of experiments, participants were given instructions about switch frequency before short sequences of trials. Thus, the high-level task representation was conceptualised as a cognitive signal that globally affects trial-to-trial switching processes across trials via expectation of task switches.

The first project started with building a robust paradigm to study meta-control influences. In each experiment, participants completed short sequences of trials in which the proportion of switch trials was varied, and instructions regarding task switch probability were manipulated. Of particular interest was the comparison of performance in conditions that had different instructions but were identical in objective switch frequency. Any difference on switching performance can be attributed to the instruction rather than the confounding effects of bottom-up factors

such as practice. Accordingly, the prediction was that switch efficiency, which was indexed by switching costs, will vary according to the instructed switch frequency. I also tested the prediction that meta-control will bias the rate of voluntarily chosen tasks switches and repeats in accordance with the instructions about switch frequency. Expanding this general overview of the project, I will now briefly preview each chapter.

Chapter 2: Three behavioural experiments were conducted to establish the effect of meta-control in task switching. These experiments relied on the novel design of instructions, which aimed to decouple the effect of expectorations about switch frequency from the experience of task switching at trial-to-trial level. The first experiment introduced the design and established the impact of the instruction on switch efficiency. In the last two studies, reward incentive was added to motivate focus on the instructions. The results suggest the main effect was motivation dependent.

Chapter 3: Building on the results of those three behavioural studies, an EEG study was conducted to provide more direct evidence of multiple levels of control. The hypothesis was instruction-induced control will operate on a more abstract level of processing instead of or in addition to lower-level motor processing. These two levels of processing were indexed by motor preparatory potentials (e.g. LRP, CNV)

versus generalised preparatory activity (e.g., alpha oscillations). My analysis focused on which of these levels would be sensitive to manipulations of switch frequency expectation by instructions.

Chapter 4: Based on the previous findings, to provide further evidence of meta-control from manipulations the instructions, two experiments reported in this chapter developed the design used in the previous chapters by inserting some trials in which participants were given free choice of the task to performance. The main hypothesis was that high-level representations will bias free choice trials. The prediction was that the switch rate on these voluntary trials would vary according to the instructed switch frequency.

Chapter 5: Experiment 6 used EEG to investigate whether preparatory processes observed in Experiment 4 would predict behaviour on voluntary task choice trials. Another aim was to test the reliability of the EEG findings found in Experiment 4.

Project 2

In a meta-control framework in which higher-order sets are defined as chunkings of sequences containing groups of trials (e.g., AABB or ABBA), one straightforward question is whether sequence transitions can produce effects that have been observed on the task level—i.e., benefits of repetition and costs of switching. In addition, past

studies have established that higher-level representations might affect task-level processing particularly on the first trials of sequences. However, as meta-control should be sustained across trials within sequences, such modulation effect on task switching performance should also be observed beyond first positions of sequences. To test these predictions, in three experiments, participants were asked to switch between short sequences of trials (2-4 trials). Instructions before sequences indicated features of the required task switches but not the specific sequence of tasks that would be required (in contrast to previous research).

Chapter 6: The first experiment in this series, tested whether the influence of sequence-level control would manifest only at sequence transition points or also on other task elements within sequences. In the first experiment, participants were asked to perform task switching in short sequences of four trials, with instructions indicating whether the sequence would contain one or two task switches. The main focus was to assess whether the influence of meta-control can be observed beyond the first trial of a sequence after a transition. Also, if meta-control interacted with trial-level processing, switching costs at first serial positions of each sequence should be eliminated. Overall, however, participants did not seem to make effective use of instructions in this experiment, and so the results provided limited evidence of meta-control.

Chapter 7: Two behavioural experiments with a modified task design are reported in this chapter, in which instructions indicated the position of a task switch in an upcoming sequence of trials (but not the particular order of tasks required). The first experiment demonstrated benefits of these instructions, and an impact of sequence-level transition on task-level switching costs at first positions of sequences. However, the results revealed a robust effect of sequence transitions only on first positions of sequences. The final experiment of the thesis tested two hypotheses (distributed attention vs. positional interference) of the effect of sequence-level transitions on task switching costs.

Chapter 8: The thesis concludes with a general discussion that begins with a brief summary of the main findings from each study. An integrative discussion considers relevant theories in cognitive control, implications for other cognitive control tasks, and limitations and future directions.

Chapter 2

Meta-control via instructions

Introduction

My first study aimed to establish behavioural evidence of meta-control in task switching. Meta-control might in principle implement its influence on switching processes of each trial through various routes, such as regulating task preparation according to the high-level task goal, coordinating tasks in sequences efficiently based on the degree of control commitment to each individual task, or better protecting individual task goals from bottom-up influences.

As mentioned in Chapter 1, switch frequency could be treated as a feature of the environment that can be used to modify a meta-control signal that estimates switch probability on each trial, and via this modulate switch processing. However, to interpret the results of switch frequency manipulations as resulting from a meta-control signal, one needs to clarify whether the effect results from reactive preparation based on the cue specified at beginning of a trial (e.g. cues that announce switch probability trial-by-trial, Dreisbach & Haider, 2006), task readiness at each trial based on switch frequency announced at the beginning of a block (e.g., shifting task-set state due to switch likelihood, Monsell & Mizon, 2006), or whether the effect

simply reflects experience-driven practice. The practice effect could have nothing to do with high-level control but rather reflects a general improvement on switch trials due to familiarity on switching task or even benefits from specific pairs of task switches (e.g., task A -> task B) due to simple associative learning such as task A tends to be followed by task B. Thus, one cannot guarantee that the switch frequency effect previously observed results from meta-control parameters rather than the experience-driven benefits of practice at switching.

The present study used a novel manipulation, based on verbal instructions, to study the influence of meta-control parameters on task switching while avoiding the potential confounding effects of low-level experience. In particular, the instructions were used to de-confound the meta-control signal from bottom-up effects of local practice and recent experience. All of the studies of this chapter were based on this novel design, in which participants were asked to perform standard cued task switching in short sequences of trials in which the proportion of switch trials was varied between 20% and 80%. Crucially, instructions about task switch probability were provided and were generally informative but were misleading in some individual sequences. When instructed that task switches would be frequent, participants actually experienced sequences with an overall switch probability of 66.6%; when instructed that switches would be rare, participants experienced sequences with an overall switch

probability of 33.3%. However, these overall probabilities were the average of two types of sequences: In sequences with "frequent switch" instructions, objective switch probability was either 80% ("Real Frequent") or 50% ("Fake Frequent"). Similarly, in sequences with "rare switch" instructions, objective switch probability was either 20% ("Real Rare") or 50% ("Fake Rare"). Accordingly, the design uses instructions to create conditions in which low-level of task experience is matched (with task switches on 50% of trials) but switch expectation differs (meta-control)—the Fake Frequent and Fake Rare conditions. With this design, one can assess relatively pure effects of meta-control by contrasting the Fake Frequent and Fake Rare switch instructions with each other, as well as with an additional No Instruction condition with the same switch rate (50%) but no instruction-based expectations.

Based on the aforementioned studies of switch frequency effects, I hypothesised that information about switch probability should encourage people to adopt different strategies for selecting and implementing tasks on each trial. For example, following frequent switch instructions, participants might commit less strongly to the task on any given trial knowing that they will soon be required to switch to a different one, or pro-actively prepare a switch after consecutive task repetitions. If task switching depends on meta-control parameters in this way, one would expect lower switching costs in the Fake Frequent condition than in the Fake Rare condition, even though

these conditions are matched for their actual switch frequency. Conversely, if participants do not use instructions, their switching performance should only sensitive to actual switch frequency, so that switching costs will be similar in the two fake instruction conditions.

To anticipate the results briefly, effects of instruction were indeed observed but were relatively weak. Subsequent analyses aimed to investigate the nature of this instruction effect, to look for more robust evidence of the predicted effects. In particular, previous studies have suggested that there are separate effects of conflict in task switching: conflict at the level of task representations irrespective of the specific responses required (which is increased in switch trials), and conflict when different responses are required by the two tasks (observed irrespective of task transition). Evidence for this separation comes from task switching studies suggesting that task-sets could be activated by intention or primed by the cue associated with a response (Koch & Allport, 2006). Moreover, it has been suggested task conflict and response conflict, which both contribute to the switching cost, could be identified relatively independently of each other through the analysis of RT distributions (Steinhauser & Hubner, 2009). Specifically, Steinhauser & Hubner (2009) modelled RT distributions as the convolution of an exponential distribution and a Gaussian distribution, which can then be fitted to empirically observed distributions via 3

parameters: The leading edge of the distribution is associated with μ (the mean of the Gaussian component) and σ (the standard deviation of the Gaussian component) parameters, whereas the skewness and thickness of the long tail are more sensitive to variations of the τ (the exponential parameter). A wide range of studies has tried to give functional meanings that may underlie the different parameters of the ex-Gaussian distribution (in particular contrast μ and τ) (e.g., Hohle, 1965) Crucially, Steinhauser and Hübner (2009) showed that manipulating response congruency in the Stroop paradigm modulates the Gaussian component, whereas manipulating the bivalency of the stimuli (i.e., whether they are associated with one task or both) mostly influences the exponential parameter. Similarly, Moutsopoulou and Waszak (2012) studied the effects of response and task conflicts induced by the retrieval of stimulus–response and stimulus–task memory traces and found a similar dissociation that response conflict related to Gaussian components whereas task conflict related to Exponential components. Together, the above studies suggest that higher order processes related to task processing are associated with τ, whereas lower order ones related to response selection are associated with μ (Matzke & Wagenmakers, 2009).

On the basis of the above studies, in addition to the standard analysis of mean RTs, I also explored the application of ex-Gaussian distribution analysis on the meta-control, to disentangle high level instruction effect from RTs in a task-switching

paradigm. My prediction was based on the assumption that high-level control process should be associated with a change on τ rather than a motor-related parameter μ. Thus, it was expected the instruction effect would reflect a change on the component of τ: Specifically, because the instruction is occasionally misleading (in the Fake Instruction conditions), insufficient or incorrect preparation would result in long RTs, which should contribute to τ.

Experiment 1

Methods

Participants

Twenty students of the University of Oxford took part in this study (11 female; all right-handed; Mean age = 23.2 years, *SD* = 4.43). All of them reported normal or corrected-to-normal vision and no colour-blindness. They received payment or course credit for participating. All participants signed informed consent before the start of testing and were debriefed after the session.

Apparatus and stimuli

The experiment was run using Psychtoolbox in Matlab (MathWorks, Inc.) on a 17-inch CRT display (resolution at 1280*1024 pixels) with a 75Hz refresh rate. Responses were recorded with a standard QWERTY-keyboard, using "f" and "j" as response keys operated with the left and right index fingers, respectively.

Stimuli consisted of numbers from 1-9 except 5. On each trial a single digit was presented, with its colour signaling the required task. For half of participants, digits in red (RGB code, [255,0,0]) or blue (RGB code, [0,0,255]) were to be categorized as lower or higher than 5, whereas green (RGB code, [0,255,0]) and purple (RGB code, [255,0,255]) digits were to be categorized as odd or even. Two colours were assigned to each task to dissociate task switching and cue switching effects (Schneider & Logan, 2007): digit colour never repeated across trials even when the task remained unchanged. All stimuli were shown in Courier font with a size of 42 on a grey background (RGB code, [168,168,168]).

Design and procedure

Participants completed a series of 9 experimental blocks, each comprising 5 sequences of 17 trials, for a total of 765 trials. Switch frequency and the validity of instruction were manipulated across sequences (see Figure 2.1). Two sequences per block were preceded by the instruction "Frequent switch (66%)". In one of these

sequences, switch frequency was 50% (termed Fake Frequent); in the other the switch frequency was 81% (termed Real Frequent). Two sequences per block were preceded by the instruction "Rare switch (33%)". In one of these sequences, switch frequency was 50% (Fake Rare); in the other the switch frequency was 19% (Real Rare). Most importantly, for each instruction type considering both sequences, the overall switch frequency matched the instruction [(81%+50%)/2~=66%, and (19%+50%)/2 ~=33%], thus encouraging participants to make use of the instructions. The remaining sequence in each block was preceded by the instruction "No Instruction" and had an objective switch probability of 50%. The first trial of the 17 in a sequence was a warm up trial (for which switch/repeat transition is undefined); switch probabilities were fixed over the remaining 16 trials based on the sequence assigned. The order of the five sequence types was randomly assigned separately for each block.

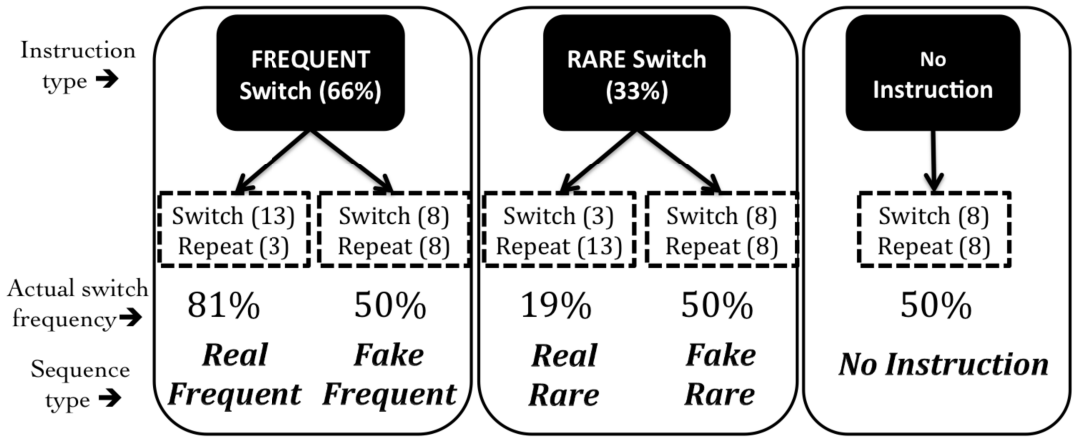


Figure 2.1. *Overview of the task design. There were 3 overall instruction conditions,*

with 66, 33, 50% switch probabilities. However, within the frequent switch condition, there were two sequence types, one in which switches were very frequent (on 13/16 trials) and one in which switches occurred on 50% of trials (8/16 trials). In the rare switch condition, again there were two types of sequences, one with very low number of task switches (3/16 trials) and another one with equal number of task switches and repeat trials. Each block contained three types of instruction across five sequences.

Each short sequence was announced by an instruction screen for 3 seconds, after which participants completed 17 trials of digit classification tasks. Each trial in the test phase started with a white rectangular frame for 1 second and was followed by a coloured digit at the center of the frame (see Figure 2.2). The target digit remained on the screen for up to 5 seconds until a response was detected. Immediately after the response, the coloured digit vanished. There then followed a fixed 1000 ms inter-trial interval, after which the next target digit appeared. The same inter-trial interval was also applied to the last trial of each sequence and followed by next instruction image. At the end of each experimental block, participants were given short break and feedback regarding their performance in that block.

Prior to these experimental blocks, participants practiced both tasks separately in two short practice blocks (16 trials each), then both tasks together in a block of 16

trials with tasks mixed in random order, then two further blocks of 17 trials in which switch frequency was 66% and 33%, with corresponding (valid) instructions at the start of these sequences. Participants had to perform at 90% accuracy or better in each block to proceed to next practice or to the experimental sessions. The whole experiment lasted about 60 minutes.

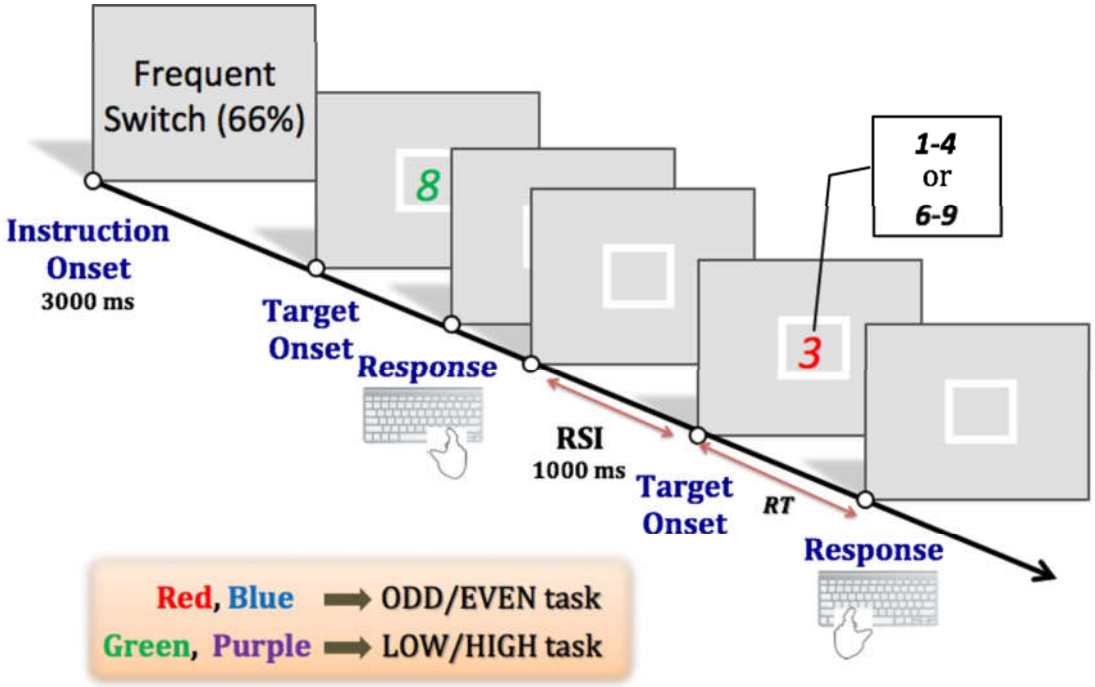


Figure 2.2. *An example of the time course of task presentation in Experiment 1. After showing an instruction for 3 seconds, each trial started with a coloured digit, participants responded with keypresses. The digit was coloured to indicate the task to be performed. RSI=response stimulus interval.*

Preprocessing and data analysis

Analyses of task switching performance excluded the first trial of each sequence, trials following errors and, for RT analyses, the error trials themselves. There was little effect of the particular task performed (low/high versus odd/even) and this variable was not included as a factor in the final data analyses. An alpha level of .05 was used to determine statistical significance. Because our main interest was to compare the two fake instruction conditions, I conducted separated ANOVA for the real and the fake instruction conditions. To emphasize the difference between the two fake instruction conditions and improve statistical sensitivity, the control (No Instruction) condition was analyzed together with real instruction data.

Ex-Gaussian distribution analysis

Ex-Gaussian distribution analysis was conducted with a computational tool written in MATLAB (Lacouture & Cousineau, 2008). In short, the empirical RT data were characterized with the ex-gaussian probability density function in terms of the three parameters. Next, an iterative approach was used to allow parameter space to search for the values that best fit a frequency distribution to be estimated. The fitting of the probability function to the data evaluated by a goodness of fit criterion in maximum likelihood estimation. After the above analysis, an inspection of Q-Q plots was conducted for each condition and each participant to ensure an acceptable

goodness of fit.

Results

Real/no instruction conditions

Across-participant average reaction time (RT) and proportion of errors (PE) are plotted in Figure 2.3, separately for the real instruction and no instruction conditions (left panel) and for the critical fake instruction conditions (right panel). I first performed repeated measures ANOVAs on RTs and PEs for the real and no instruction sequences, with factors of Task Transition (repeat, switch) and Sequence Type (Real Frequent, Real Rare, No Instruction) to assess if our paradigm will replicate the switch frequency effect observed previously (e.g., Dreisbach & Haider, 2006). Consistent with this, the RT analysis revealed reliable main effects of Task Transition, $F(1, 19) = 24.0$, $MSE = 244{,}363$, $p < .01$, $\eta_p^2 = .56$, indicating a robust switching cost of 90 ms overall, a reliable main effect of Sequence Type, $F(2, 38) = 9.1$, $MSE = 43{,}938$, $p < .01$, $\eta_p^2 = .32$, and a reliable interaction between these factors, $F(2, 38) = 8.8$, $MSE = 30{,}689$, $p < .01$, $\eta_p^2 = .14$. Follow-up pairwise tests were conducted to contrast the switching costs between conditions revealed that switching costs were greater in the Real Rare condition than in the Real Frequent condition, $t(19) = 3.4$, $p < .01$, and were greater in Real Rare condition than No Instruction condition, $t(19) = 3.9$, $p < .01$, whereas

switching costs did not differ between the Real Frequent and No Instruction conditions, $t(19) = 1.4$, $p = .19$. The distinct switching costs between the two real instruction conditions replicate the switch frequency effect observed previously (e.g., Monsell & Mizon, 2006). For the error data, the ANOVA revealed only a reliable main effect of Task Transition, $F(1, 19) = 5.1$, $MSE = .004$, $p = .04$, $\eta_p^2 = .21$, with participants making errors more frequently on task switch trials than task repeat trials. Numerically, this error cost of switching was largest in the No Instruction condition, but the interaction between Sequence Type and Task Transition was not reliable, $F < 1$, $p = .53$. The main effect of Task Sequence was not reliable as well, $F < 1$, $p = .68$. Collectively, these results indicate that switching costs vary inversely with switch frequency, as previously observed.

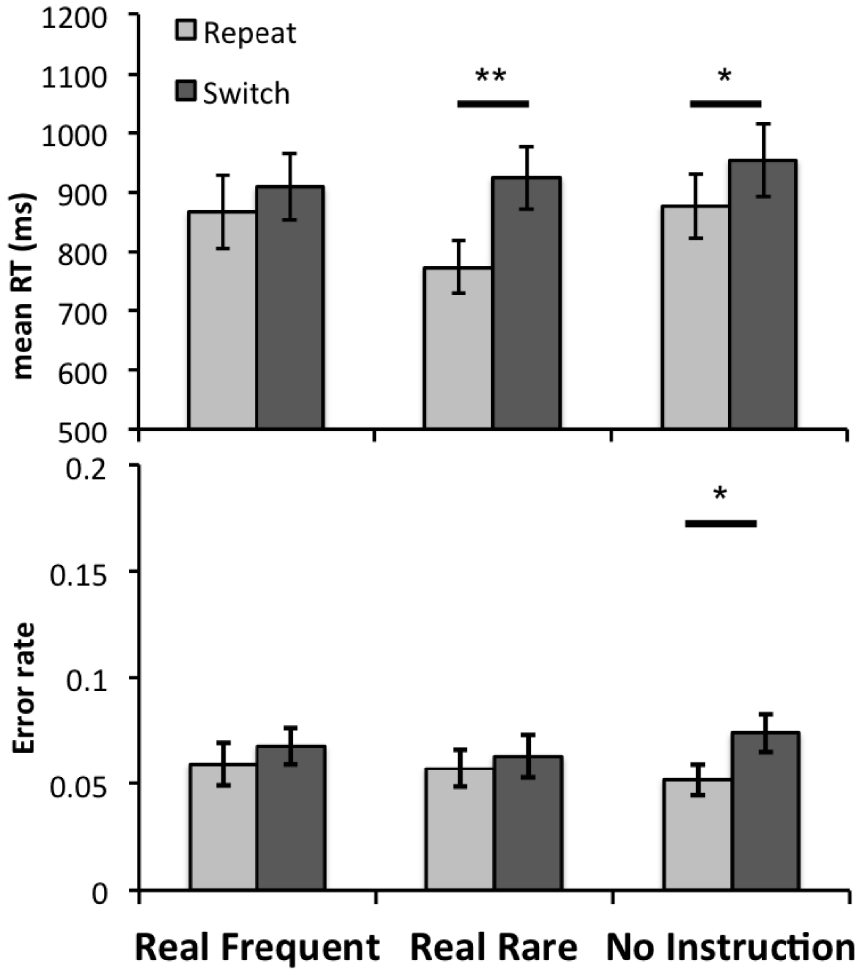


Figure 2.3. *Data from the real and no instruction conditions of Experiment 1. Mean reaction time and mean proportion of errors as a function of switch and repeat trials for the real and no instruction conditions. * indicates p <0.05, ** indicates p <0.01. Error bars indicates standard errors of the mean.*

Fake instruction conditions

The crucial analysis concerned the contrast between the two fake instruction conditions, specifically whether switching costs would be greater in the Fake Rare condition (in which task switches were unexpected) than in the Fake Frequent

condition (in which task switches were expected) despite having the same objective switch frequency. A repeated measures ANOVA with factors of Task Transition (repeat, switch) and Sequence Type (Fake Frequent, Fake Rare) revealed reliable main effects of Task Transition, $F(1, 19) = 22.0$, $MSE = 187{,}197$, $p < .01$, $\eta_p^2 = .54$, indicating the typical switching cost, and Sequence Type, $F(1, 19) = 4.7$, $MSE = 12{,}153$, $p = .04$, $\eta_p^2 = .20$, with slower RTs overall in the Fake Rare condition, but no significant interaction, $F(1, 19) = 2.4$, $MSE = 2{,}555$, $p = .14$, $\eta_p^2 = .11$. Thus, although switching costs were numerically larger in the Fake Rare condition (108 ms) than in the Fake Frequent condition (85 ms), this difference was not consistently observed across participants. This pattern was, however, consistently observed in the proportion of errors (see Figure 2.4), where there was no reliable main effect of Sequence Type, $F < 1$, but there was a main effect of Task Transition, $F(1, 19) = 8.1$, $MSE = 0.009$, $p = .01$, $\eta_p^2 = .30$, and a significant interaction between these factors, $F(1, 19) = 15.1$, $MSE = 0.008$, $p < .01$, $\eta_p^2 = .44$. This interaction was driven by a greater error cost of switching in the Fake Rare than the Fake Frequent conditions. Follow-up pairwise comparisons revealed that more errors were made on switch trials than repeat trials only in the Fake Rare instruction condition, $t(19) = 5.9$, $p < .01$, but not in the Fake Frequent condition, $t < 1$.

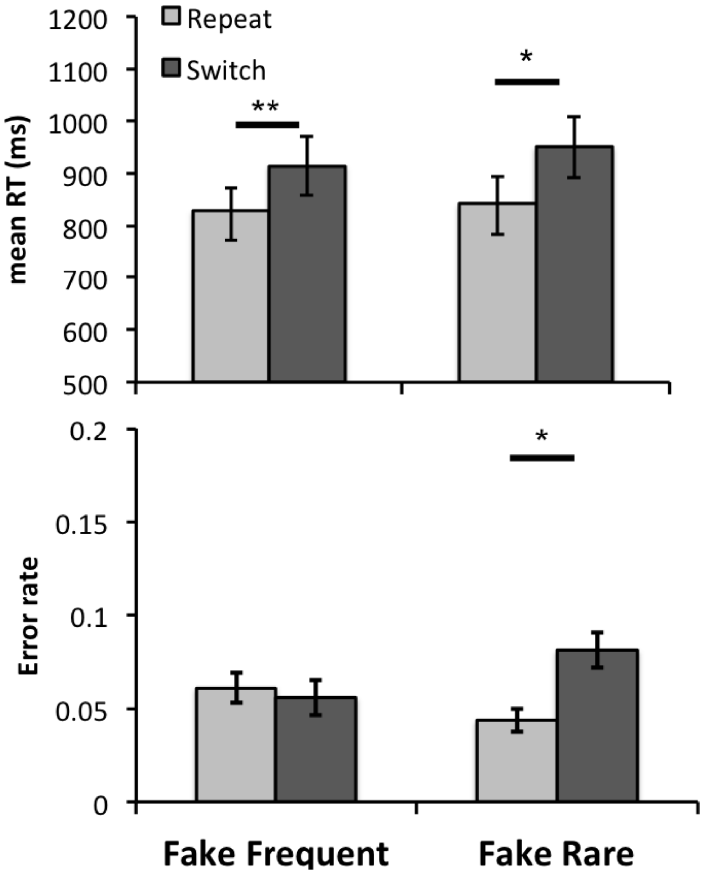


Figure 2.4. *Data of fake instruction conditions from Experiment 1. Mean reaction time and mean error rate as a function of switch and repeat trials for the real and no instruction conditions. * indicates p <0.05, ** indicates p <0.01. Error bars represent standard error of mean.*

Ex-Gaussian analysis

Though an instruction effect was detected on error rates, the RT analysis did not reveal consistent effects of instruction between the two fake instructions. As has been discussed by past studies, fitting RTs to Ex-Gaussian distribution can successfully dissociate task and response levels of processes (e.g., Steinhauser & Hübner, 2009;

Moutsopoulou & Waszak, 2012). In particular, the use of the distribution fitting of RT has been shown to be a reliable analysis method to detect differences between conditions that traditional ANOVA statistics were not sufficient to detect. For instance, task and response levels of conflict can be dissociated through the distinct components of the ex-Gaussian distribution. Therefore, I used Ex-Gaussian analysis to explore whether there might be instruction effect on different levels of RT measurement. As with the conventional ANOVA analysis, only correct trials were entered into the ex-Gaussian distribution analysis. The ex-Gaussian analysis was conducted in MATLAB with the published scripts adopted from Lacouture & Cousineau (2008). The three parameters, μ, σ, and τ, estimated from the analysis then were entered into two separate repeated measures ANOVAs for both real and fake instructions, with the factors of sequence type and task transition.

My analysis focused on the results from the crucial fake instruction conditions, because there were very few observations of some conditions (e.g., task repetitions in Real Frequent) so that poor fits of the model were obtained for several participants (as evaluated in Q-Q plot). Each dependent variable was entered into a two-way repeated measures ANOVA, with variables of Sequence type (Fake Frequent, Fake Rare) and Task transition (task repetition, task switch). Figure 2.5 depicts estimates of ex-Gaussian parameters for each condition. The ANOVA analysis revealed opposite

results in the Gaussian related parameters and the Exponential parameter. The main effect of Task transition can both be found in μ, $F(1, 19) = 22.3$, $MSE = 94{,}526$, $p < .01$, $\eta_p^2 = .53$, and σ, $F(1, 19) = 17.0$, $MSE = 11{,}758$, $p < .01$, $\eta_p^2 = .47$, but not reliably in τ, $F(1, 19) = 1.9$, $MSE = 17{,}407$, $p = .19$, $\eta_p^2 = .09$. In contrast, an effect of Sequence type was observed exclusively in the exponential parameter, τ, $F(1, 19) = 4.5$, $MSE = 11{,}961$, $p < .05$, $\eta_p^2 < .01$, but not either in μ, $F < 1$, or σ, $F < 1$. No reliable interaction between sequence type and task transition was detected for any of the parameters (Fs < 2.3, ps > .15).

To relate these findings to the standard analysis above, whereas mean RTs in the Fake Instruction conditions were sensitive to both sequence type and task transitions, the ex-Gaussian analysis indicated separation between these effects, with sequence type affecting the exponential parameter (τ) whereas task transition affected the Gaussian parameters (μ and σ). These findings suggest that task transition, reflected in the Gaussian parameters, was mainly sensitive to response level of interference, whereas instructions, reflected in the exponential parameter, influenced a higher order of processing, which is consistent with past studies (e.g., Matzke & Wagenmakers, 2009).

To complete the analysis, I also conducted an additional analysis to test whether Gaussian parameters would be sensitive to the response congruency effect. Past studies

have indicated that response congruency of stimuli mainly affects the μ and σ parameters whereas task conflict is mainly detected by τ (Steinhauser & Hübner, 2009; Moutsopoulou & Waszak, 2012). This is rooted in the idea that conflict types affect different stages of processing therefore should affect distinct properties of RT distribution. Accordingly, all of the trials were categorized into two groups based on response congruency and then entered into an ex-Gaussian distribution analysis. The results revealed significant higher μ, $t(19)= 6.7, p < .01$ and σ, $t(19)= 6.8, p < .01$, values on incongruent trials than congruent trials. Surprisingly, the exponential parameter, tau, also responded to such effect, $t(19)= 4.1, p < .01$. Collectively, response congruency effects were found to be sensitive to Gaussian parameters which have been commonly found (e.g., Steinhauser & Hübner, 2009; Moutsopoulou & Waszak, 2012). Nevertheless, such effect was also emerged on exponential parameter, which is usually associated with task-level conflict.

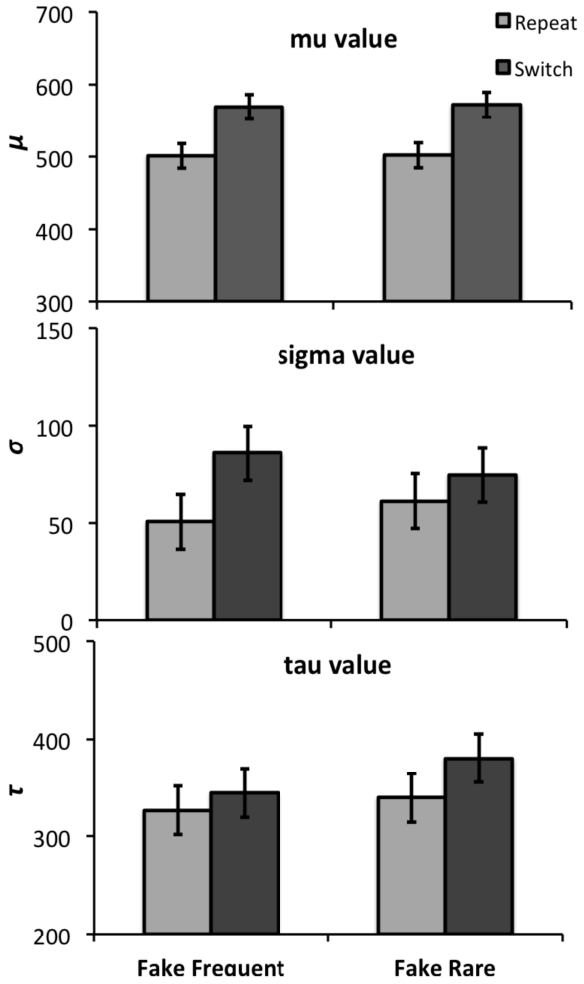


Figure 2.5. *The three estimated parameters from the ex-Gaussian distribution in Experiment 1. The parameters were plotted as a function of task transitions (task repetitions, light gray bars vs. task switches, dark gray bars and fake instructions (Fake Frequent vs, Fake Rare). Error bars represent standard error of mean.*

Discussion

The aim of this study was to establish a paradigm with a novel design in which we could obtain evidence of meta-control relating to variations in switch frequency, using an instruction manipulation to control for the confounding effects of practice at task

switching. Overall, the results of Experiment 1 were consistent with the prediction that switching costs should be larger both when task switches are objectively rare and, crucially, also when instructions create the *expectation* that task switches will be rare, even in the absence of differences in objective switch frequency. Unexpectedly, this effect was only consistently observed in analysis of error rates; a small numerical trend in the RT data did not approach significance. As will become apparent, this pattern was consistently observed across experiments.

To further pursue the instruction effects on RT measures, the RT data were entered into an ex-Gaussian distribution analysis. For the ex-Gaussian analysis, in the exponential parameter, only the effect of the instruction was found. This finding was consistent with the prediction that the exponential parameter should be sensitive to high-level processing of the instruction, which is in line with past studies (Moutsopoulou & Waszak, 2012). This specification on exponential parameter could be explained as instruction-related processing (meta-control) preceded response-related processes and therefore incurred a longer-lasting influence, which is reflected in the skewness of the distribution. However, the finding that Gaussian parameters were mainly sensitive to task switches was less expected (cf., Moutsopoulou & Waszak, 2012), which implies that task switching here reflected a motor-related process. Thus, although the ex-Gaussian analysis confirms the notion that this approach can pull apart

different cognitive processes from a single RT measure, the correct interpretation of the parameters is unclear. Taken with ongoing debate about the functional dissociations on different parameters (e.g., Steinhauser & Hubner, 2009) the present ex-Gaussian results are suggestive but not sufficiently clear to warrant continuing in subsequent experiments.

Taken together, from these results it seems that the instruction manipulation was successful, such that participants were particularly likely to make task switching errors when instructions led them to expect frequent task repeats. Experiment 2 built on this instruction effect to test whether meta-control could be motivationally adjusted.

Experiment 2

Experiment 2 introduced a reward incentive manipulation to our basic design, with two related aims. The first aim was to seek an effect of instruction on RT switching costs. Thus, although the results of Experiment 1 were broadly consistent with our predictions, reliable switching cost differences between the crucial Fake Frequent and Fake Rare conditions were restricted to error rates. The present experiment used a reward incentive scheme that placed emphasis on fast responding but with a parallel

requirement to make fewer than 10% errors. The emphasis on fast responding was intended to encourage participants to attend to and act on the instructions, to maximize their performance, rather than simply ignore the instructions and wait for each coloured digit and react accordingly. As such, it was anticipated that the effect of instructions might increase. At the same time, I anticipated that the error rate limit would encourage participants to slow down when they needed, in particular when surprised by a task switch in sequences with "rare switch" instructions, such that the instruction effect could emerge in the reaction time data.

The second aim was related but more conceptually motivated. To the extent that instruction effects reflect meta-control, I might expect them to depend on participants' motivation to act upon the instructions, given the proposal that control is effortful and therefore only exerted when benefits outweigh costs (Holroyd & Yeung, 2012; Shenhav, Botvinick, & Cohen, 2013) as evident in studies showing that reward motivation has robust influences on cognitive control and goal-directed behaviour (Botvinick & Braver, 2015; Frober & Dreisbach, 2016). Incentive-induced performance improvements in control have been observed in a range of tasks. In the task switching paradigm, for example, Kleinsorge and Rinkenauer (2012) examined the pronounced effect of incentives on task switching by providing a monetary bonus on a trial-to-trial basis. When reward availability was associated with one of tasks and announced prior

to testing, the reward reduced switching costs overall even to the task not associated with any reward. However, when the bonus-task association varied on each trial, the reward effects remained visible on the bonus-related task but were accompanied by worsened performance on the task that was not associated with a bonus. These findings not only affirm that incentive motivation can enhance cognitive control, but also indicate that these effects can be selective and adaptive. Based on the above studies, the prediction for this study was that the switching cost difference between the Fake Frequent and Fake Rare conditions should be enhanced in conditions with reward incentives compared to a no reward control condition.

Methods

Participants

An additional 20 participants were recruited for this study (11 female; Mean age = 26.35 years, *SD* = 3.41). All participants signed informed consent and were debriefed after the session. Participants were either paid £8 or received course credits for their participation plus £0-16 extra reward depending on their performance.

Apparatus, design, stimuli, and procedure

The apparatus, design, stimuli, and procedure were very similar to those of

Experiment 1, with the exception of the introduction of reward manipulation. Thus, in half of the 17-trial sequences, participants were given the opportunity to gain reward (£0.50) for good performance. This opportunity was signaled to them at the start of the sequence with the information "Reward in this sequence" added to the screen with the switch probability instructions (e.g., "Frequent switch (66%)"), which appeared at the beginning of each sequence for 3000 ms as in Experiment 1. The criteria to gain reward were: achieve above 90% accuracy, with mean RT in the current sequence that is faster than the previous sequence with the same type of instruction without reward. At the end of each Reward sequence, £0.50 was awarded and shown on the screen if these criteria were met; otherwise the experiment proceeded to the next sequence. In No Reward sequences, participants were simply told to emphasize both speed and accuracy, but with no additional incentive.

In total, there were 11 experimental blocks for a total of 935 trials. The first block was used for measuring the reward criterion, thus the first block was always a No Reward condition. For the subsequent ten blocks, half of blocks were No Reward blocks, where all of sequences were no reward sequences. In contrast, all sequences in the other half of blocks were offered the possibility of monetary reward. The order of these ten blocks was randomly assigned. Feedback regarding performance including current gains of reward was delivered at the end of each block. The experiment began

with four blocks of practice as in Experiment 1. The reward manipulation was explained to the participants before the formal testing and was introduced for the first time in the experimental blocks.

Results

Real/no instruction conditions

I first report the data from the real instruction conditions, in which objective switch probability varied substantially and in line with the instructions. The ANOVA included factors of Task Transition (repeat, switch) and Sequence Type (Real Frequent, Real Rare, No Instruction) as in Experiment 1, but added a new factor of Reward (reward, no reward sequence). First, a small switching cost of 59 ms was found but was not significant, $F(1, 19) = 3.0$, $MSE = 16{,}043$, $p = .10$, $\eta_p^2 = .14$, Figure 2.6. In general, RTs were found to be faster in the reward condition than in the no reward condition, 860 ms vs. 801 ms, $F(1, 19) = 14.6$, $MSE = 206{,}917$, $p < .01$, $\eta_p^2 = .44$. RTs also differed between instruction conditions, $F(2, 38) = 10.3$, $MSE = 72{,}410$, $p < .01$, $\eta_p^2 = .35$, which was mainly driven by overall longer RTs in Real Frequent sequences than RTs in Real Rare sequences, (with Bonferroni correction, $p < .01$. The interaction between Sequence Type and Task Transition was highly significant, $F(2, 38) = 7.4$, $MSE = 70{,}161$, $p < .01$, $\eta_p^2 = .28$. This significant interaction replicated the switch frequency

effect observed in Experiment 1 and reported previously (e.g., Monsell & Mizon ,2006). The three-way interaction was not reliable, $F(2, 38) = 1.3$, $MSE = 5{,}823$, $p = .30$, $\eta_p^2 = .06$, indicating no reliable modulation of the effect according to reward. No other interaction reached significance, $F < 1$.

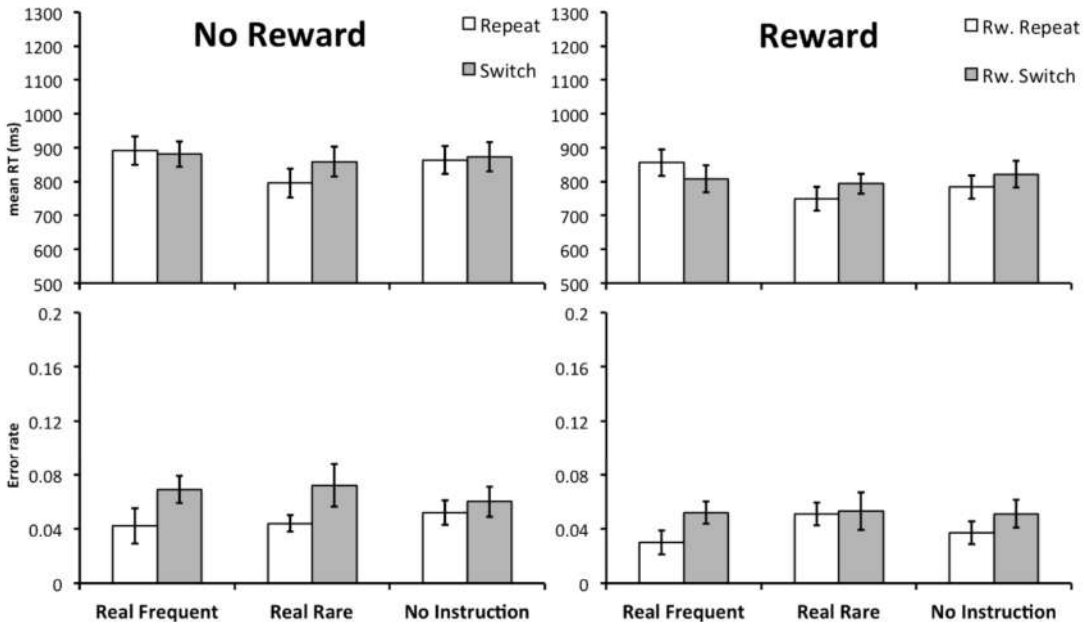


Figure 2.6. *Data of real/no instruction conditions from Experiment 2. Mean reaction time and error rate as a function of switch and repeat trials for the three instruction conditions. Error bars represent standard error of mean.*

For the error rate data, as can be seen from the bottom two panels of Figure 2.6, reward clearly reduced error rate overall, 5.7% vs. 4.6% error proportions, $F(1, 19) = 5.3$, $MSE = .007$, $p = .03$, $\eta_p^2 = .22$. Consistent with previous studies, participants also

made fewer errors on task-repeat trial than task-switch trials, $F(1, 19) = 9.3$, $MSE = .017$, $p < .01$, $\eta_p^2 = .33$. None of the interactions reached significance, all $p > .30$.

Fake instruction conditions

For the fake instruction condition data (see Figure 2.7), I applied a three-way repeated measures ANOVA on the RT data with factors of Reward (no reward, reward), Sequence Type (Fake Frequent, Fake Rare) and Task Transition (task repeat, task switch). The reward effect was highly significant as in the real instruction conditions, $F(1, 19) = 8.2$, $MSE = 119{,}326$, $p < .01$, $\eta_p^2 = .30$, which indicated a success of the reward manipulation. The overall switching cost was also small in the fake instruction sequences, with RTs of switch trials on average longer than repetition trials (by 33 ms), a reliable difference, $F(1, 19) = 11.8$, $MSE = 43{,}836$, $p < .01$, $\eta_p^2 = .38$. Overall RTs between Fake Rare and Fake Frequent were similar, $F(1, 19) = 3.1$, $MSE = 11{,}083$, $p = .10$, $\eta_p^2 = .14$. No interactions reached significance, including the critical interactions between Sequence Type and Task Transition, $F(1, 19) = 2.0$, $MSE = 4{,}285$, $p = .17$, $\eta_p^2 = .10$, and between Reward, Sequence Type, and Task Transition, $F < 1$. This suggests that there was no clear instruction modulation effect on RTs between the Fake Rare and the Fake Frequent conditions. In addition, even though the critical two-way interaction did not reveal reliable the switch frequency effect, its numerical trend (overall

switching costs for Fake Frequent and Fake Rare: 23 ms vs. 43 ms) was still in accordance with the real instruction conditions.

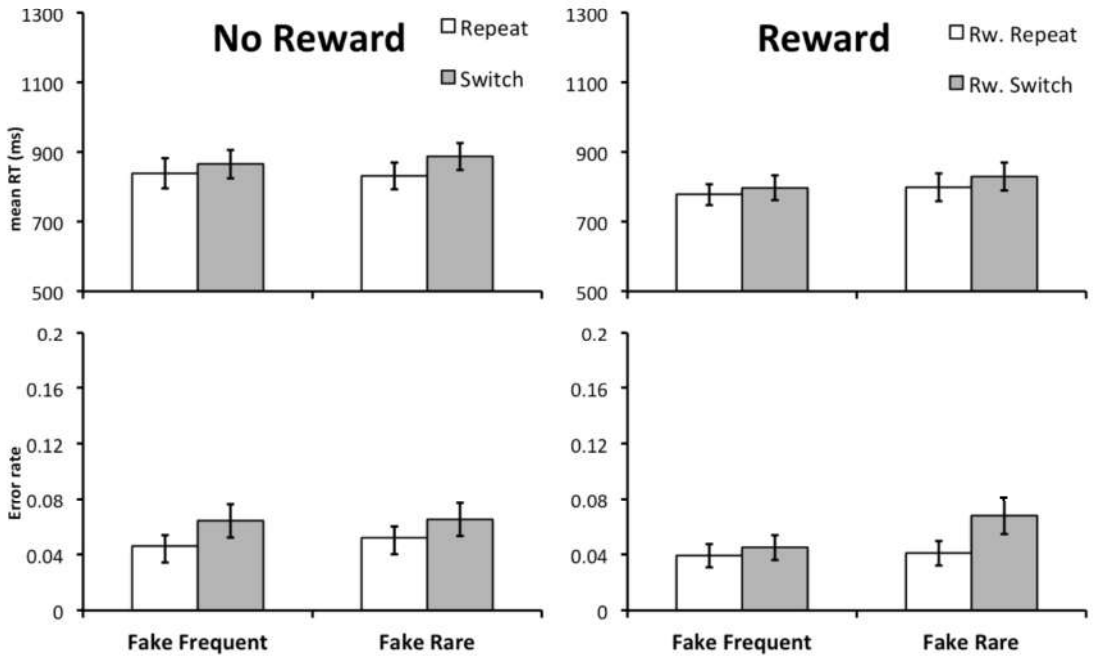


Figure 2.7. *Data of fake Instruction conditions from Experiment 2. Mean reaction time and error rate as a function of switch and repeat trials for the two instruction conditions. Error bars represent standard error of mean.*

Error rate data for the fake instruction conditions did not show a significant sensitivity to reward overall, $F(1, 19) = 3.3$, $MSE = .003$, $p = .08$, $\eta_p^2 = .15$, although there were slightly lower error rates in reward than no reward blocks (4.7% vs. 5.7%). A marginal main effect of Task Transition was found, $F(1, 19) = 4.4$, $MSE = .009$, $p = .05$, $\eta_p^2 = .19$, with a small switching error cost of 1.5%. Overall, no two-way interactions,

all $F < 1$, $p > .50$, nor the three-way interaction reached significance, $F(1, 19) = 1.3$, $MSE = .001$, $p = .27$, $\eta_p^2 = .06$. However, numerically, the switching error costs between the two fake instruction conditions were similar in the no reward condition but quite different in the reward condition. In particular, the larger switching error cost in the Fake Rare conditions (than Fake Frequent) of the reward sequences mirrored the results of Experiment 1. However, these effects were not statistically reliable. The interaction between Sequence Type and Task Transition was not reliable, $F < 1$.

Discussion

The present study utilized reward motivation to encourage attention to instructions and fast and accurate responding in order to detect an instruction effect on RTs. The reward manipulation was effective in improving task performance, reducing both RTs and error rates (cf. Manohar et al., 2015). Also, a robust switch frequency effect on RTs in the real instruction conditions was observed again. However, I did not find an instruction modulation effect on RTs between the Fake Rare and Fake Frequent conditions, but there was a numerical trend, which partially replicated the error rate results in Experiment 1. Moreover, the mean RT switching costs of Fake Rare sequences were numerically higher than Fake Frequent sequences, which was consistent with the trend of switch frequency effect.

However, it is difficult to interpret these weak instruction effects because switching costs in this study were very small—on average just 23 ms and 1.6% error difference on average, as compared with typical RT switching costs of 100-200 ms in both alternating-runs (e.g., Rogers & Monsell, 1995) and task-cueing studies (e.g., Dreisbach, Haider, & Kluwe, 2002). Though we aimed through reward to enhance the sensitivity of RTs to instruction effects, if any effect of instruction on switching costs was observed it was in error rates (although here it was also not significant).

Given the small magnitude of observed switching costs, the present paradigm may not be ideally suited to observing modulations of switching costs by instruction and/or reward. One reason for these small switching costs could be that simultaneous presentation of task cue and target might have encouraged participants to adopt a strategy of learning direct associations between cue-stimulus compounds and the associated responses (e.g., learning to respond with a right index finger to the digit "7" in red), rather than by forming a true task set based on classifying the stimuli (Dreisbach & Haider, 2006; Forrest, Monsell, & McLaren, 2014; Logan & Bundesen, 2003). For instance, when participants treated tasks as collections of individual stimulus-response mappings, switching costs tend to be small (Dreisbach & Haider, 2009), which is exactly the results observed in this experiment. This strategy would not only bypass the formation of task set but also impair the utility of meta-control.

Experiment 3 therefore involved the same reward incentive manipulation but used a modified task cueing procedure that was designed to encourage participants to treat cues and stimuli as distinct events rather than compound stimuli.

Experiment 3

In Experiment 3, the task cue and target digit were presented separately rather than as features of the same target stimulus. The task cue was now a colored frame that preceded the target digit by a 100 ms interval. I chose a short cue-stimulus interval of 100 ms interval to maximize the switching cost (e.g., Monsell & Mizon, 2006). I also used one colour cue per task, rather than two. Previous studies using two cues per task tended to show smaller switching cost (Schneider & Logan, 2011). The prediction was the same as in the previous experiment, of an impact of fake instructions that should be manifest in particular in the high motivation (reward) condition, perhaps also apparent in the RT data as well as error rate switching costs.

Methods

Participants

19 participants (13 female; Mean age = 21.05 years, *SD* = 4.16) from University of Oxford took part in this study. They were either paid £8 or course credit for their participation plus £0-16 extra reward depending on their performance.

Procedure and design

The apparatus, design, stimuli, and procedure were very similar to those of Experiment 2. However, the required task was now cued on each trial by a coloured frame that appeared 100 ms before the digit inside a white fixation frame (Figure 2.8). Each task was associated one colour only – either red or blue. For half of participants, blue was associated with low/high task whereas red was associated with odd/even task. The colour and task mapping was counterbalanced across participants. Following the response on each trial (or a 5-s timeout period), the digit and coloured frame disappeared to leave only the white fixation frame for a 1000 ms inter-trial interval. All other experimental details, including the crucial instruction and reward manipulations, were the same as in Experiment 2.

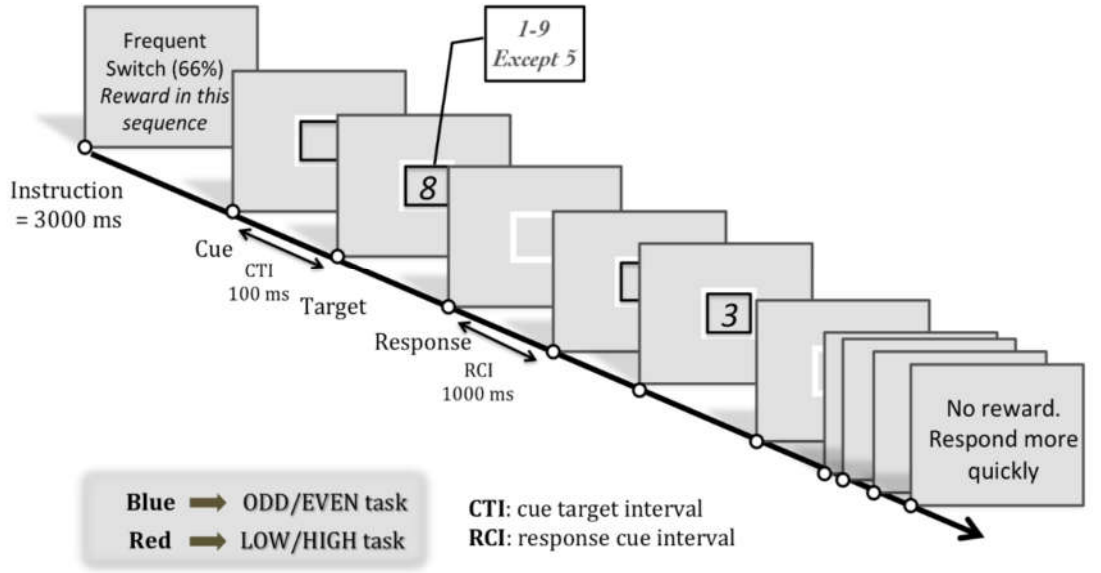


Figure 2.8. *The procedure in Experiment 3. The task and design were identical to the previous experiment except for two main changes. For each trial in each sequence, the task cue preceded target digit for 100 ms, and only single colour was used for each task.*

Results

Real/no instruction conditions

I begin with the results of the real/no instruction conditions (Figure 2.9). The RT data were entered into a repeated measures ANOVA with factors of Task Transition (repeat, switch), Sequence Type (Real Frequent, Real Rare, No Instruction) and Reward (no reward, reward). First, a reliable main effect of Reward confirmed that the reward manipulation was successful in reducing RTs, 719 ms vs. 639 ms, $F(1, 18) = 23.4$, $MSE = 360{,}453$, $p < .01$, $\eta_p^2 = .57$. Both Sequence Type, $F(2, 36) = 9.3$, $MSE = 58{,}347$, $p < .01$, $\eta_p^2 = .34$, and Task Transition, $F(1, 18) = 105.0$, $MSE = 1{,}158{,}211$, p

< .01, η_p^2 = .85, were revealed to be significant as well. The highly significant Task Transition factor indicated that a robust and a substantial switching cost was obtained in this version of task (mean switching costs of 143 ms). The interaction between Sequence Type and Task Transition was again significant, $F(2, 36) = 9.1$, $MSE = 30{,}143$, $p < .01$, $\eta_p^2 = .34$. In addition, the interaction between Reward and Task Transition also reached significance, $F(1,18) = 11.9$, $MSE = 43{,}000$, $p < .01$, $\eta_p^2 = .06$), indicating that reward motivation decreased switching costs overall. Other interaction terms did not approach statistical significance, all $F < 1$, which included the 3-way interaction between Reward, Sequence Type and Task Transition.

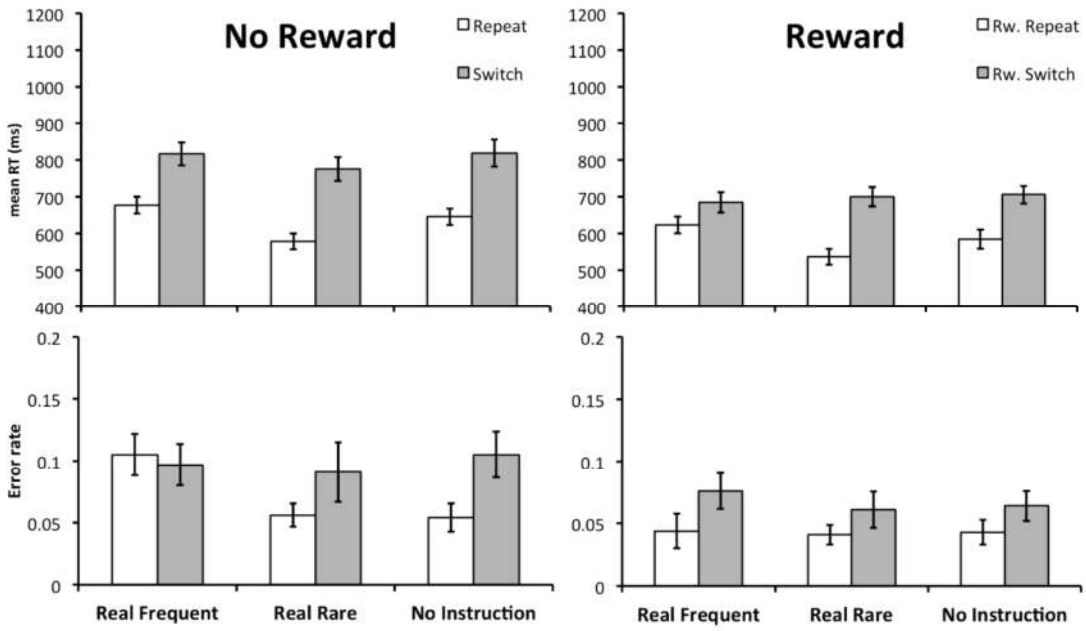


Figure 2.9. *Switch performance of real/no instruction conditions from Experiment 3. Mean reaction time and mean proportion of errors as a function of switch and repeat*

trials for the three instructions. "Rw." indicates conditions with reward offer. Error bars represent standard error of mean.

For the error rate data, all of the main effects were significant, including Reward, $F(1, 18) = 3.1$, $MSE = .051$, $p < .01$, $\eta_p^2 = .32$, with an improvement from 8.5% to 5.5% when Reward was available, Sequence Type, $F(2, 36) = 4.1$, $MSE = .007$, $p = .03$, $\eta_p^2 = .18$, with fewer errors in conditions: Real Rare vs. Real Frequent, and Task Transition, $F(1, 18) = 7.3$, $MSE = .037$, $p = .01$, $\eta_p^2 = .29$, with an overall switching error cost of 2.5%. The interaction between Sequence Type and Task Transition was not reliable, $F(2, 36) = 1.2$, $MSE = .003$, $p = .30$, $\eta_p^2 = .06$, nor were other two-way interaction terms, all Fs < 1.2, all ps > .30, but the three-way interaction between Reward, Sequence Type and Task Transition reached significance, $F(1, 18) = 4.3$, $MSE = .007$, $p = .02$, $\eta_p^2 = .19$. This effect was mainly driven by a larger switching error cost difference between the two real instruction conditions in the no reward condition (switching error costs: -0.8% vs. 3.5% for Real Frequent vs. Real Rare sequences) than in the reward condition (switching error costs: 3.2% vs. 2.0%).

Overall, from the results of RTs and error rates, the switch frequency effects and reward effect were both observed again (as in the last study) and importantly the magnitude of switching costs on RTs have returned to a normal range as observed in

past studies (e.g., Monsell & Mizon, 2006), which I attribute to ruling out the confounding possibility of an associative learning strategy (e.g., Dreisbach, Goschke, & Haider, 2006; Forrest, Monsell, & McLaren, 2014). After confirming these effects were all observed as anticipated, the necessary preconditions are in place to investigate instruction effects in the fake instruction conditions.

Fake instruction conditions

Mean RTs from the fake instruction sequences were subjected to a repeated measures ANOVA with factors of Reward (no reward, reward), Sequence Type (Fake Frequent, Fake Rare), and Task Transition (task repetition, task switch). The results revealed that RTs decreased overall with reward, $F(1, 18) = 49.8$, $MSE = 252{,}603$, $p < .01$, $\eta_p^2 = .73$. A reliable overall switching cost of 139 ms was found, as indicated by a significant main effect of Task Transition, $F(1, 18) = 60.0$, $MSE = 738{,}845$, $p < .01$, $\eta_p^2 = .77$ (see Figure 2.10). Overall RTs for the two fake instruction conditions were similar, as indicated by non-significant main effect of Sequence Type, $F < 1$. For the interaction terms, I only found a significant interaction between Reward and Task Transition, $F(1, 18) = 13.5$, $MSE = 23{,}720$, $p < .01$, $\eta_p^2 = .04$, with numerically smaller magnitude of switching costs in the reward conditions (164 ms vs. 115 ms). RT switching costs were almost identical between the Fake Frequent and Fake Rare switch conditions, $F < 1$, in

a manner that was unaffected by reward incentive as reflected in a non-significant 3-way interaction, $F < 1$.

For the proportion error data, the difference between the two fake conditions was reliable, $F(1, 18) = 4.5$, $MSE = 0.013$, $p < .01$, $\eta_p^2 = .37$, with a greater proportion of errors overall in Fake Rare (8.2 %) than Fake Frequent (6.3 %). More errors were made on task-switch trials than task-repeat trial, 8.7 % vs. 5.8 %, $F(1, 18) = 20$, $MSE = 0.033$, $p < .01$, $\eta_p^2 = .52$. Error rates were numerically lower in reward than no reward (6.5 % vs. 8.1%), but the difference was not significant, $F(1, 18) = 3.2$, $MSE = 0.01$, $p = .10$, $\eta_p^2 = .15$. This non-significant reward effect on error data suggests the RT benefit of reward is not due to speed-accuracy trade-off. The factor of Reward interacted with Sequence Type, $F(1, 18) = 6.3$, $MSE = 0.004$, $p = .02$, $\eta_p^2 = .26$, (see Figure 2.10 right), which suggested more errors in reward Fake Rare than reward Fake Frequent sequences. I also found a larger error cost of switching in Fake Rare than Fake Frequent sequences as evident in a reliable interaction between Sequence Type and Task Transition, $F(1, 18) = 4.8$, $MSE = 0.006$, $p = .04$, $\eta_p^2 = .21$. The key prediction was that a larger error switching cost will be observed in the Fake Rare condition than the Fake Frequent condition. A follow-up 2-way repeated measures ANOVA on the error rate data from the reward condition, with factors of Sequence Type and task transition, revealed a significant two-way interaction indicating that a larger error cost of switching was found in the

Fake Rare condition than the Fake Frequent condition, $F(1, 18) = 4.9$, $MSE = .005$, $p = .04$, $\eta_p^2 = .06$. A corresponding ANOVA applied to error rates in the no reward condition revealed no reliable interaction, $F < 1$.

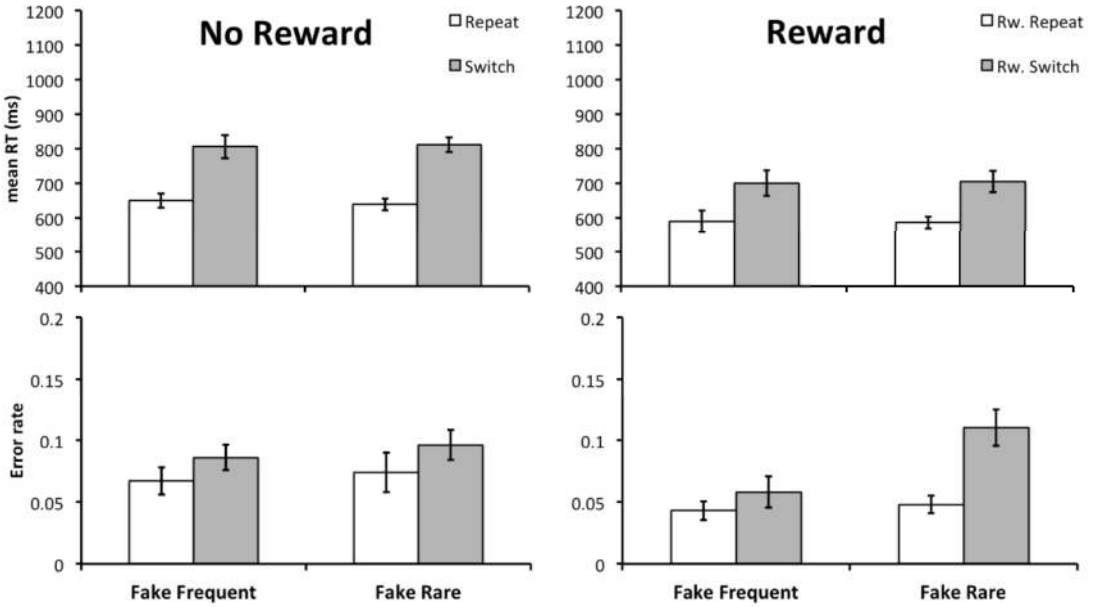


Figure 2.10. *Switch performance of the fake instruction conditions from Experiment 3. Mean reaction time and mean proportion of errors as a function of switch and repeat trials for the two instructions. Error bars represent standard error of mean. Rw.: reward. Error bars represent standard error of mean.*

Discussion

Experiment 3 aimed to obtain robust switching costs to test the instruction effect on RT measurement. There were four major findings in this experiment: (1) the reward manipulation successfully improved performance in the context of a task cueing design,

(2) robust switching costs were observed, (3) the predicted modulation of the instruction effect was found, and the effect was larger with reward than with no reward, and (4) error measurement was still sensitive to the instruction manipulation. Overall, these results suggested there was a global meta-control influence in task switching and this influence was only observed when the participants were motivated to use the instructions

A larger switching error cost was observed in Fake Rare switch than Fake Frequent switch conditions on error rates (Figure 2.10). This pattern was not consistent with the expectation that instruction effects would be apparent both in RT and error measures, but instead the instruction effect was evident solely on error rates. In this respect the reward manipulation may not seem to be successful given the reward should encourage accurate and fast responding that might allow an RT effect to be evident. Apparently, simple speed-accuracy tradeoffs cannot explain the results of switching error difference here. Indeed, there are some studies finding that reward can improve both RT and accuracy simultaneously (e.g., Manohar et al., 2015). Manohar et al., (2015) suggested that reward could recruit more control but at the same time incurred a "cost" on control. The control cost is proposed to improve accuracy of performance. They found when this cost of control factor was considered; reward can improve RT but also increase accuracy.

It is surprising that the effect of instruction on switching error cost, comparing the Fake Frequent and Fake Rare conditions, was not seen in No Reward blocks here, given that this effect was observed in Experiment 1 in which reward was never available. Kleinsorge & Rinkenauer (2012) have suggested that performance enhancement through reward incentive is selective and adaptive. When reward is associated with a specific task, improved performance is only observed on that task but worsened for the non-associated task. Based on this study, it is plausible that when no reward and reward blocks are intermixed, the control signal from the instruction became reward dependent.

General discussion

This first series of three behavioural studies aimed to test the idea of meta-control with a novel experimental design. In the design, participants' beliefs about switch probability were manipulated through explicit instruction, and the instruction varied across short sequences of trials. Critically, participants received different instructions regarding switch frequency, but nevertheless carried out task with exactly the same switch frequency in a subset of sequences. The crucial prediction for these sequences was that the switching cost would vary according to the instructed switch frequency even though the actual objective switch frequency was the same. Experiment 1

provided a first test of this prediction. Experiments 2 and 3 extended the approach and modified the paradigm to test the dependence of instruction effects on motivation, manipulated via reward incentives.

Experiment 1 demonstrated behaviourally that instruction played a role above experience as evidenced by increased switching error costs in the Fake Rare compared with the Fake Frequent condition. Experiment 2 and 3 manipulated reward to demonstrate that this effect was motivation-dependent, as evidenced by a larger effect of instructions exclusively in reward trials. Such motivation dependent control is in line with the interplay between motivation and cognitive control (Botvinick & Braver, 2015). Overall, the three experiments provided evidence for the hypothesis that expected switch frequency can have a global influence on switching costs even while controlling for the actual experienced sequence of events. These findings provide new evidence for the notion of the meta-control by using instructions to isolate high-level meta-control influences on switching processes from other bottom-up processes (e.g., stimulus associations or practice effects on switching) that confound interpretations of previous findings.

These results have implications for theories of cognitive control on how top-down cognitive control is required to protect task goals from interference from local switch information (e.g., responses from the last trial) in situations of switching between

multiple tasks. It has been proposed that the cognitive control system might serve as a shielding mechanism that protects task goals from interference (Millington, Poljac, & Yeung, 2013) and to prevent irrelevant information (e.g., from distracting stimulus attributes) from being processed (Dreisbach & Haider, 2009). Furthermore, the amount of this task shielding has been suggested to be flexibly tuned to the task requirements: Shielding is associated with faster overall responding but increased switching costs (e.g., Dreisbach & Haider, 2009), so that strong task shielding might not be worth implementing in situations with frequent switches. In contrast, in situations with few task switches, shielding mechanisms will result in a clearer performance benefit overall. One way to test whether the shielding mechanism is tuned to different instructions would be to examine congruency effects under different instruction conditions. If shielding did filter information based on relevance to the current task, response congruency effects should differ between instruction conditions. However, the current task design did not aim to investigate congruency effects and many participants had too few trials in relevant conditions to analyse these effects.

In the current studies, through instructions the participants could dynamically adjust the amount of task shielding (to focus attention on now relevant task-set and prevent interference from now irrelevant task) in accordance to task requirements (switching tasks frequently or rarely). Recently, it has been shown that this demand can

be adjusted to different contexts. For instance, response congruency effects were found to be adjusted in different locations in a dual-task paradigm (Fischer, Gottschalk, & Dreisbach, 2014). In this study, the key manipulation was that response incongruent trials were particularly frequent at one of the possible stimulus locations, whereas response congruent trials were particularly frequent at another location. Their results indicated participants could adjust the amount of task shielding according to the location. Moreover, the shielding mechanism has been found to prevent interfering information from being processed in the first place rather than being selected reactively on each trial (Dreisbach & Haider, 2009). These two studies suggest an additional control signal might exist operating above trial-by-trial level of processing, which is in line with the notion of the meta-control. For instance, Dreisbach & Haider (2009) have proposed a global shielding mechanism that can prevent irrelevant information from being processed prior to each trial rather than the traditional conflict monitoring theory (Botvinick, Braver, Barch, Carter, & Cohen, 2001) that specifically focuses on sequential modulation of response conflict. Finally, the current studies might be reminiscent of the notion of sequence monitoring control (Desrochers, Burk, Badre, & Sheinberg, 2015). The basic idea is that a sequence monitoring system exists to keep track of progress toward a high-level goal for sequences of several individual tasks while handling potential exceptions that might attract habitual actions. Meta-control is

similar to sequence monitoring control in terms of temporal abstraction, which principally concerns perturbations of coordinated several subgoals in a longer time frame. However, the current studies differ from these earlier ones (e.g., Schneider & Logan, 2006; Lien & Ruthruff, 2004; Koch, Philipp, & Gade, 2006) in two main ways. First, the paradigm in those studies usually involves memorizing a sequence of actions, which is primarily dependent on working memory. Also, meta-control operates on a more abstract level rather than tracking series of motor actions.

Conclusion

In the three experiments, I sought to use instructions to build a temporally extended control signal and assessed its impact on trial-to-trial transitions in a task-switching paradigm. This was achieved through a novel design that teased apart switch expectancy from actual switch experience. Overall, the results demonstrated that switch expectations could serve as meta-control signal that modulates cognitive control for switching processes, as evidenced by switching error cost differences between the two fake instructions. Importantly, such adjustment appears to be motivation dependent, indicating a link between motivation and meta-control.

Chapter 3

Characterising instruction (meta-control) effects on task-level processing

Introduction

Experiments 1-3 revealed initial evidence of meta-control and established a reliable methodology. The research focus in Experiment 4 shifted to explore further evidence of meta-control in neural data. Using EEG, I aimed to characterise the precise mechanism by which instructions influence task switching performance, in particular by looking for evidence of two contrasting (but not mutually exclusive) ways in which effects of meta-parameters might be expressed.

First, when switch frequency is expected to be high, a participant who just performed Task A might then pro-actively prepare for Task B (and vice versa) in anticipation that this will be the task required. If so, then established neural markers of task switch preparation ought to be enhanced when instructions indicate high switch frequency (i.e., they should be enhanced in the Fake Frequent vs. Fake Rare condition). This view is to a certain degree related to the idea that the implementation of cognitive control can be adjusted dynamically on the basis of expected conflict (MacDonald, Cohen, Stenger, & Carter, 2000).

The other mechanism I considered is more global in nature. According to this view, participants can adopt a meta-level set that is conducive either to stable task performance or task switching, such that they commit less strongly to the current task when switch frequency is high (facilitating switching) or more strongly when switching is rare (facilitating repeated task performance). Then, when anticipating a task switch, one will commit a specific task. This idea relates to the hypothesis that task sets serve as attentional filters that shield the current task from interference but increase the cost of switching tasks (e.g., Dreisbach & Haider, 2006, 2009), as well as to the hypothesis that the strength of attentional filtering of irrelevant information varies strategically according to task context (Botvinick, Braver, Barch, Carter, & Cohen, 2001; Entel, Tzelgov, & Bereby-Meyer, 2014). According to this view, the strength of filtering depends on high-level expectations about the likelihood of task switches.

As markers of task switch preparation, I measured the lateralized readiness potential - LRP (Coles, 1989), and oscillatory activity in the mu (9–13 Hz) and beta (18–26 Hz) ranges, referred to as motor-related amplitude asymmetries - mu- and beta-MRAAs, respectively (de Jong, Gladwin, & M't Hart, 2006), and the frontal contingent negative variation – CNV (Astle, Jackson, & Swainson, 2006, 2008; Vandamme, Szmalec, Liefooghe, & Vandierendonck, 2010). LRP and LRP-like potentials, which originate from motor cortex, are detected contralateral to the response

effector in preparation for movement. The CNV is believed to reflect motor readiness or stimulus anticipation for an upcoming target. In general, the above measures could allow us to assess whether high-level control affects task-specific (motor) preparation in a strategic manner.

As a marker of global attentional filtering, I measured parieto-occipital alpha power, in the range of 8–14 Hz, as a candidate mechanism by which neuronal activity could index general task preparation or task focus (Hughes, Mathan, & Yeung, 2013; Macdonald, Mathan, & Yeung, 2011). Alpha power has been associated with conflict processing, with reduced alpha power after experiencing conflict (Compton, Arnstein, Freedman, Dainer-Best, & Liss, 2011). This post-conflict adaptation is thought to reflect an important aspect of cognitive control, namely, the online adjustment of attention in order to meet current goals. From the meta-control point of view, alpha power changes could reflect higher-level control induced from instructions. Specifically, participants should adjust their attention adaptively in order to filter out task-irrelevant information for each instruction condition. Importantly, similar to switching costs showing sensitivity to switch frequency, Stroop interference is modulated by the proportion of congruent and incongruent trials (e.g., Egner, 2014). This contextual modulation implies there might be a tonic and sustained variation in levels of cognitive control. The high level of task set specifically adjusts attentional

filtering and operates in this global fashion. When switch frequency is high, it is better to expand attention to both of the tasks. On the other hand, when switch frequency is low, attention should focus on the current task. Together, combining preparatory ERP components and oscillatory activity in the alpha band enables me to dissociate two levels of task preparation on which instruction affect switching process. In this way I aimed to better understand the nature of the instruction effect observed in Experiments 1-3.

Experiment 4

The aim of this experiment was to investigate how meta-control modulates the preparation process on the individual trial level, therefore I combined EEG with the paradigm developed in the previous experiments. I assumed the modulatory effects of instruction will be evident on preparation processes evident in the EEG. Among several preparation processes, I focused on motor preparation and general task preparation, which could be functionally treated as lower- and higher levels of preparation, respectively. The preparatory potentials adopted in this study were LRPs, mu- and beta-MRAAs and the CNV. To use LRPs as an example: assuming that tasks had been assigned to separate hands, one would expect a larger LRP for the hand

associated with the same task (task repeat) after a response in the rare switch instruction condition than the frequent switch instruction condition, since using the same hand (i.e., prepare for a task repetition) is a better strategy. Similarly, the CNV is believed to be partly related to motor preparation that occurs as one prepares to respond to a target stimulus. I predicted that the magnitude of the CNV will be larger in frequent switch than rare switch instructions because this component has been shown to be enhanced on switch trials, thus the CNV is expected to be increased in the frequent switch condition.

On the other hand, instructions could operate at a higher level of processing relating to task intentions (e.g., Kiesel et al., 2010). There is long-standing evidence indicating that the interaction between the intention for the current task and the past lingering task set plays a critical role in the task-switching process (Kiesel et al., 2010; Vandierendonck, Liefooghe, & Verbruggen, 2010). Thus, after switching tasks one may build a clear intention for a new task, but nevertheless respond slowly due to some residual attention lingering on irrelevant information that competes with relevant information for a correct response (e.g., Yeung, Nystrom, Aronson, & Cohen, 2006). The strength of intention for a task may be modified through adjusting a global state. Specifically, the global state might adjust goal shielding (e.g., Dreisbach & Haider, 2009) to prevent interference incurred from switching task goals. To index global state, alpha power was measured, which has been commonly associated with general task

preparation or task focus (e.g., Hughes, Mathan, & Yeung, 2013; Macdonald, Mathan, & Yeung, 2011). In particular, alpha power should differ between Fake Frequent and Fake Rare conditions. Following past findings that switching reduces alpha power, lower alpha power should be observed in Fake Frequent in comparison to Fake Rare conditions due to enhanced task engagement for efficient switching.

Methods

Participants

22 additional volunteers (14 female; Mean age = 22.23 years, *SD* = 4.48) were recruited from the University of Oxford community in exchange for course credits or payment. They were either paid £10 per hour or course credit for their participation plus £0-16 extra reward depending on their performance. None reported a history of neurological or psychological disorder.

Apparatus, design, stimuli, and procedure

The procedure followed the same design as Experiment 3 but with two notable changes. First, to allow measurement of task preparation via lateralized motor potentials, responses for the two tasks were distinct (rather than using the same keys, as in Experiments 1-3) and associated with different hands: half of participants used their

left hand to respond in the odd/even task and their right hand to indicate low/high judgements, and for the other half of participants this mapping was reversed. Second, participants completed 14 blocks for a total of 1190 trials (vs. 11 blocks and 935 trials in the previous study) because more trials were required to obtain stable ERPs. Participants sat in a dimly lit, electrically shielded room. Stimuli were presented on a 20-inch CRT (Trinitron, Dell) monitor with a 75 Hz refresh rate using the MATLAB toolbox Psychtoolbox3. Stimuli were viewed from approximately 70 cm.

EEG Data Acquisition

EEG data were recorded from Ag-AgCl electrodes embedded in a fabric cap (QuikCap, Neuroscan, El Paso, TX, United States of America) from 32 channels: FP1, FPz, FP2, F7, F3, Fz, F4, F8, FT7, FC3, FCz, FC4, FT8, T7, C3, Cz, C4, T8, TP7, CP3, CPz, CP4, TP8, P7, P3, Pz, P4, P8, POz, O1, Oz, O2. Additional electrodes were placed on the right mastoid, above and below the left eye, and on the outer canthi of both eyes. The ground was placed at location AFz. All electrode recordings were referenced to the left mastoid and offline re-referenced to linked mastoids. Electrode impedances were kept below 50 kΩ. The data were continuously recorded using SynAmps2 amplifiers (Neuroscan), sampled at 1000 Hz and bandpass filtered at 0.1–200 Hz, with gain of 2816 and 29.8 nV resolution.

EEG Data Analysis

Ocular artifacts were corrected using a regression-based approach (Semlitsch et al., 1986). After ocular artifact correction, the EEG data were downsampled to 250 Hz, then low-pass filtered at 15 Hz and high-pass filtered at 0.1 Hz. Trials were rejected if the voltage change in the epoch were larger than 100 μV in the electrodes: Fz, FCz, Cz, CPz, and Pz. We also excluded the first trial of each instruction sequence and trials with errors or following errors.

In the present paradigm, participants can start to prepare for the upcoming task immediately after response of the preceding task. EEG and ERP analysis therefore focused on the period between the response on trial n-1 and onset of the task cue on trial n, which is a 1 second of response-cue interval (RCI) in which participants could in principle begin to prepare for next trial (e.g., by anticipating the task that will be required).

Response-locked epochs were extracted from the continuous data in time windows from -1000 ms before each response to 1200 ms after each response (which includes the RCI and the subsequent 200 ms). In analyses of ERP components (the CNV and LRP), epochs from each channel were baseline corrected relative to the period between -1000 and -800 ms prior to the response on trial n − 1. This choice of

baseline was firstly chosen to prevent many events (e.g., retrieval of stimulus-response rule, reconfiguration processes) mixing together at this period and then checking through visual inspection of waveforms. Similar results were observed with different baselines. The CNV was quantified as a slow frontal negativity from 400 ms after the response until the time of the next cue onset. Based on this time window, CNV activities were averaged from electrode in frontal region including F3, FC3, C3, Fz, FCz, Cz, F4, FC4, and C4.

LRP activities were measured based on the different amplitudes between electrodes C3 and C4. Mu-MRAA (9–13 Hz), beta-MRAA (18–26 Hz), and alpha power (8–12 Hz) were measured by band pass filtering the EEG epochs from C3 and C4 channels for mu- and beta-MRAA and from electrodes P7, P3, PZ, P4, P8 and POZ for alpha power. To avoid distortions on the edges of epochs, I applied the Hilbert transform (Hilbert function in Matlab) on the continuous data, and then extracted epochs from -1000 ms before response of trial n-1 trial to 1200 ms after this response. The LRP and mu- and beta-MRAA were then calculated using averaged EEG amplitude at C3 and C4 following the equation (Coles 1989): $\frac{(C3-C4)\text{right hand}+(C4-C3)\text{left hand}}{2}$. For the motor preparatory potentials, the time window of interest was the same as the response-locked potentials, from 400 ms after the response until the time of the next cue onset. As for alpha power, the time window

of interest was from 200 ms after the response until the time of the next cue onset.

Results

In what follows, I first present analyses of the behavioural data that aim to replicate the findings of Experiment 3 regarding the impact of switch frequency instructions and their sensitivity to reward incentives. I then present analyses of the EEG data that aim to provide insight into the mechanisms underpinning the observed behavioural effects.

Behavioural results

Real/no instruction conditions

As above, my analysis began with the real and no instruction conditions (Figure 3.1), using the same ANOVA with factors of Reward (no reward, reward), Sequence Type (Real Frequent, Real Rare, No Instruction), and Task Transition (task repetition, task switch). In the RT analysis, all main effects and interactions reached significance. First, the main effect of Reward indicated the effectiveness of the reward manipulation, $F(1, 21) = 20.9$, $MSE = 135{,}320$, $p < .01$, $\eta_p^2 = .50$, with faster overall RTs under reward vs. no reward incentive (589 vs. 636 ms). A significant effect of Sequence Type, $F(2, 42) = 4.1$, $MSE = 7{,}953$, $p = .02$, $\eta_p^2 = .16$, indicated that RTs were overall fastest in the Real

Rare conditions and slowest in the No Instruction conditions. An effect of Task Transition, $F(1, 21) = 74.0$, $MSE = 1{,}215{,}615$, $p < .01$, $\eta_p^2 = .78$, reflected a considerable switching cost of 136 ms overall. There were reliable interactions between Reward and Task Transition, $F(1, 21) = 6.4$, $MSE = 20{,}648$, $p = .02$, $\eta_p^2 = .23$, and between Sequence Type and Task Transition, $F(1, 21) = 13.4$, $MSE = 34{,}645$, $p < .01$, $\eta_p^2 = .39$. The first interaction indicated reduced switching costs with reward from 153 ms to 118 ms. The second interaction replicated previous observations that switching costs were reduced when task switches occurred frequently, with this effect being more strongly apparent in in the Reward condition than in the no reward condition, as reflected in a reliable three-way interaction between Sequence Type, Task Transition and Reward, $F(2, 42) = 9.3$, $MSE = 15{,}157$, $p < .01$, $\eta_p^2 = .21$. Follow-up analyses indicated that the switch frequency effect was only reliable in the reward condition, $t(21) = 5.2$, $p < .01$, but not in the no reward condition, $t < 1$.

In a corresponding analysis of error rate data, I found only reliable main effects of Reward, $F(1, 21) = 9.2$, $MSE = .024$, $p < .01$, $\eta_p^2 = .31$, and Task Transition, $F(1, 21) = 9.7$, $MSE = .016$, $p < .01$, $\eta_p^2 = .32$, reflecting reduced errors rates with reward incentive and on repeat compared with switch trials. Other main effects and interactions were all far from significant, $p > .31$, including the interaction of Sequence Type and Task Transition, $F(1, 21) = 1.2$, $MSE = .002$, $p = .31$, $\eta_p^2 = .06$.

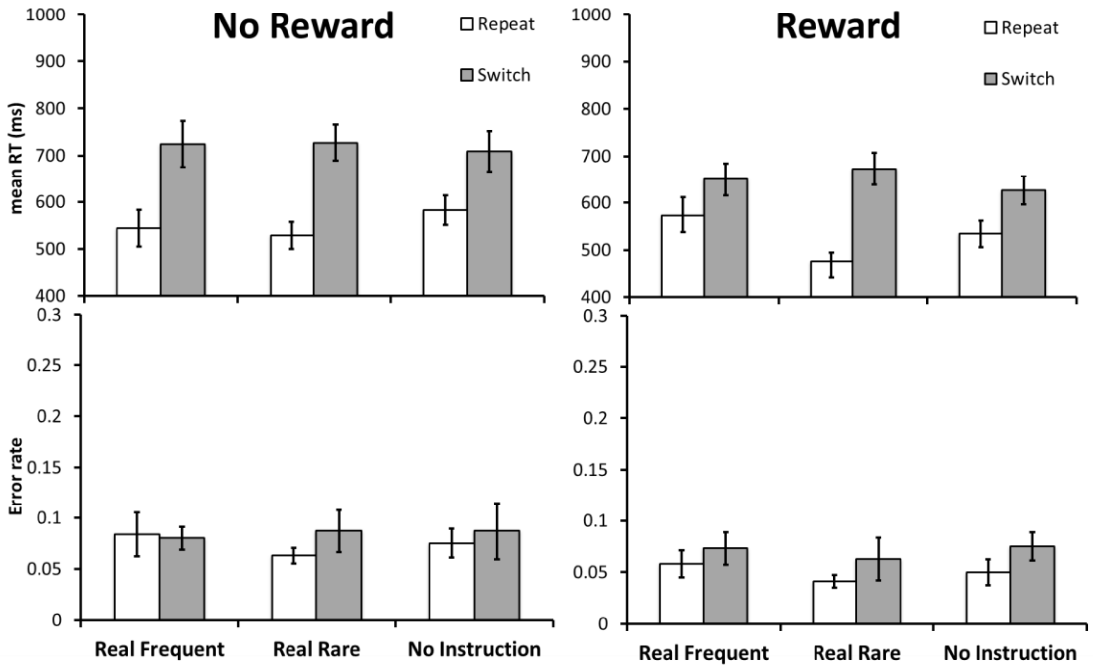


Figure 3.1. *Behavioural performance in the real and no instruction conditions from Experiment 4. Mean reaction time and mean proportion of errors as a function of switch and repeat trials for the three instructions. Error bars represent standard error of mean.*

Fake instruction conditions

Mean RTs and error rates were entered into separate three-way repeated measures ANOVAs with factors of Reward (no reward, reward), Sequence Type (Fake Frequent, Fake Rare) and Task Transition (repeat, switch). Analysis of the mean RT data results from the fake instruction conditions revealed that RTs decreased overall with Reward, $F(1, 21) = 20.2$, $MSE = 126{,}658$, $p < .01$, $\eta_p^2 = .49$, and were slower on switch vs. repeat

trials, $F(1, 21) = 74.6$, $MSE = 798{,}281$, $p < .01$, $\eta_p^2 = .78$. There were larger switching costs overall in reward trials than no reward trials (see Figure 3.2), as indicated by a reliable interaction between Reward and Task Transition, $F(1, 21) = 12.4$, $MSE = 49{,}860$, $p < .01$, $\eta_p^2 = .37$. The three-way interaction was not reliable, $F < 1$. Thus, as in the previous experiment, the RT analysis revealed a reliable overall effect of reward but little modulation of performance according to instruction.

For the error rates, all of the main effects and interactions were significant. Error rates were lower in reward blocks than in the no reward blocks, $F(1, 21) = 12.2$, $MSE = .03$, $p < .01$, $\eta_p^2 = .37$, higher on switch trials than repeat trials, $F(1, 21) = 30.7$, $MSE = .072$, $p < .01$, $\eta_p^2 = .59$, and higher in Fake Rare sequences than Fake Frequent sequences, $F(1, 21) = 36.7$, $MSE = .069$, $p < .01$, $\eta_p^2 = .64$. Of principal interest was the significant interaction between Reward, Sequence Type, and Task Transition, $F(1, 21) = 9.5$, $MSE = .018$, $p < .01$, $\eta_p^2 = .31$, which replicated the previous experiment showing a higher error cost of switching in Fake Rare sequences that was restricted to the reward condition. To explore this 3-way interaction further, I conducted two-way repeated measures ANOVAs on data from reward and no reward blocks separately. These analyses suggested that error cost of switching difference between the two fake instruction conditions was clearly apparent in reward blocks, $F(1, 21) = 9.3$, $MSE = .033$, $p < .01$, $\eta_p^2 = .21$, but not in no reward blocks, $F < 1$. This difference indicates

that the instruction effect was dependent on reward motivation.

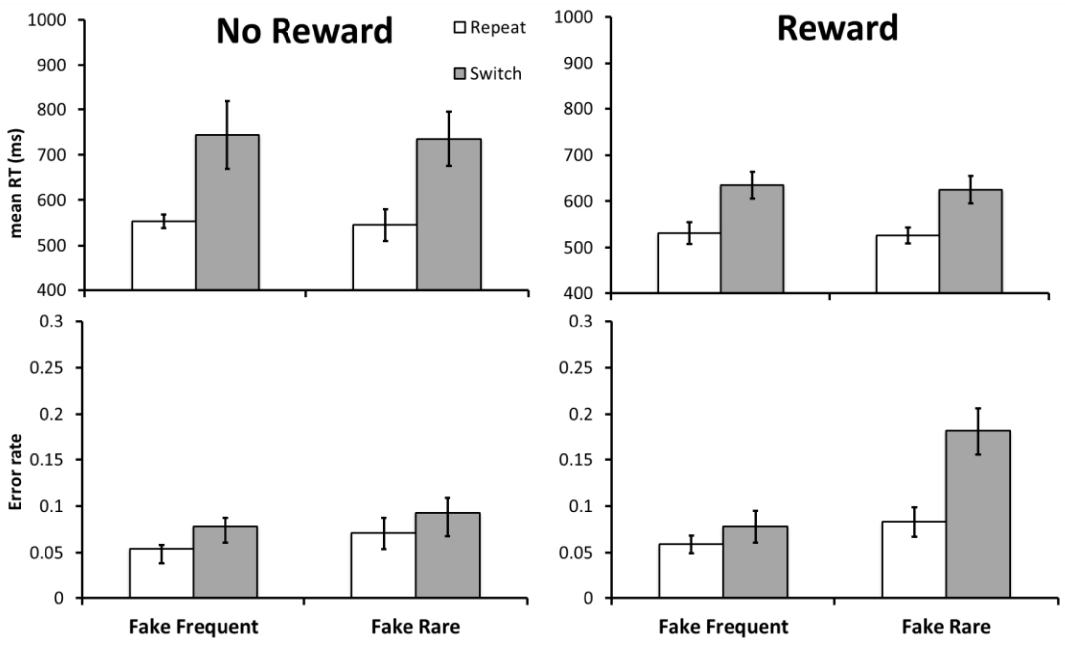


Figure 3.2. *Behavioural performance in the fake instruction conditions from Experiment 4. Mean reaction time and mean proportion of errors as a function of switch and repeat trials for the two instruction conditions, separately for no reward and reward blocks. Error bars represent standard error of mean.*

Collectively, these behavioural results replicate the findings of the previous experiments in showing reliable effects of instructions on switch frequency, even when controlling for the switch rates actually experienced, that are strongly modulated by performance incentives. These findings indicate once again that instructions can be effective in inducing meta-control states that influence task switching performance. Of

interest, then, are the neural correlates of these meta-control states as they are reflected in the EEG. In particular, I investigated modulation effects of meta-control that are instruction-related (contrasting between Fake Frequent and Fake Rare); and influenced by reward. Our EEG analyses focused first on well-characterized indices of task preparation and execution, and on alpha oscillations as a marker of global control state

ERP results

LRPs & mu-and beta-MRAAs

By mapping the two tasks to separate hands, I was able to measure preparation for a particular task in terms of the lateralization of cortical motor activity (de Jong et al., 2006; Poljac & Yeung, 2014). Due to the fact that there were very few trials of task switches or repetitions in some cells of the full factorial design in the real instruction conditions, I could only perform robust statistical comparisons on the fake instruction conditions. Figure 3.3 presents grand-averaged LRP for real instruction conditions, calculated as the voltage difference between electrodes placed over left and right motor cortex (C3 and C4, respectively), with each line plotted according to the hand used for the response on the previous trial. The classical LRP is apparent as a negative-going potential that rises sharply to peak slightly before the recorded keypress response (at 0 ms on the x-axis of the plots). The peak occurs slightly before the response reflecting

the discrepancy between formation of the intention to move in motor cortex (as measured by the LRP) and actual pressing of the response key (to which the ERP waveforms are time-locked).

Of interest was the continuation of this lateralised activity after the response, following an initial oscillatory rebound (seen here in the period 0-200 ms post-response) but before cue presentation for the next trial (at 1000 ms on the x-axis of Figure 3.3). Our main hypothesis was that preparatory activity will be adjusted according to the instructions and will be more pronounced in reward trials. More specifically, when participants expect frequent switches, we might predict anticipatory motor preparation of the opposite hand to the one just used, thus a more positive LRP should be observed in the frequent switch as compared with rare switch sequences both in fake and real instruction conditions. First, for real instruction conditions, I plotted the response-locked lateralization potentials according to the task performed regardless of reward or task transition. As can be seen from Figure 3.3, after 800 ms before the response, an apparent separation starts to develop between frequent and rare switch conditions. The separation between the two real instructions here reflects the fact that the readiness for responses was different. The more negative LRPs in the Real Rare conditions indicate in general the participants tended to prepare the same task (task repeat) with the hand used in the previous trial.

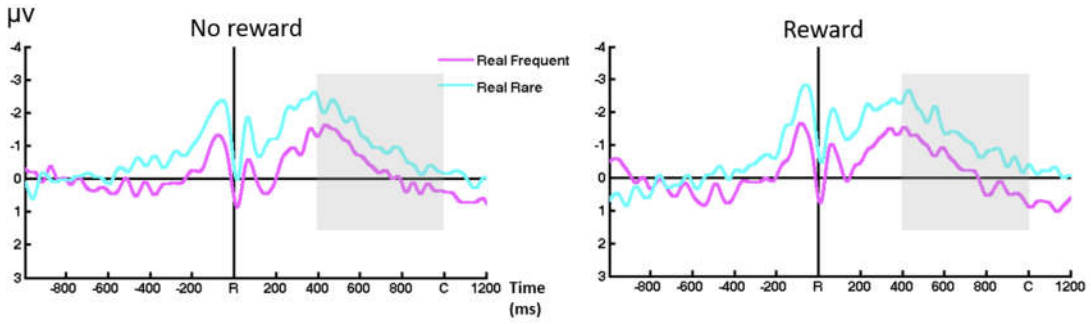


Figure 3.3. *Lateralised readiness potentials averaged across reward and task transitions for the two real instruction conditions. The signal is time locked to the response on the previous trial (labeled R on the x-axis), plotted according to the hand used for the response on the previous trial. R = response of trial n-1, C = cue onset of trial n.*

In this section, the main focus is on the Fake instruction conditions, which are the most important to this experiment. The LRP was analysed using a repeated measures ANOVA with factors of Reward (No Reward, Reward) and Sequence Type (Fake Frequent, Fake Rare). No main effect was statistically reliable, both *p*s > .27. The critical interaction between Reward and Sequence Type was not reliable, $F < 1$. Nevertheless, a trend of more positive LRP can be observed in the frequent switch condition in a "late" 200-ms period just prior to task cue onset (see Figure 3.4 right panel). This trend is in accordance with the prediction that more negative LRPs should

be observed in Fake Rare instructions, indicating that the participants tended to respond with the same hand that was associated with the same task (task repeat).

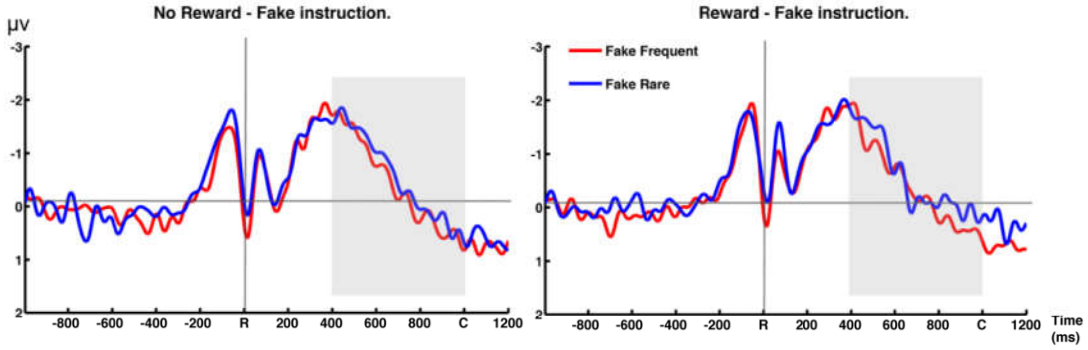


Figure 3.4. *Grand-averaged LRP of the fake instruction conditions. The right graphs are the plots for the reward condition whereas the left graphs are data from no reward trials. The signal is time locked to response on previous trial (labeled R on the x-axis), plotted either according to the hand used for the response on the previous trial. Grey rectangles indicate the time window for the statistical comparison. R = response of trial n-1, C = cue onset of trial n.*

Based on the same formula as the LRP, a corresponding analysis was conducted on the Hilbert-transformed data to measure motor-related asymmetries in the beta and mu bands (Figure 3.5). No main effects nor any interaction terms reached significance for MRAAs in either frequency band, all $F < 1$. These findings seem to suggest the lateralised activity was not modulated by the instruction. However, as can be seen from

Figure 3.5, there is no obvious evidence of lateralization. One might suspect lateralised activity was not established in the first place. To clarify this, I further looked at the overall motor potential in the two frequency bands. In Figure 3.6, clear more negative-going waves are observed just before responses in the two frequency bands despite task transition and instructions. This additional analysis assures that normal motor desynchronisation still can be observed before a response, so that the lack of lateralized effects does not have a clear explanation. These findings imply instruction did not directly affect motor related preparation.

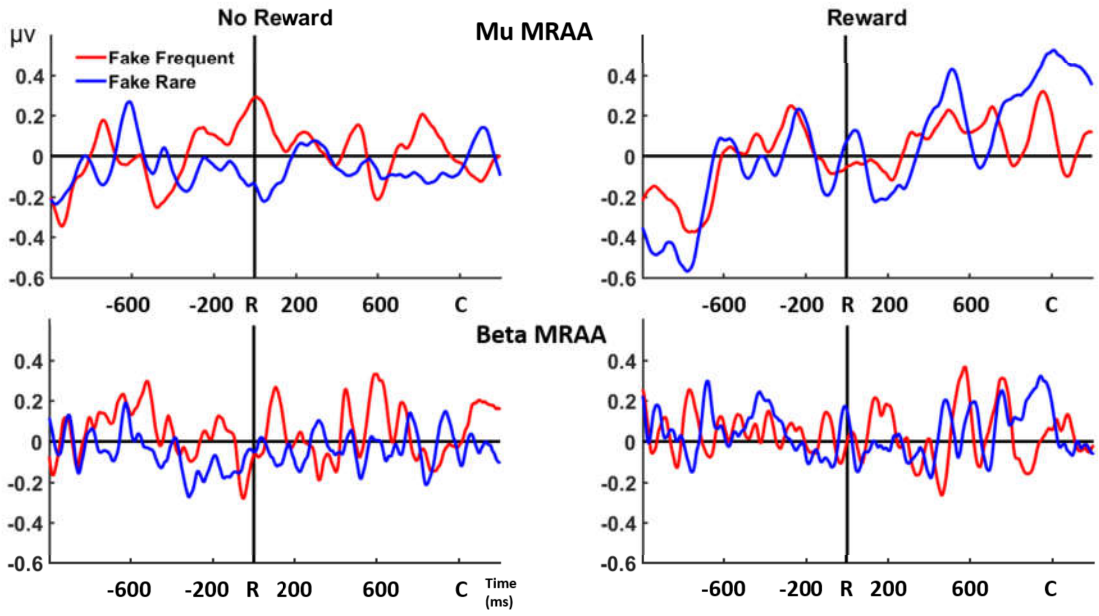


Figure 3.5. *Motor-related amplitude asymmetries (MRAAs) in beta band (18–26 Hz) and mu band (9–13 Hz) as a function of the two fake instruction conditions. The signal is time-locked to the response on trial n-1, plotted either according to the hand used for*

the response on the previous trial. R = response of trial n-1, C = cue onset of trial n.

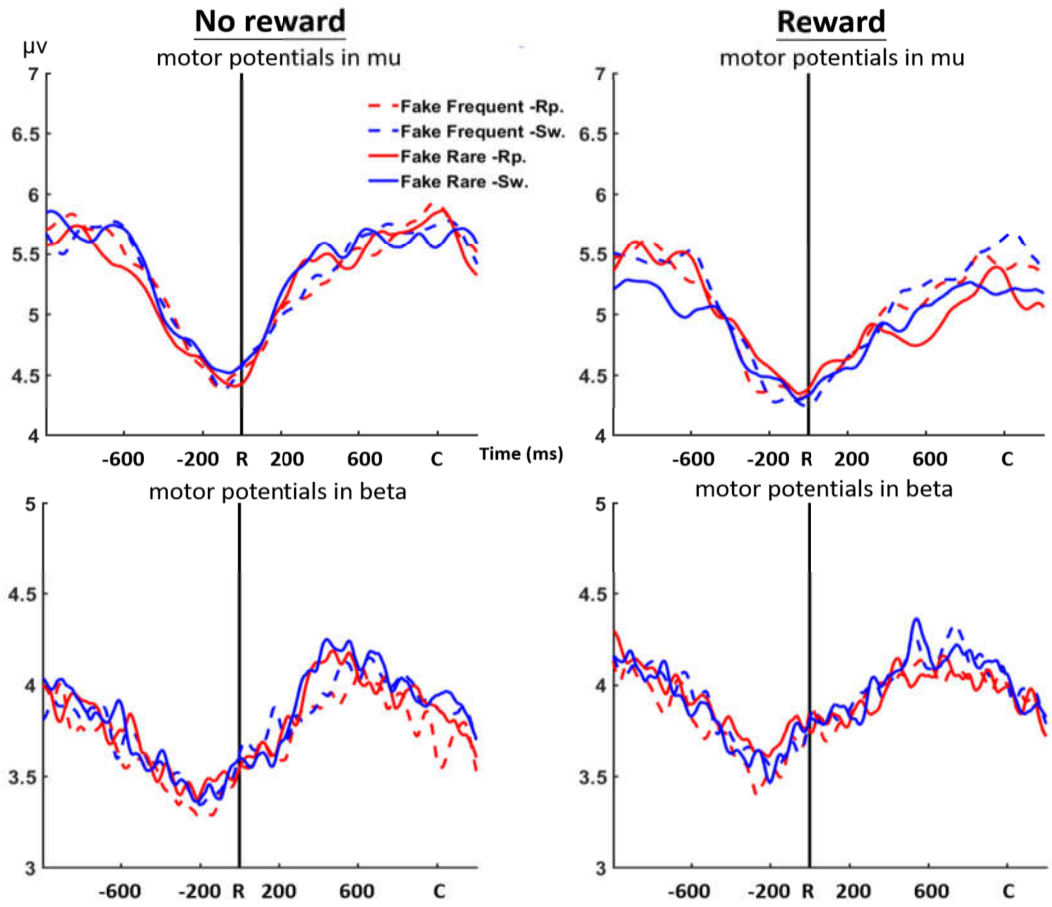


Figure 3.6. *Overall EEG power modulations in the mu and beta frequency bands. Each line plots mu or beta power averaged across electrodes C3 and C4 and across trials with left and right-hand responses. The signal is time-locked to the response on trial n – 1. R = response of trial n-1, C = cue onset of trial n.*

CNV

The CNV has previously been studied as a marker of anticipatory preparation for

an upcoming task switch (e.g., Astle et al., 2006, 2008). To the extent that effects of switch frequency (real or instructed) reflect an active strategy whereby participants anticipate task switches when told they will occur frequently and begin the task reconfiguration process even in advance of task cues, I might expect an enhanced CNV following the response on one trial and before stimulus presentation on the next. To test this prediction, I quantified the CNV at anterior electrodes (F3, Fz, F4, FC3, FCz, FC4, C3, Cz, and C4) as a slow-wave negative potential in the period from 400 ms after the response on trial n-1 and the onset of the cue on trial n. Average voltage during this period was submitted to a 2×2 repeated measures ANOVA with factors of Reward (No Reward, Reward) and Sequence Type (Fake Frequent, Fake Rare) for both real and fake instruction conditions. I started with data of the real and no instruction conditions (Figure 3.7). The main effect of Reward, $F(1, 21) = 8.8$, $MSE = 13.3$, $p < .01$, $\eta_p^2 = .30$ was seen. Overall, more negative going CNVs were observed in No Reward trials. In addition, a marginal main effect of Sequence Type was detected, $F(2, 42) = 2.9$, $MSE = 5.3$, $p = .07$, $\eta_p^2 = .12$, with more negative CNVs in Frequent switch instruction than Rare switch and No Instructions. The rest of the interactions were all below statistical significance, all $p > .20$.

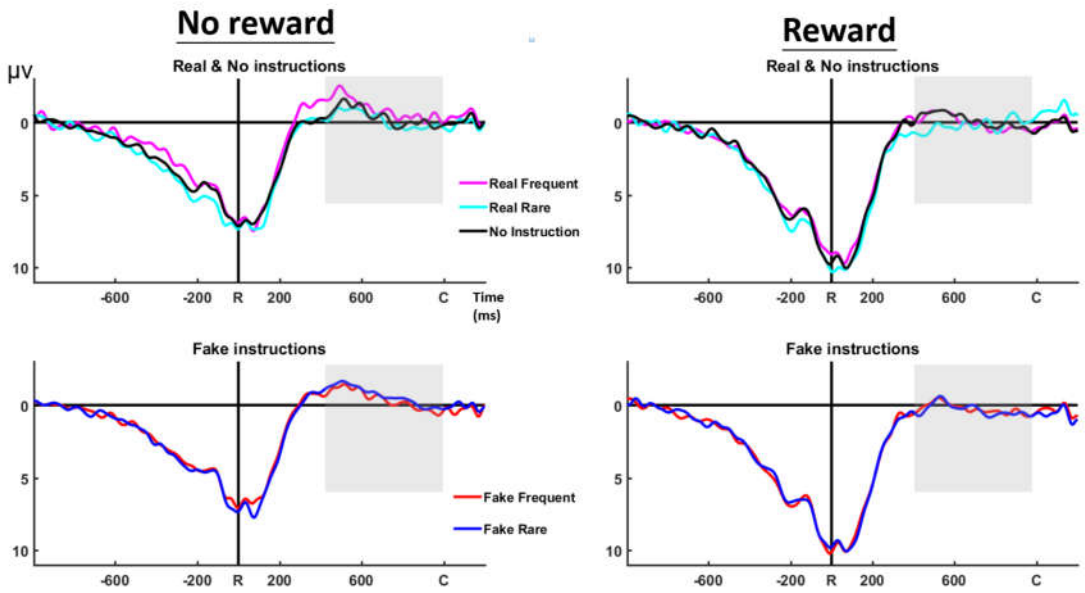


Figure 3.7. *Grand average CNVs for switch and repeat trials for all of the instructions during the response cue interval. Grey rectangles indicate the time window for the statistical comparison. R = response of trial n-1, C = cue onset of trial n.*

As for the data from the fake instruction conditions (bottom row of Figure 3.7), firstly, a more negative CNV in No Reward trials was observed, $F(1, 21) = 12.1$, $MSE = 30.9$, $p < .01$, $\eta_p^2 = .37$. During the same time window, no main effect of Sequence Type was detected, $F < 1$. Similarly, the rest of the interaction terms were all insignificant, all $p > .06$. The CNVs did not differentiate between the two Fake instruction conditions. This suggests the instructions did not modulate response preparatory process directly.

Alpha oscillation

Finally, I turned to the alpha oscillation measure. The core hypothesis was that

instruction will change attentional state as reflected in an adjustment of alpha power. Alpha power was measured using the Hilbert-transform on 8-14 Hz filtered EEG data over parietal-occipital scalp sites, based on channels: P7, P3, PZ, P4, P8 and POZ. Figure 3.8 plots grand-averaged alpha power at posterior scalp sites. One clear feature from the figures is that alpha power is suppressed around response initiation and then gradually returns to a relatively stable level in the inter-trial interval (RCI). The key measure of interest is the magnitude of such rebounds in the response cue interval as a function of instruction types. A straightforward prediction from previous work showing alpha suppression during the inter-trial-interval (e.g., Compton et al., 2011) is that alpha power should be greater if participants expect task switches to be less likely (Real Rare, Fake Rare) because attentional filter/task shielding expands its focus. In the following analysis, no instruction data was not included to focus on contrasting the two switch frequencies instructions and also maximize statistical sensitivity.

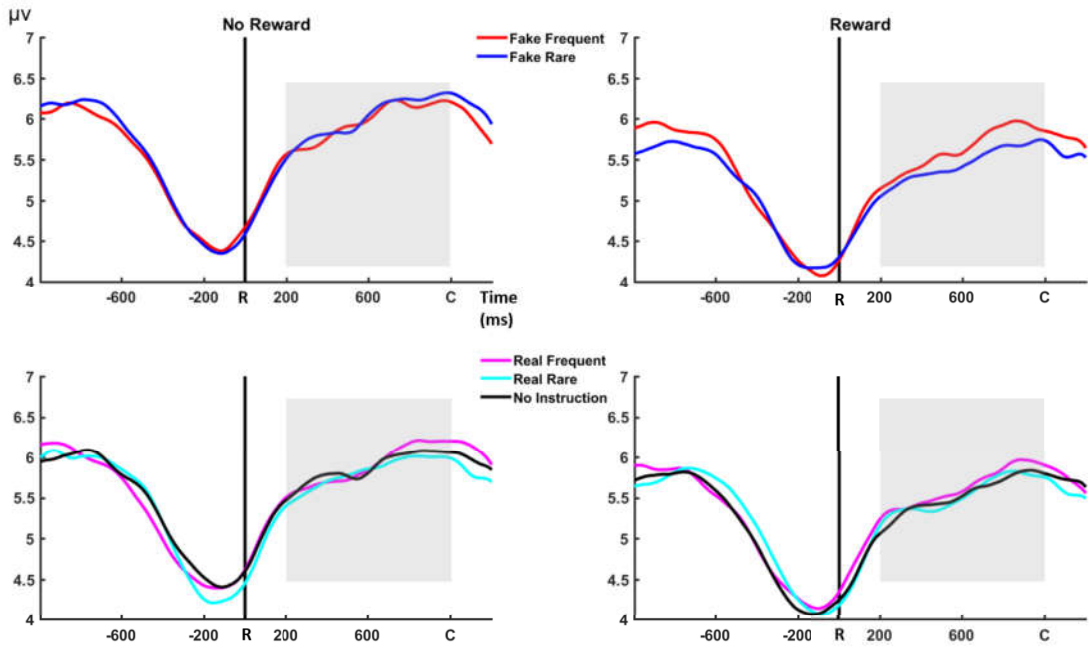


Figure 3.8. *Grand-averaged amplitude-modulated EEG signal filtered at alpha frequencies and is time-locked to the response on trial n − 1. Each colour represents different instruction conditions. The grey region indicates the data used for statistical analysis. R = response of trial n-1, C = cue onset of trial n.*

An ANOVA with factors of Reward (no reward, reward) and Sequence Type (Real Frequent, Real Rare) on the real instruction data revealed that both main effects were reliable, with reduced alpha power in the Reward condition compared to the No Reward condition, $F(1, 21) = 8.5$, $MSE = 2.13$, $p < .01$, $\eta_p^2 = .29$, and increased alpha power in the Real Frequent switch condition compared to the Real Rare switch condition, $F(1, 21) = 6.9$, $MSE = .66$, $p = .02$, $\eta_p^2 = .25$. These two factors did not reliably interact, $F < 1$. The main effect of Reward indicates more task focus or general

task preparation was devoted when participants were motivated by reward incentives. Contrary to the prediction, when switch was likely, a larger alpha power was observed whereas a smaller alpha power was found in rare switch instructions.

A two-way repeated measures ANOVA was similarly conducted on the data from fake instruction conditions, with factors of Reward and Sequence Type. This analysis revealed significant main effects of Reward, $F(1, 21) = 19.\ 5$, $MSE = 3.90$, $p < .01$, $\eta_p^2 = .48$, and Sequence Type, $F(1, 21) = 5.6$, $MSE = .31$, $p = .03$, $\eta_p^2 = .22$. Replicating the result observed in real instruction conditions, alpha power was substantially reduced in reward blocks as compared with no reward blocks (see the top-right Figure 3.8). This finding implies incentive motivation promotes stronger general task preparation. The reliable main effect of Sequence Type indicated different general states might be operated between frequent and rare switch instructions. Again, it is surprising to observe an opposite pattern of alpha power from some perspectives as alpha is often found to be lower when switch trials occur more frequently. Furthermore, a marginal interaction between Reward and Sequence Type was detected, $F(1, 21) = 3.8$, $MSE = .33$, $p = .06$, $\eta_p^2 = .16$, with an apparent alpha differences between Fake Frequent and Fake Rare in reward sequences but not in no reward sequences. Though this critical interaction was only marginally significant, it hints that when participants were motivated, the adjustment of general states might only operate in reward conditions.

This finding actually mirrors the behavioural effects, in which reduced error costs of switching were only observed in reward trials as well.

Discussion

The primary aim of this experiment was to investigate the instruction effect in more depth through preparatory potentials relevant to motor and general task level control. I was particularly interested in whether instructions will affect general task preparation and reflect its influence on alpha oscillations. Besides, I also tested the relationship between reward incentive and the instruction modulation effects (on preparatory potentials). Firstly, as expected the behavioural results of switching error costs were replicated as have been demonstrated in the previous behavioural studies. From the EEG and ERP results, the LRP results and LRP-like mu and beta MRAA results suggested no clear instruction modulation effects at the motor preparation level: I found no clear separations of CNV, LRP, LRP-like activities between the Fake Frequent and Fake Rare conditions during the response-cue interval. These activities were all associated with motor-related preparation. Because the magnitude of LRPs did not differentiate between the two instruction conditions during the response-cue interval, this suggests proactive motor preparation for next task target (mapped to one hand) did not vary according to the instruction. These results suggest that the influence

of meta-control was not apparent in terms of low-level motor preparation for performing an expected task, but rather could indirectly affect a more abstract level of cognitive processing.

This reasoning implies that meta-control induced by instruction may not directly bias preparation for a specific task. Instead it might regulate preparation indirectly, such as balancing goal-shielding. The latter possibility is supported by the alpha power results, which showed higher alpha power during the response-cue (inter-trial) interval in the Fake Frequent condition, in which participants expected to switch often, than in the Fake Rare condition in which instructions led participants to expect more task repetitions.

Alpha power as an index of distinct control states for different instructions

There are several accounts of the functional role of alpha power, one of the most common is that alpha power relates to task engagement (e.g., Macdonald, Mathan, & Yeung, 2011), with reduced alpha power when engaging a task. According to this account, one straightforward prediction is that less alpha power should be observed in a frequent switch condition, because effortful switches are expected to associate more alpha suppression or lower alpha. Studies have suggested alpha power an index of an inability to suppress the irrelevant task dimension (e.g., Gladwin & de Jong, 2005;

Poljac and Yeung, 2012). It is surprising that our results were not in accordance with this simple account. Instead the results are consistent with an alternative account that is derived from the meta-control hypothesis and other similar control theories (e.g., Dreisbach & Haider, 2006). Although it is widely accepted that control adjustments can act locally (e.g., Botvinick, Braver, Barch, Carter, & Cohen, 2001), some studies also suggest control could operate even globally across blocks of trials (Dreisbach & Haider, 2006). A proactive adjustment of goal-shielding (e.g., Dreisbach & Haider, 2006) would be a possible candidate in response to a shift of a block of instruction. Specifically, meta-control could modulate switching efficiency according to instruction based on a mechanism similar to goal-shielding. Goal-shielding can reduce interference from competing stimulus dimensions by narrowing the focus of attention toward the currently relevant features. That is, when switch probability is low, the attentional filter will shrink to focus only on task-relevant dimensions or features, which should facilitate task repetitions, whereas when switch probability is high the filter could expand to both dimensions of tasks for efficient switching. From another possible explanation, a narrowly focused attentional filter is inevitably prone to making errors on unexpected task switches, which then recruits more cognitive control that could lead to the reduced alpha power observed here. That is, when the filter is strong, switch errors will result, and control will be recruited, reflected in reduced alpha. This

explanation can be supported by a study showing that a synchronization of high 10-12 Hz alpha has been associated with inaccurate attentional switching performance (Verstraeten & Cluydts, 2002). Finally, the alpha results and the behavioural effects on switching error costs were both found in reward trials, which indicates the attentional filter mechanism could be motivation dependent.

Reward effects on the two levels of preparatory potentials

Another effect that has repeatedly been found in this series of studies was the reward modulation effect. Alpha power was found to be lower in blocks with reward incentives whereas CNVs were enhanced in No Reward trials. Besides the role of motor preparation in the CNV, the formation of intention or intentional control for the stimulus prior to target onset has also been emphasised (Chen & Hsieh, 2015). Based on this reasoning, one would expect enhanced CNVs in reward trials where the intention for a task has been biased by the instruction. However, CNVs were only apparent in No Reward sequences but not in Reward trials, and the study was not designed to test different sensitivity to intentions of the two tasks.

The suppressed alpha power during sequences with reward incentive is in line with incentive-induced performance enhancements in task switching (Gladwin & de Jong, 2005). In task switching studies, greater alpha desynchronization is observed in

individuals with fast, accurate, and stable task performance compared with slow and inaccurate performers (Verstraeten & Cluydts, 2002). The overall reduced alpha power suppression in reward trials is likely to be related to phasic arousal or alertness. I suggest the alpha modulation effect between the Fake Frequent and Fake Rare condition might be a modulation effect on task (e.g., task-relevant information being filtered or not) not response-specific preparation, but the overall reward effect could reflect alertness, attentional demand or expectancy.

Conclusion

The EEG results from Experiment 4 provide insight into the mechanisms by which instructions about switch frequency affect task switching performance. There were no effects of instruction on lateralized motor activity, suggesting that meta-control did not directly prepare either one of the two tasks. Instead, the key difference observed here was alpha activity in the inter-trial interval between instruction conditions, with greater activity in Fake Frequent than Fake Rare conditions. The finding of alpha power was interpreted in terms of strategic modulation of task shielding (e.g., Dreisbach & Haider, 2009). The amount of this task shielding needs to flexibly tune to task requirements such as whether switches occur frequently or rarely. Recently, some studies have suggested that task shielding can be triggered globally so that interfering information

can be prevented from affecting processing in the first place rather than through local, conflict-triggered task shielding (Dreisbach & Haider, 2009). The instructions in the current studies could be mediated by this global shielding mechanism.

Chapter 4

Task choices can be biased by meta-control

Introduction

The findings of Experiments 1-4 suggest that task selection and performance are affected by higher-level mental task representations. To search for further evidence supporting this suggestion, the present experiments extended the instruction manipulation used in previous studies by combining this with a voluntary task switching procedure. In the present experiment, occasional trials requiring participants to choose the task to perform were introduced into the cued switching design used in the previous experiments. Voluntary task switching was first introduced by Arrington and Logan (2004). As described in Chapter 1, in voluntary task-switching paradigms, participants are instructed to select between tasks randomly according to their own will or preference. As a result, with apparent demand for voluntary selection, the VTS procedure has been utilized as a valid tool for exploring endogenous control. Based on this reasoning, I predicted that instructions regarding switch frequency, as a manipulation of meta-control, would affect proportions of voluntary task repetitions and switches.

One obvious reason to introduce voluntary trials in a switch frequency

environment was that it allowed me to study relatively pure influences of "top-down" control without the confounding of experience-driven control. Previous voluntary task selection studies have rarely addressed this issue. However, recent studies by Fröber and Dreisbach (2016) (that were published after the present work was carried out) found that expected reward can bias the cognitive control system toward stable behaviour in a voluntary task-switching design. The stability of behaviour was assessed through switch frequency, with fewer task switches observed when reward was expected to be high. Importantly, they also found that voluntary task switches are more common in a context in which task switches occurred frequently. This study shows how the voluntary task-switching procedure can be used to assess cognitive states (and their bias toward either flexibility or stability).

The main purpose of Experiment 5 was to test the prediction that instructions about switch frequency would bias task selection in voluntary selection trials. This finding would demonstrate a relatively "pure" top-down control effect, excluding bottom-up influences of experience or practice that are known to affect voluntary task-switching performance (Arrington & Reiman, 2015). In the task switching literature, one well-studied expression of past experience is between-task competition, in particular the asymmetrical cost when participants switch between tasks differing in strength. For example, Yeung (2010) asked participants to switch between an easy

(spatially compatible) location classification and a more difficult (arbitrarily mapped) shape classification. Participants consistently exhibited small bias toward relatively difficult task. Along similar lines, Orr et al. (2012) showed that detection of response conflict recruits cognitive control and leads to an increased activation of current task, so that the task is more likely to be chosen again on the subsequent trial. In addition, although individuals are typically instructed to select both tasks equally, most studies still observe a strong tendency for participants to repeat the task they just performed (repetition bias). This tendency has been proposed to reflect a decaying influence on task selection that derives from the initial exposure to a stimulus of previous trial (Arrington, Weaver, & Pauker, 2010). In a study by Arrington (2008), participants' choice of categorization rule to apply to noun stimuli was affected by the exposure of task type for the first trial with that noun (Arrington, 2008) and by the location of the stimulus (Arrington & Rhodes, 2010).

Weaver and Arrington (2013) have studied hierarchical representations in voluntary task switching paradigms. Their participants were asked to switch between four task elements and the task selection of voluntary trials was influenced by a hierarchy that grouped task elements temporally or spatially during practice session. Their main hypothesis focused on whether this hierarchical representation would persist during the testing even though this structure was no longer required. Their

results revealed that task choice was biased toward within-aggregate task switches. While task choice was available equally on each trial, participants chose to persist in the performance of task elements that belonged to the same aggregate task as the task element performed on the previous trial.

This brief overview of voluntary task-switching research indicates that task selection combines goal-directed and stimulus-driven factors. Thus, the key aim of the current experiment was to demonstrate intention-driven influences on task choice that are clearly distinct from bottom-up influences such as stimulus priming. Analyses focused on two dependent measures: voluntary choice and RTs of cued trials. As in previous experiments, analysis focused on the two fake instruction conditions (Fake Rare vs. Fake Frequent), to test the prediction that the tendency to shift to another task should be enhanced in the Fake frequent condition relative to the Fake rare condition. The novel aspect of this experiment was testing this prediction in relation to voluntary task choice, in addition to traditional performance costs of cued task switching. Once again, the real instruction conditions provide a baseline contrast in which bottom-up experience of switches also differed.

Experiment 5

Methods

Participants

Twenty-one students from the University of Oxford took part in this study (12 female; Mean age =19.1 years, SD =1.20). All of them reported normal or corrected-to-normal vision and no colour-blindness and received payment or course credit for participating. All participants signed informed consent before the start of testing and were debriefed after the session.

Design and procedure

The design was generally similar to my previous experiments, with participants performing short task switching sequences that were preceded by instructions about expected switch frequency. The novel manipulation was that five voluntary trials were introduced in each sequence. On these trials, a third cue was used, which indicated that participants had to choose for themselves which task to perform on the upcoming stimulus. To identify the task used by the participants, the tasks were mapped to two separate hands. Therefore, the task performed on these voluntary trials can be inferred from the hand used.

Again, three types of instructions regarding switch frequency were given to participants (Frequent Switch, Rare Switch, No Instruction), and for some blocks in each condition the actual switch frequency was equal to 50%. Switch frequency was calculated based on the cued trials and independent of the inclusion of voluntary trials. Task transition for the trials after voluntary trials was based on the participants' choice on these voluntary trials. For instance, if the participant chose to repeat a task (e.g., odd/even task) on a voluntary trial and the next cued trial was selected randomly as a task switch, the next task would be cued as a low/high task trial. After the first trial in a sequence, in which participants were never given voluntary choice over the task to perform, 21 trials followed which consisted of 16 cued trials and 5 voluntary trials. Cued trials were the same as in previous experiments, with red and blue frames indicating the required task. The 5 voluntary trials, indicated by a grey cue frame (RGB code, [100,100,100]), were randomly inserted into each instruction sequence with the constraint that they never occurred on consecutive trials. In these voluntary trials, participants were told to choose one of tasks without any restrictions. Participants were required to respond within 5000 ms after stimulus onset. As in Experiments 2-4, randomly half of the blocks were incentive sequences. Reward information was delivered at the beginning of each sequence and the criterion for gaining reward remained the same (above 90% accuracy and RT better than baseline). Performance on

voluntary trials was also considered for reward delivery.

Before the experimental blocks, all participants began with six short practice blocks. First, participants were familiarized with both tasks separately in two short practice blocks (16 trials each). These practices were followed by a practice at switching between the two tasks in random order. The next two practice blocks varied switch frequency, at 66% in one block and 33% in the other, with these probabilities explicitly instructed. In the final practice block, voluntary trials were introduced in the switch frequency environment. To ensure participants' familiarity with these requirements, a 90% accuracy criterion was set in each practice block. The whole practice session lasted about 15-20 minutes.

The practice session was followed by ten experimental blocks (110 trials each). The details of block design were identical to previous experiments with five short sequences and each sequence was announced by a specific instruction. Similarly, the reward message occurred in 50% of sequences and was presented with the switch frequency information. The procedure of each trial was the same as previous experiments (see Figure 4.1). The whole experiment lasted about 60 minutes.

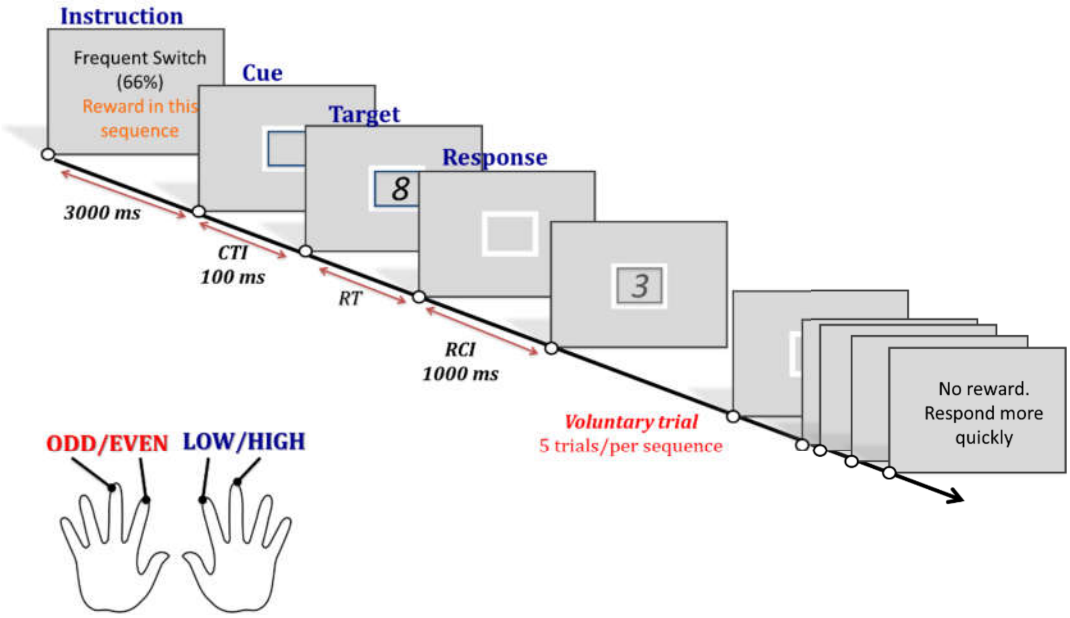


Figure 4.1. *Behavioural task of Experiment 5. Participants were told to respond to the target digit that appeared inside the coloured frame and select the appropriate task according to the colour of the frame. The same procedure was applied to the voluntary trials except the coloured frame was in grey. In this example, the odd/even task (with red frame) was mapped to left hand while the low/high task (with blue frame) was responded by right hand.*

Apparatus and stimuli

The experiment was run using Matlab Psychtoolbox (Psychology Software Tools, Sharpsburg, PA) on a 17-inch CRT display (resolution at 1280*1024 pixels) with a 75 Hz refresh rate. Responses were recorded with a standard QWERTY-keyboard, using "z" and "x" as left response keys with the index and middle fingers for one of tasks. For the other task, "n" and "m" response keys were used and responded with the right index

and middle fingers. The mapping of tasks to hands was counterbalanced across participants.

Preprocessing and data analysis

Data analysis focused on RTs and error rates as in previous experiments, but also on participants task choices in voluntary selection trials. The first trial of each block, error trials, and trials following an error were excluded from the RT and choice analyses (15.3% of trials). Task type (low/high versus odd/even) had little effect and so this variable was not included as a factor in the final data analyses. An alpha level of .05 was used to determine statistical significance. Because my main interest was to compare the two fake instruction conditions, I conducted separate ANOVAs for the real and fake instruction conditions. To emphasize the difference between the two fake instruction conditions and increase statistical sensitivity, data from the No Instruction condition were analyzed together with the real instruction conditions. Data from three participants were excluded from the voluntary analyses because they did not select tasks at random indicating a strong bias to one of tasks, which suggests their free choice might have been driven by a task preference not the instruction. For analyses of the voluntary trials, the identity of the chosen task was defined as the hand of participant used to respond. Consequently, an error on voluntary trials was determined as

responses with the wrong finger of chosen hand.

Results

Real instruction conditions – performance on cued trials

The first analysis aimed to replicate the basic effects of real switch frequency instructions on cued task switching performance. A repeated measures ANOVA was performed on mean RTs (Figure 4.2), with factors of Reward (reward vs. no reward), Sequence Type (Real Frequent, Real Rare, No Instruction), and Task Transition (repetition, switch). A reliable main effect of Reward indicated that the reward manipulation was successful in reducing RTs, $F(1, 20) = 63.4$ $MSE = 573{,}681$, $p < .01$, $\eta_p^2 = .76$ (see Figure 4.2). The other main effects were also significant: Sequence Type, $F(2, 40) = 13.8$, $MSE = 114{,}133$, $p < .01$, $\eta_p^2 = .41$, and Task Transition, $F(1, 20) = 65.1$, $MSE = 1{,}531{,}009$, $p < .01$, $\eta_p^2 = .77$. Reward incentives benefitted the sequence types to different degrees, $F(2, 40) = 9.6$, $MSE = 40{,}795$, $p < .01$, $\eta_p^2 = .33$. Follow-up contrasts with Bonferroni correction indicated a larger reward benefit in the Real Frequent than Real Rare conditions, $p = .03$, and No Instruction, $p < .01$, conditions. The standard switch frequency effect was found again, as indicated by the interaction between Sequence Type and Task Transition, $F(2, 40) = 3.9$, $MSE = 19{,}933$, $p = .03$, $\eta_p^2 = .16$. Moreover, this interaction further interacted with Reward, $F(2, 40) = 11.5$, $MSE =$

33,473, $p < .01$, $\eta_p^2 = .36$, with reduced switch frequency effects in reward blocks.

The same ANOVA was applied to the error rate data (see bottom panels of Figure 4.2). The results indicated that performance in the reward blocks was overall better than in no reward blocks, $F(1, 20) = 12.7$, $MSE = .025$, $p < .01$, $\eta_p^2 = .39$. Error rates of task-switch trials were higher than task-repetition trials, $F(1, 20) = 8.7$, $MSE = .028$, $p < .01$, $\eta_p^2 = .30$. No interactions reached statistical significance, including the interaction between Sequence Type and Task Transition, $F < 1$, which suggests the switch frequency effects were not consistently observed in the error rate measure.

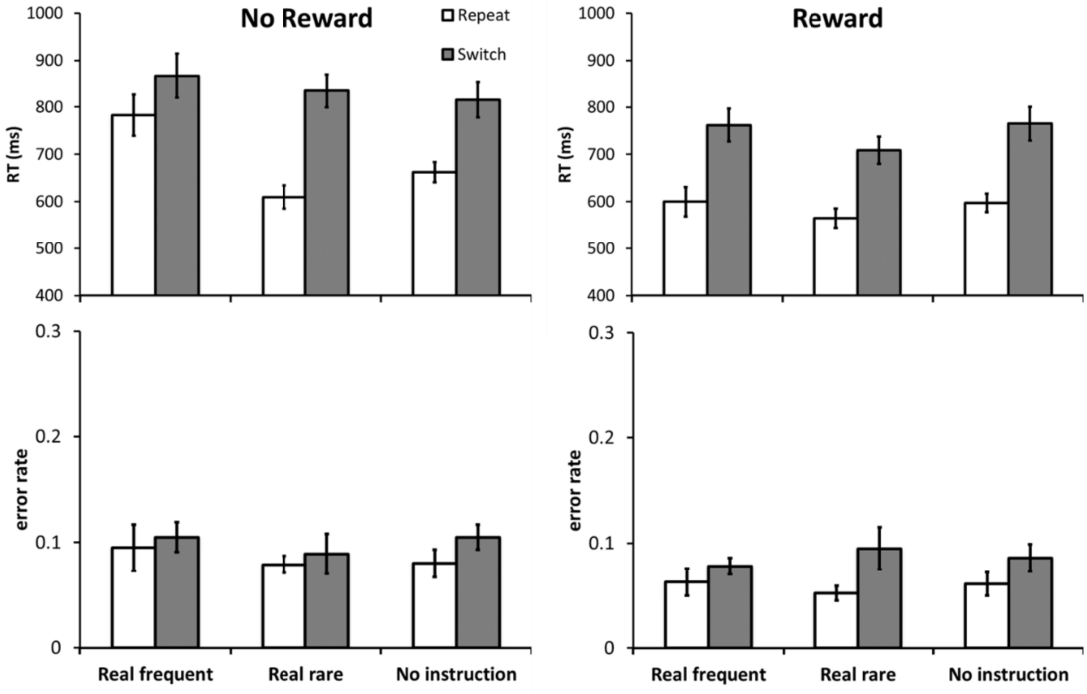


Figure 4.2. *Mean reaction times and error rates in the real instruction conditions in Experiment 5 as a function of reward (right vs. left panels), instruction type, and task transition. Error bars indicate standard error of the mean.*

Fake instruction – performance on cued trials

Replicating the key analysis of previous experiments, a repeated measures ANOVA was conducted on data from sequences with fake instructions, using factors of Reward (no reward, reward), Sequence Type (Fake Frequent, Fake Rare), and Task Transition (task repetition, task switch). The results yielded only two significant main effects: Reward and Task Transition. As can be seen from Figure 4.3, overall RTs of the reward condition were much faster than the no reward trials, $F(1, 20) = 17.5$, $MSE = 98{,}297$, $p < .01$, $\eta_p^2 = .47$. The significant main effect of Task Transition indicated a robust switching cost of 157 ms, $F(1, 20) = 50.4$, $MSE = 1{,}029{,}070$, $p < .01$, $\eta_p^2 = .72$. As in previous experiments, RT switching costs in the Fake Frequent and Fake Rare conditions were of similar magnitude, as reflected in a non-significant interaction between Sequence Type and Task Transition, $F < 1$.

A corresponding analysis of the error rates from the fake instruction conditions (Figure 4.3) revealed that participants overall made more errors in the Fake Rare sequences than the Fake Frequent sequences, $F(1, 20) = 10.0$, $MSE = .03$, $p < .01$, $\eta_p^2 = .33$, and made more errors on switch trials than repeat trials, $F(1, 20) = 57.2$, $MSE = .21$, $p < .01$, $\eta_p^2 = .74$. There were reliable interactions between Reward and Sequence Type, $F(1, 20) = 7.3$, $MSE = .02$, $p = .01$, $\eta_p^2 = .27$, and between Sequence Type and

Task Transition, $F(1, 20) = 10.9$, $MSE = .04$, $p < .01$, $\eta_p^2 = .35$. Most importantly, the critical three-way interaction was also reliable, $F(1, 20) = 6.6$, $MSE = .02$, $p = .02$, $\eta_p^2 = .25$, once again confirming the observation of a larger switching error cost in Fake Rare than Fake Frequent sequences in reward blocks, $t(20) = 2.6$, $p < .01$, but no such differences in no reward blocks, $t < 1$. These findings are consistent with the hypothesis that switch performance was affected by meta-control and replicated the previous behavioural studies in which instruction influence was mainly detected in error rates measure.

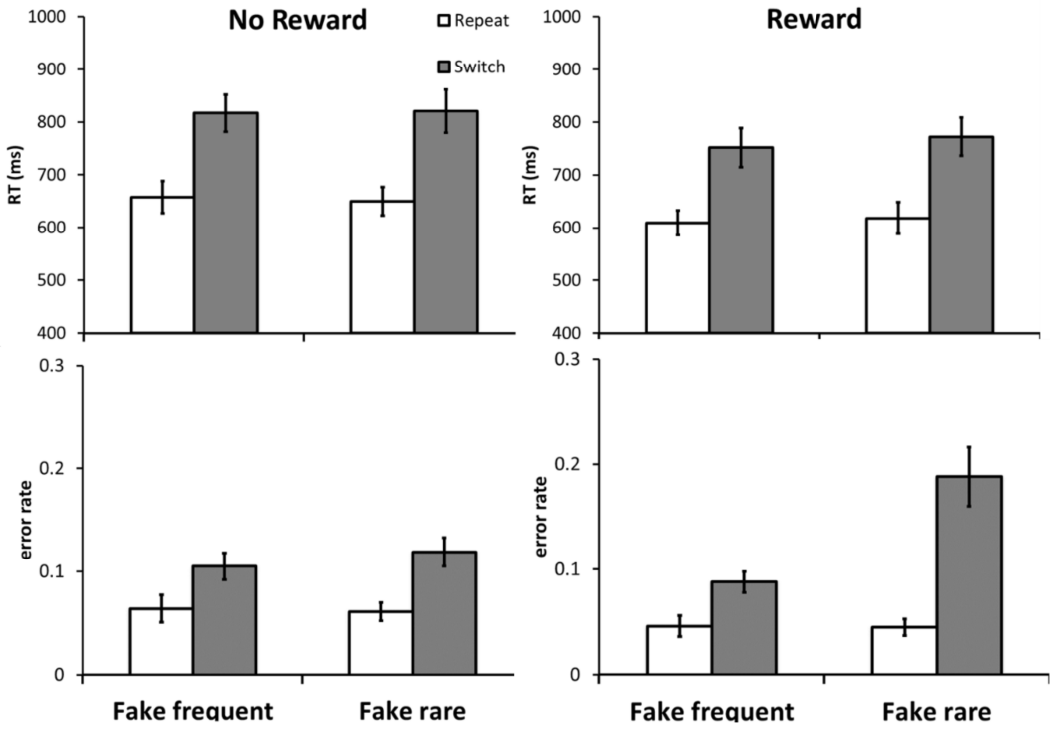


Figure 4.3. *Mean reaction times and error rates of the fake instruction conditions in Experiment 5 as a function of reward, instruction, and task transition. Error bars stand*

for the standard error of the mean.

Task vs. response errors on cued trials

In this experiment, the two tasks were mapped to separate hands to allow us to determine which task was chosen on voluntary choice trials. This manipulation also allows us to distinguish two kinds of errors on cued trials—where participants perform the wrong task (i.e., respond with the incorrect hand) versus where they perform the correct task but choose the wrong response within that task (i.e., respond with the correct hand but incorrect finger). This approach has been used previously, (e.g., by Muhle-Karbe, Adres & Brass, 2014), to show distinct preparation for tasks vs. actions.

I expected that the manipulation of instruction (fake instruction) should lead to incorrect anticipation of task, leading to increased rates of Wrong hand errors in the Fake Rare condition on task switch trials. To address this question, the percentages of each error type were analysed separately using repeated measures ANOVAs with the factors Reward, Instruction, and Task transition.

Response-set error (Wrong finger type) vs. Task-set error (Wrong hand type)

For the Wrong finger error type, a repeated measures ANOVA with factors of Reward, Sequence Type, and Task Transition was conducted for the fake instructions

on these errors. As for the fake instructions (Figure 4.4), the response set errors seem not to differ between the two fake instructions, as suggested by non-significant main effect of Sequence Type, $F < 1$. Only the factor of Task Transition was significant, $F(1, 20) = 26.9$, $MSE = .021$, $p < .01$, $\eta_p^2 = .57$.

On the other hand, for the Wrong hand type, again with a 3-way repeated measures ANOVA, analysis of task-set selection errors yielded a significant main effect of Task Transition, $F(1, 20) = 20.0$, $MSE = .048$, $p < .01$, $\eta_p^2 = .50$, and a marginal main effect of Sequence Type, $F(1, 20) = 4.2$, $MSE = .004$, $p = .06$, $\eta_p^2 = .17$. Most importantly, a marginal interaction of Reward × Sequence Type × Task Transition was found, $F(1, 20) = 4.0$, $MSE = .004$, $p = .06$, $\eta_p^2 = .17$, supporting the observation that a larger proportion of task-set errors occurred in particular in Fake Rare but not in Fake Frequent sequences (see the bottom-right panel of Figure 4.4). Though the pattern was only marginally significant, the trend was consistent with the prediction that Fake Rare instruction should lead to incorrect anticipation that the task would repeat, leading more task-set errors when the task in fact switched. Also, the pattern is reminiscent of the key results found in the previous behavioural studies, with larger switching error costs in Fake Rare compared to Fake Frequent sequences. Moreover, the results indicated the majority of errors in the Fake Rare sequences were task-set selection errors, which implies the influence of the meta-control. In short, the two types of errors revealed

quite different patterns in which task-set errors but not response errors were specifically increased in task switch trials of Fake Rare instructions. This suggests the errors observed in the Fake Rare conditions could be mainly attributed to task selection errors at an abstract level of representation.

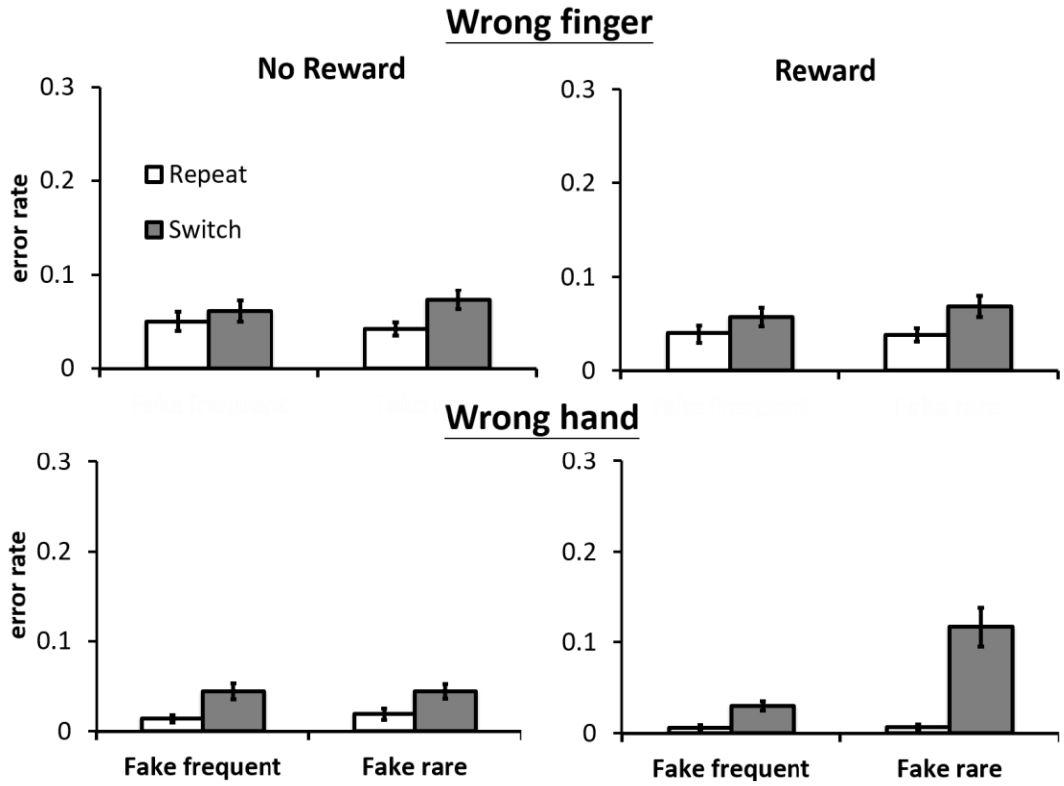


Figure 4.4. *Mean error rates of Wrong finger type and Wrong hand errors in the Experiment 5 as a function of reward, the instruction types, and task transitions. Wrong finger errors were defined as using incorrect fingers while using the correct hand. Wrong hand errors were defined as using incorrect hands irrespective of fingers to respond. Error bars denote the standard error of the mean.*

Task choices on voluntary trials

Task choice was assessed as a key measure of meta-control effects in a task-switching environment with some freedom. Voluntary task-switching trials were sorted into task transitions based on the hand used to respond. Of primary interest was the comparison of proportions of task repetitions and switches on these voluntary trials between the frequent switch and rare switch sequences. If meta-control was biasing task selection, then the proportion of voluntary switches should be greater when instructions indicate that task switches are frequent than when instructions indicate that switches are unlikely. Moreover, the expected pattern should be apparent with both real and fake instruction conditions.

Figure 4.5 displays the proportion of the voluntary repetition and voluntary switch trials in real and no instruction conditions. The repetition bias reported in previous voluntary task-switching studies (e.g., Millington, Poljac, & Yeung, 2013) was present in this data, such that the proportion of task repetitions was high overall, regardless of instruction. Since proportions of task repetition and task switch are complementary, a repeated measures ANOVA with factors Reward and Sequence Type was performed on the single measure of task switch proportion. Consistent with the prediction the switch proportion would be higher in Real Frequent conditions, there was a significant main

effect of Sequence Type, $F(1, 20) = 24.1$, $MSE = .60$, $p < .01$, $\eta_p^2 = .55$. Follow-up planned comparisons with Bonferroni correction revealed that all pairwise comparisons were significant. Of interest, participants chose more switches in Real Frequent conditions than Real Rare, $p < .01$, and No Instruction conditions, $p = .02$ (cf. Fröber & Dreisbach, 2017). No reliable differences in switch proportions were found between reward and no reward conditions, $F(1, 20) = 3.0$, $MSE = .02$, $p = .10$, $\eta_p^2 = .13$. The interaction between Reward and Sequence Type was not reliable, $F < 1$.

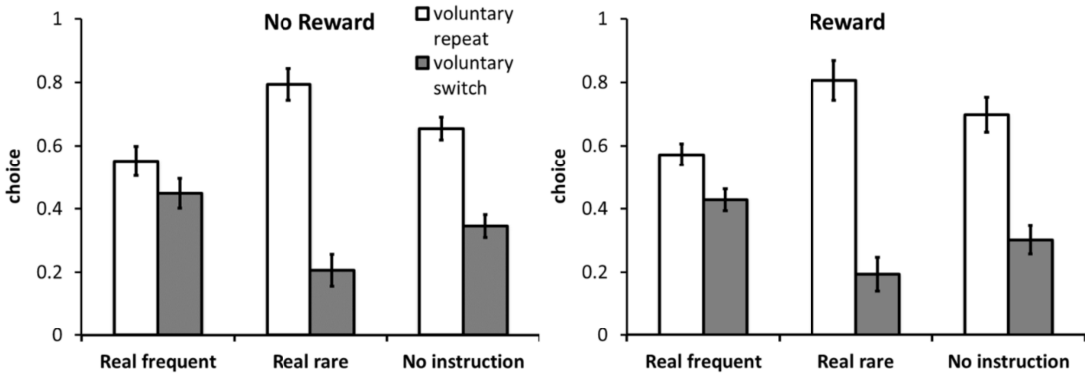


Figure 4.5. *Proportions of task repetitions and task switches on the voluntary trials in Experiment 5 for the real instruction and no instruction conditions. Choices are plotted as a function of reward and instruction. Error bars denote the standard errors of the mean.*

For task choices in sequences with fake instructions (Figure 4.6), a corresponding ANOVA was performed with factors of Sequence Type (Fake Frequent vs. Fake Rare)

and Reward (reward vs. no reward). A higher proportion of voluntary task switches was observed in Fake Frequent than in Fake Rare sequences, which was confirmed by the significant main effect of Sequence Type: $F(1, 20) = 6.6$, $MSE = .13$, $p = .02$, $\eta_p^2 = .25$. Neither the main effect of Reward, $F < 1$, nor the interaction between Sequence Type and Reward was statistically reliable, $F < 1$.

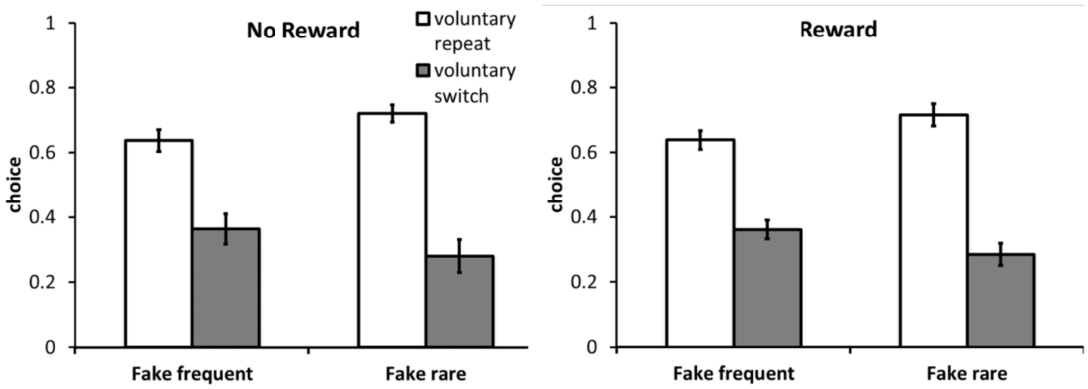


Figure 4.6. *Proportion of task repetitions and switches on the voluntary trials in Experiment 5 for fake instruction sequences, as a function of reward and instruction. Error bars denote standard errors of the mean.*

Since participants were not told to select both task equally on these free choice trials, participants' choice of task was examined to ensure the results were not driven by the types of task. The two tasks were designed to have equal difficulty, so it is expected the proportion should be roughly similar. Most participants did not show a particular preference. However, three participants showed a strong bias against the low/high task

(choosing the odd/even task on > 90% of voluntary trials). To rule out the possibility that the choice results here might be confounded with this bias, follow-up analyses excluded these three participants and the same ANOVA was applied again. In short, the main results remained significant. The main effect of Sequence Type was reliable both in real instruction conditions, $F(2, 34) = 19.7$, $MSE = .51$, $p < .01$, $\eta_p^2 = .54$, and in fake instruction sequences, $F(2, 34) = 4.6$, $MSE = .11$, $p < .05$, $\eta_p^2 = .21$.

Discussion

Experiment 5 sought evidence of meta-control by assessing task choices on voluntary trials in a cued multitasking environment. Performance on cued trials replicated the results of Experiments 1-4, showing increased error costs of switching when instructions indicated that task switches would be rare (regardless of objective likelihood). Further analysis of error types indicated that errors in the key fake instruction condition were due to competition at the task level instead of the response level. Crucially, on voluntary choice trials, a corresponding effect was observed such that participants were more likely to make voluntary task switches when instructed that switches would occur frequently than rarely, even when comparing conditions matched for actually-experienced switch frequencies.

The novel part of this study is to combine voluntary procedure into cued trials to

reveal the hierarchical influence. Compared to the cued task switching procedure, voluntary switching is performed at participants' own will, so it has often been associated with endogenous control. In the current study, as expected the meta-control operated both in externally cued environment and internally generated tasks. However, as mentioned in the introduction, task selection bias can be achieved through goal-directed and stimulus-driven factors. One straightforward follow-up question will be whether the instruction bias effects on the voluntary and cued trials both operate on the task level. More specifically, the control status associated with EEG alpha changes should again be observed.

Chapter 5

Mechanisms of meta-control bias of task preparation in voluntary and cued task switching

Introduction

Experiment 4 showed that switch-frequency instructions, as a manipulation of meta-control, modulate EEG alpha oscillations during cued task switching. In Experiment 5, instructions about switch frequency were shown to bias task selection on voluntary trials. In the present experiment, I investigated how instruction-based meta-control modulates preparatory components of voluntary task switching. This is an open question given that some studies indicate that neural mechanisms in voluntary task switching are quite different to those underlying instructed task-switching (e.g., Chen & Hsieh, 2015; Kang, Diraddo, Logan, & Woodman, 2014). Therefore, it not clear that the preparatory processes observed in Experiment 4 will be the same as the ones observed in the context of voluntary choice. In addition to revealing new findings from voluntary choice trials, Experiment 6 allowed me to test the reliability of the EEG findings from cued task switching in Experiment 4. Analysis focused in particular on inter-trial alpha power effects. Finally, this EEG study extended Experiment 4 by associating the alpha power effect with voluntary choice. With this

connection, meta-control here can be related to top-down influence at the level of task selection, which further emphasizes the notion that meta-control affects task-level processing.

Experiment 6

The experiment followed broadly the same design as Experiment 5, with a few modifications for the EEG testing. The behavioural results were anticipated to replicate the results in Experiment 5. Specifically, meta-control manipulated through switch frequency instruction should modulate switch efficiency as reflected in switching error costs and voluntary switch proportions. The main purpose was to replicate the alpha power results in cued trials and to associate alpha power with voluntary task choice. First, regarding replication of the Experiment 4 EEG results on alpha power on cued trials, it was expected that the frequent switch instructions would be associated with higher alpha power than the rare switch instructions. Second, alpha power should predict voluntary switch, such that trials with higher alpha power in the response-cue interval should be associated with a higher proportion of voluntary switches.

Methods

Participants

Twenty-one healthy participants from the Oxford community, aged between 18 and 35 years (Mean =25.71, SD =4.41), of whom 10 were women, were either paid £10 or given course credits for participating, supplemented by a monetary bonus for the reward incentive manipulation. All participants reported normal or corrected-to-normal vision and no colour-blindness. None reported any history of neurological or psychological disorder. All participants signed informed consent before the start of testing and were debriefed after the session.

Apparatus and stimuli

Participants were tested in a dimly lit and electrically shielded room. The experiment was run using MATLAB Psychtoolbox3 on a 20-inch CRT (Trinitron, Dell) monitor with a 75 Hz refresh rate and display resolution of 1280×1024 pixels. Stimuli were viewed from approximately 70 cm. Half of participants responded to the odd/even task with their left hand while using their right hand to perform low/high judgements. For the other half of participants this mapping was reversed. Responses were collected with a QWERTY-keyboard, using “z” and “x” keys for one task (left hand), and “n” and “m” keys for the other task (right hand).

In general, the design and procedure were the same as Experiment 5. In short, participants' task was to perform either the low/high or the odd/even task based on the colour of a frame preceding the target digit. Occasionally, on 5 out of 22 trials in each sequence, the colour frame were in grey (RGB code, [100,100,100]) indicating free-choice trials.

Design and procedure

The overall design was similar to Experiment 5, but with some modifications for EEG testing. In particular, to ensure enough voluntary choice trials from each instruction condition for EEG analysis, the No Instruction condition was excluded from this study. Thus, in this version of design, each experimental block consisted of four short sequences with Real Frequent, Real Rare, Fake Frequent, and Fake Rare switch instructions. The order of the four sequences was randomly assigned within blocks. The testing session comprised 12 experimental blocks for a total of 1056 trials. Data collection lasted around 60-80 minutes. Reward incentives were again included in this experiment, following the same scheme as in Experiments 2-5.

Preprocessing and analysis of behavioural data

Only correct trials and not following error were included for further analysis.

The first trial of each sequence was also excluded because task transition was undefined for these trials. Behavioural performance data were analysed with separate repeated measures ANOVAs with factors of reward, instruction, task transition, conducted on error rates and mean correct RTs as dependent variables. To further explore the instruction effect with or without the confound of actually-experienced switch frequency, parallel ANOVAs were conducted separately for the real and fake instruction conditions.

EEG Data Acquisition

EEG data were recorded using Ag-AgCl electrodes embedded in a fabric cap (QuikCap, Neuroscan, El Paso, TX, United States of America) from 32 channels: FP1, FPz, FP2, F7, F3, Fz, F4, F8, FT7, FC3, FCz, FC4, FT8, T7, C3, Cz, C4, T8, TP7, CP3, CPz, CP4, TP8, P7, P3, Pz, P4, P8, POz, O1, Oz, O2. Additional electrodes were placed on the right mastoid, above and below the left eye, and on the outer canthi of both eyes. The ground was placed at location Fz. All electrode recordings were referenced to the left mastoid and offline re-referenced to linked mastoids. Electrode impedances were kept below 50 kΩ. The data were continuously recorded using SynAmps2 amplifiers (Neuroscan), sampled at 1000 Hz and bandpass filtered at 0.1–200 Hz, with gain of 2816 and 29.8 nV resolution.

EEG Data Analysis

Ocular artifacts were corrected using a regression-based approach (Semlitsch et al., 1986). After ocular artifact correction, the EEG data were resampled down to 250 Hz. The data were then bandpass filtered offline from 0.1 to 15 Hz. Trials were rejected if voltage differences larger than 100 μV were observed in the electrodes: Fz, FCz, Cz, CPz or Pz. The first trial of each instruction sequence and trials with errors or following errors were removed from further analysis.

EEG analysis focused on the period of the RSI, in which advance preparation was possible prior to the short cue-target interval: When participants were instructed about switch frequency, to optimize performance for reward bonus, participants could in principle start to prepare for the upcoming task immediately after responding on the preceding trial. The EEG analysis therefore focused on task preparation beginning at the time of the response in the previous trial and lasting until the cue onset in the current trial. This time window focus is imprecise in terms of defining the onset of preparation, but this approach was appropriate given the assumption that different preparation sets persist throughout entire instruction sequences.

Response-locked epochs were extracted from the continuous data for the time window between 1000 ms before the response and 1200 ms after it. Alpha power (8–

12 Hz) was quantified using the same procedure as in Experiment 4. In brief, the raw EEG data from electrodes P7, P3, PZ, P4, P8 and POZ was filtered in alpha range, then the Hilbert transform (Hilbert function in Matlab) was applied, before response-locked epochs were extracted.

Behavioural results

The behavioural analysis mainly served to replicate the key behavioural effects found in previous experiments.

Real instructions – performance on cued trials

This analysis aimed to test the reliability of both the instruction and reward manipulations. I first report the results of the ANOVA with factors of Reward (No Reward, Reward), Sequence Type (Real Frequent, Real Rare), and Task Transition (task repetition, task switch), applied to data from the real instruction conditions (see Figure 5.1). For the RT analysis, all of the main effects were reliable: Reward, $F(1, 20) = 18.0$, $MSE = 172{,}839$, $p < .01$, $\eta_p^2 = .47$, Sequence Type, $F(1, 20) = 6.8$, $MSE = 52{,}586$, $p = .02$, $\eta_p^2 = .25$, and Task Transition, $F(1, 20) = 49.5$, $MSE = 694{,}778$, $p < .01$, $\eta_p^2 = .71$. Reward incentives caused RTs to improve from 709 ms to 645 ms, RTs were lower in Real Rare than Real Frequent conditions (644 ms vs. 699 ms), and

switching costs were robust in this experiment, averaging 128 ms (613 ms vs. 741 ms). The interaction between Sequence Type and Task Transition was significant, $F(1, 20) = 5.1$, $MSE = 11{,}816$, $p = .04$, $\eta_p^2 = .20$, indicating the standard effect of switch frequency, with a larger switching cost of 146 ms in Real Rare conditions compared with 112 ms in Real Frequent conditions. The three-way interaction, which may indicate a reduced switch frequency effect with reward, was not detected in this study, $F < 1$, in contrast to Experiment 3. No other interaction was significant, all Fs < 2.5, ps > 0.1.

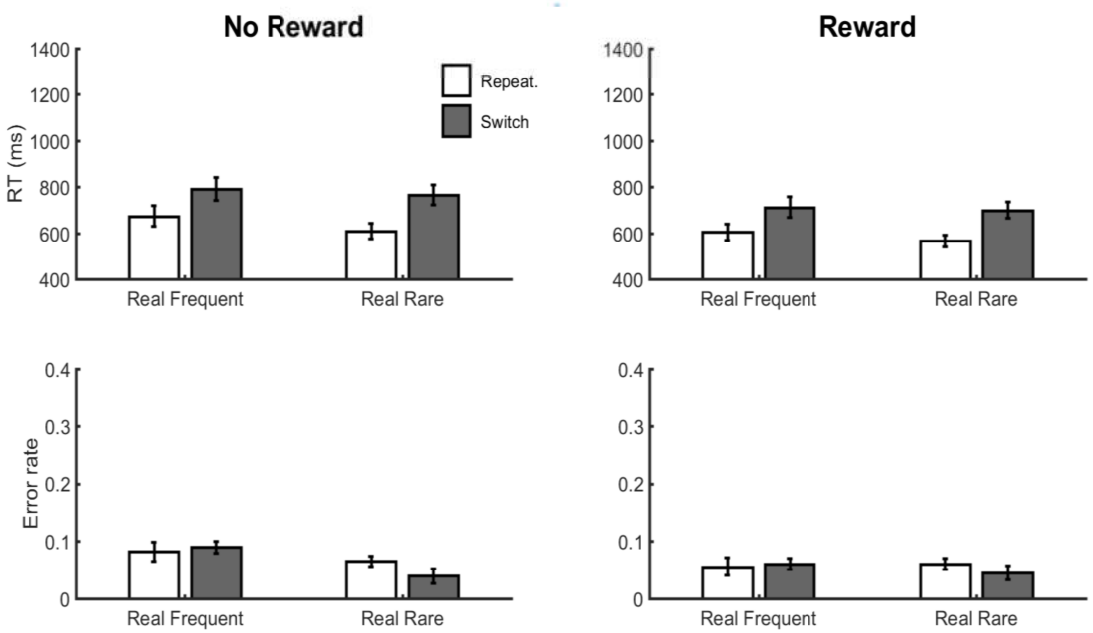


Figure 5.1. *The behavioural results for the real instruction conditions of Experiment 6. Each panel follows the same legend description and illustrates the data as a function of reward, sequence type, and task transition. Error bars denote the standard error of*

the mean.

Error rates were overall lower in the Real Rare conditions than in the Real Frequent conditions, $F(1, 20) = 7.6$, $MSE = .02$, $p = .01$, $\eta_p^2 = .27$. Reward numerically diminish errors overall but not reliably, $F(1, 20) = 2.8$, $MSE = .01$, $p = .11$, $\eta_p^2 = .12$. A similar number of errors overall were made both on task repetition and task switch trials, $F < 1$. Participants tended to commit more errors in the Real Frequent conditions selectively in no reward trials, which is suggested by a marginal interaction between Reward and Sequence Type, $F(1, 20) = 4.1$, $MSE = .008$, $p = .06$, $\eta_p^2 = .17$. A reduced switching error cost was seen in the Real Rare compared to the Real Frequent conditions, however, in a marginal manner, $F(1, 20) = 3.4$, $MSE = .008$, $p = .08$, $\eta_p^2 = .15$. Finally, the three-way interaction was not reliable, $F < 1$.

Fake instructions – performance on cued trials

As for the fake instruction sequences (see Figure 5.2), both Reward, $F(1, 20) = 13.2$, $MSE = 125{,}768$, $p < .01$, $\eta_p^2 = .40$, and Task Transition, $F(1, 20) = 54.0$, $MSE = 615{,}906$, $p < .01$, $\eta_p^2 = .73$, had significant effects on RT, replicating the effects described above for real instruction conditions, whereas the effect of Sequence Type was not reliable, $F < 1$. Reward interacted with Task Transition, $F(1, 20) = 5.5$, $MSE =$

7,990, $p = .03$, $\eta_p^2 = .22$, indicating reduced switching costs with Reward incentives. Again, the switch frequency effect was not obvious in terms of RTs in the fake instruction sequences, $F(1, 20) = 1.5$, $MSE = 1{,}227$, $p = .23$, $\eta_p^2 = .07$. No other reliable interactions were observed, $p > .05$.

In an analysis of error rates with factors of Reward, Sequence Type, and Task Transition in the fake instruction sequences, no main effects were reliable, all $F < 1$. Surprisingly, this experiment did not replicate the consistent finding of a higher error cost of switching in the Fake Rare sequences with reward incentive (Figure 5.2), reflected in a nonsignificant interaction between Sequence Type and Task Transition and an insignificant three-way interaction, Fs < 1. The anticipated effect seemed to be replaced by a marginal interaction between Reward and Sequence Type, $F(1, 20) = 3.4$, $MSE = .004$, $p = .08$, $\eta_p^2 = .15$, with a somewhat higher error rate in the Fake Rare than the Fake Frequent condition in reward sequences but not in no reward sequences. Overall, the reward manipulation was successful. However, surprisingly, the higher switching error costs was not clear in the Fake Rare conditions, which was observed previously. This result might indicate the manipulation of instruction did not work in this study.

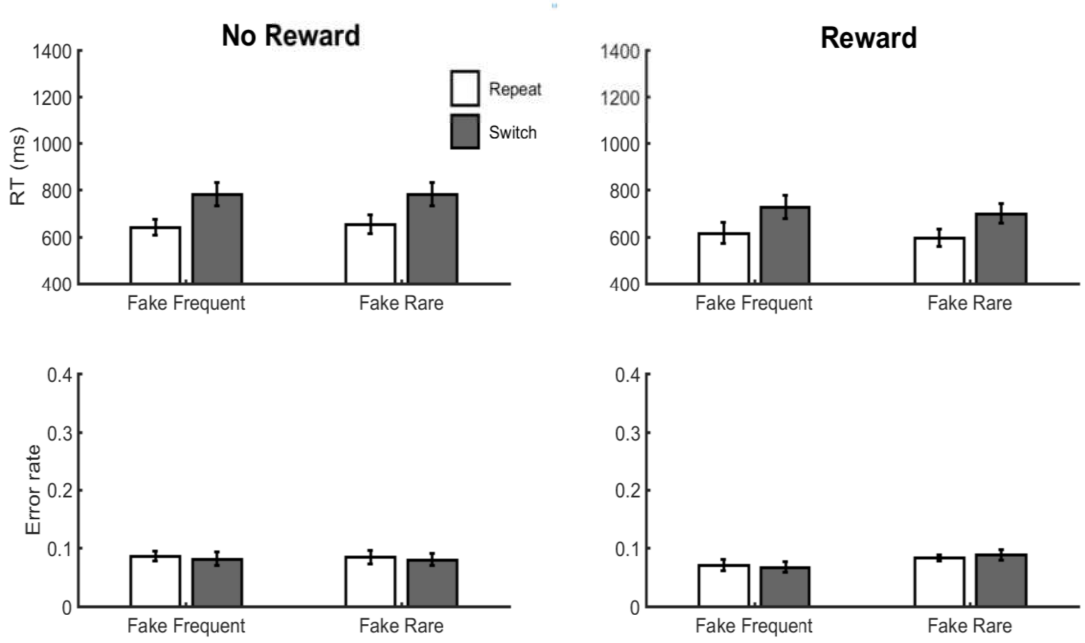


Figure 5.2. *The behavioural results of fake instructions for Experiment 6. Each panel follows the same legend description as the previous figure.*

Task choice on voluntary trials

This analysis aimed to replicate the results seen in Experiment 5, in which voluntary switch rates were higher in both Fake and Real Frequent switch conditions. A two-way repeated-measures analysis of variance including factors of Reward and Sequence Type was conducted on voluntary switch rates separately for the real and fake instruction conditions (Figure 5.3). The ANOVA from the real instruction conditions revealed a significant main effect of Sequence Type, $F(1, 20) = 10.1$, $MSE = .001$, $p < .01$, $\eta_p^2 = .34$, and a marginal interaction between Sequence Type and Reward, $F(1, 20) = 4.0$, $MSE = .022$, $p = .06$, $\eta_p^2 = .17$. As anticipated, the main effect

of Sequence Type indicated greater rate of voluntary task switches in Real Frequent than Real Rare conditions. This main effect was consistent with the prediction that instruction and experience of switching biases free-choices. Follow-up pairwise comparisons indicated that participants chose to switch more often in Real Frequent instruction than Real Rare instruction in sequences without reward incentives, $t(20) = 3.5$, $p < .01$, but not reliably so in sequences with reward, $t(20) = 1.6$, $p = .12$.

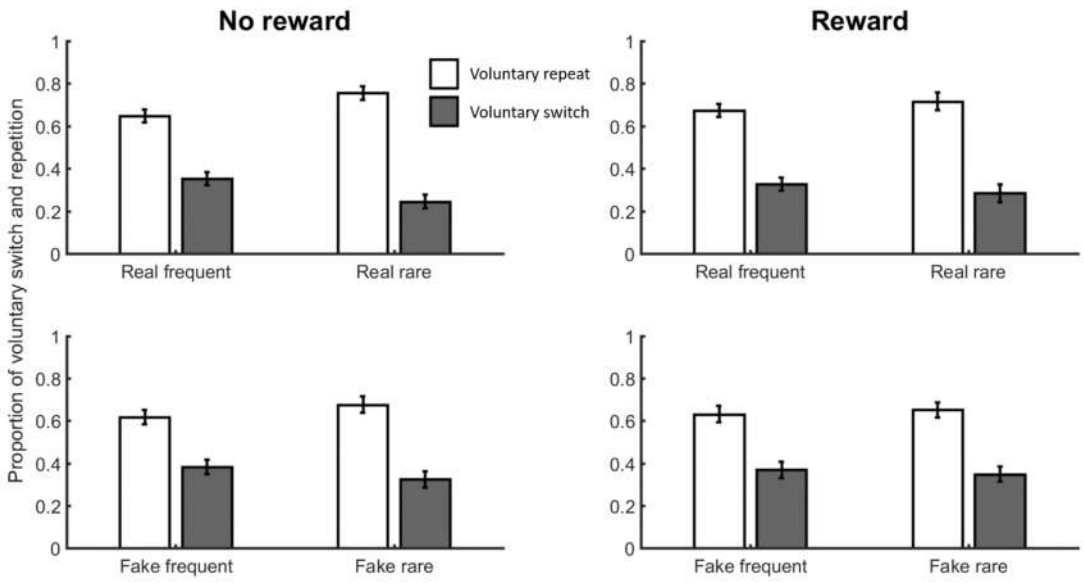


Figure 5.3. *The results of the voluntary trials in Experiment 6. The proportions of voluntary task repetition and voluntary task alternation as a function of reward and instruction. The left and right panels represent the results from the real instruction conditions and the fake instruction conditions respectively. Error bars denote the standard error of the mean.*

The same two-way repeated measures ANOVA was applied to data from fake instruction sequences. A similar pattern of higher voluntary switch rates can be seen in the data from Fake Frequent instruction sequences (Figure 5.3). The predicted main effect of Sequence Type was reliable, $F(1, 20) = 5.2$, $MSE = .03$, $p = .03$, $\eta_p^2 = .21$ indicating a reliable higher voluntary switch rate of 38% in Fake Frequent compared to 34% in Fake Rare sequences. Unlike the real instruction conditions, the interaction between Reward and Sequence Type was not seen here, $F < 1$. Finally, to complete the analysis I also ruled out other potential concerns, such as task selection bias. This additional analysis revealed broadly similar results even after excluding four participants who showed a strong task preference (selecting over 90% of either Odd/Even or Low/High task on voluntary trials).

In general, RT data analyses reveal little evidence of instruction effects. However, some hints could be found in terms of task choice: The instruction biased voluntary switch rate in a way that was consistent with switch frequency regardless of the sequence type (fake or real).

EEG results

Alpha oscillations

In Experiment 4, the impact of instruction about switch frequency was evident in

inter-trial alpha power. Thus, my first analysis of the present EEG data focused on activity in the alpha range. The purpose of this analysis was to replicate the results observed in Experiment 4. Next, I aimed to extend the alpha power results to voluntary choice.

As described in Experiment 4, alpha power is associated with different control states that appear to vary with instructed switch frequency. As shown in Figure 5.4 below, the overall shape of the alpha power waveform was as expected, consisting of a large drop during task performance then a rebound during the inter-trial interval. A 2 × 2 (Reward × Sequence Type) repeated measures ANOVA conducted on EEG alpha power in the critical inter-trial interval in fake instruction sequences revealed significant main effect of Reward, $F(1, 20) = 11.7$, $MSE = 2.29$, $p < .01$, $\eta_p^2 = .37$. The main effect of Sequence Type was not significant, $F < 1$. Two panels of Figure 5.6 revealed more alpha suppression in Reward sequences than in No Reward sequences (right panel vs. left panel). The interaction of Reward × Sequence Type, which was found marginally significant in Experiment 4, was not reliable in this study, $F < 1$. Comparing the current results to the alpha power results in Experiment 4, the reduced alpha power in reward trials was replicated. However, alpha power did not differ between Fake Frequent vs. Fake Rare instruction conditions, which was not consistent with the results in Experiment 4.

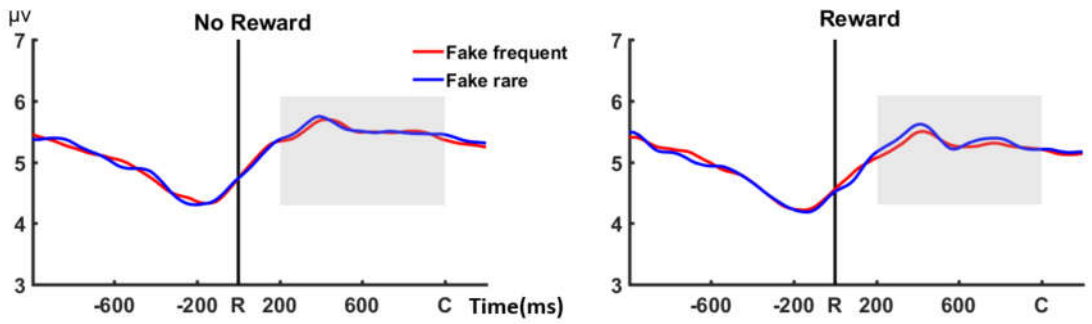


Figure 5.4. *Alpha power results from the Fake instructions in Experiment 6. Mean average amplitude-modulated EEG signal after filtering at alpha frequencies. The signal was time-locked to the onset of the response on trial n-1. In the two panels, the signal is depicted for the two instruction types of reward and no reward conditions. The shaded area indicates the time window of interest used for statistical analysis. The vertical solid lines indicate the onset of response. R=response onset of trial n-1; C= cue onset of trial n.*

To complete the analysis, the same analyses were performed on the real instruction data. Alpha suppression by reward was not evident here, $F(1, 20) = 1.2$, $MSE = .49$, $p = .29$, $\eta_p^2 = .06$, see Figure 5.7, but numerically the effect was consistent with the prediction (No Reward vs. Reward: 5.96 vs. 5.79). The main effect of Sequence Type was also not reliable 6, $F(1, 20) = 2.4$, $MSE = .27$, $p = .14$, $\eta_p^2 = .11$, in contrast to the clear effects observed in the first EEG study (Experiment 4), but

Reward marginally interacted with Sequence Type, $F(1, 20) = 4.3$, $MSE = .71$, $p = .05$, $\eta_p^2 = .18$. Follow-up pairwise comparisons revealed that alpha power was higher in Real Frequent than Real Rare conditions when reward incentives were available, $t(20) = 3.1$, $p < .01$, but did not differ in the no reward condition, $t < 1$.

In general, the alpha results of Experiment 4 were replicated partially here, with higher alpha power associated with the Real Frequent than Real Rare conditions. However, such association was not detected in fake instruction sequences.

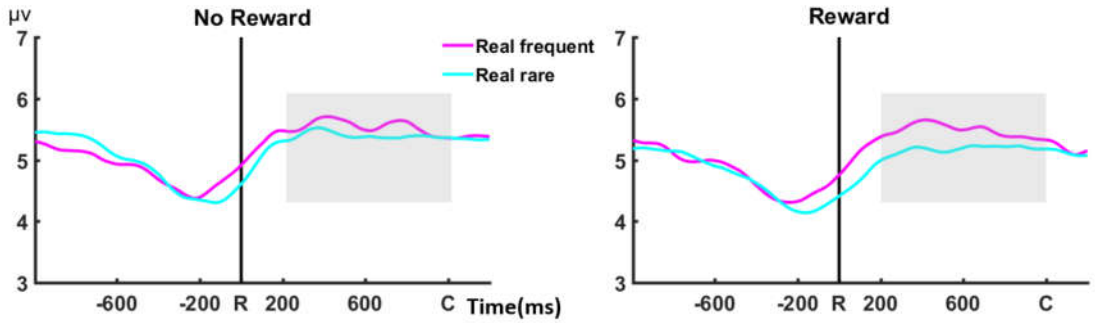


Figure 5.5. *Alpha power results of the real instructions in Experiment 6. Mean average amplitude-modulated EEG signal filtered at alpha frequencies. The signal was time-locked to the onset of the response on trial n-1. In the two panels, the signal is depicted for the two instruction types of reward and no reward conditions. The shaded area indicates the time window of interest used for statistical analysis. The vertical solid lines indicate the onset of response. C= cue onset of trial n; R=response onset of trial n-1.*

Next, I turned to directly associate voluntary switch rate and alpha power. Based on the results in Experiment 4, higher alpha power was related to a control state with relaxed attentional filter (i.e., in frequent switch instruction sequences). In this case, the magnitude of alpha power during the inter-trial interval of voluntary trials should predict voluntary switch rate, with greater alpha power predicting higher voluntary switch rate. To test this prediction, I focused on alpha power during response-cue intervals preceding voluntary trials. Figure 5.6. plots the alpha power separately for trials with voluntary switches and repeats as a function of sequence type and reward. Since there were not enough voluntary trials in real instruction conditions for many participants (e.g., voluntary task switches in the Real Rare condition), the analysis was only conducted on fake instruction conditions.

A repeated measures ANOVA with factors of Reward (No reward, Reward), Sequence Type (Fake Frequent, Fake Rare), and Voluntary Switch (voluntary repeat, voluntary switch) was performed on these voluntary trials data. No main effect was reliable, all Fs < 1. The interaction between Reward and Voluntary Switch, which was crucial for the prediction, was not significant, $F(1, 18) = 1.0$, $MSE = .11$, $p = .33$, $\eta_p^2 = .53$. This indicates alpha power during the RCI did not separate before voluntary repeats and voluntary switches. Moreover, such pattern was not manifest in the

reward condition. Other two-way interactions were both not reliable, $p > .21$. An unexpected interaction between Reward, Sequence Type, and Voluntary Switch reached significance, $F(1, 18) = 6.9$, $MSE = 3.8$, $p = .02$, $\eta_p^2 = .28$, which was driven by an opposite pattern of alpha power relating to voluntary switches in reward and no reward conditions. Follow-up separate 2-way ANOVAs for the No reward and Reward conditions were conducted. Only the interaction between Sequence Type and Voluntary Switch in the No reward condition was detected, $F(1, 18) = 7.7$, $MSE = 4.1$, $p = .01$, $\eta_p^2 = .30$. To clarify the 2-way interaction, follow-up *t*-tests were performed accordingly. In trials without reward, higher alpha power preceding voluntary task switches was found in the Fake Frequent condition than Fake Rare condition, $t(18) = 2.0$, $p = .06$. As for voluntary repeat trials, clearly reduced alpha power was found in No reward Fake Rare compared to No reward Fake Frequent sequences, $t(18) = 2.8$, $p = .01$. This finding partly supports the prediction that alpha power should precede voluntary task switch trials. More broadly, alpha power seems to be reduced before trials that are not consistent with the dominant trial type in the sequence (in No Reward sequences).

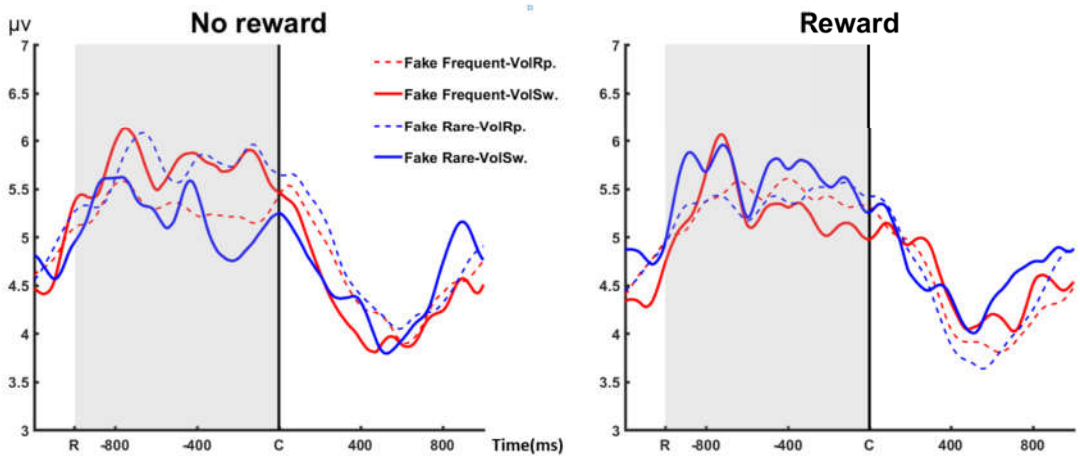


Figure 5.6. *Voluntary switch rates from the higher alpha power trials as a function of instruction and reward. Error bars denote standard errors of the means. VolRp. = voluntary repeat; VolSw. = voluntary switch. The shaded area indicates the time window of interest used for statistical analysis.*

Discussion

The aims of this study were to test the reliability of the alpha power results in Experiment 4 and to associate alpha power with voluntary task choice. Using a scalp electrophysiological approach, the current study tested the main hypothesis that alpha power, as an index of meta-control that is sensitive to instructions, will correlate with voluntary switch rate. The study revealed the standard switch frequency effect in real instruction conditions but the critical behavioural evidence of meta-control, an effect of fake instructions on cued task switching costs, was not clearly detected. In Experiments 1, 3, 4 and 5, effects of meta-control were inferred from higher error

rates on switch trials in Fake Rare vs. Fake Frequent sequences. This effect was not replicated here. However, fake instructions did affect other aspects of performance. In particular, higher voluntary switch rates were observed in frequent switch instruction sequences regardless of whether the instructions were real or fake, replicating the main new behavioural finding of Experiment 5. For the EEG results, the alpha power results of Experiment 4 were replicated in the real instruction conditions but not in the fake instruction condition. In the following, these main results will be discussed separately in more focus.

The failure to replicate the switch error effect in fake instruction sequences raises a concern over the success of establishing meta-control from the instruction in this study. In sequences with valid instructions, participants still showed a standard effect of switch frequency. However, as real instruction conditions confound experience-driven and expectancy-driven control, the switch frequency effect in the current study might mainly result from control that emerges spontaneously during the task and operates on the basis of conflict monitoring adjustment via experience with stimulus or response conflicts. From the behavioural data, it raises a possibility that a pure high level of influence was not effective, which could due to several possibilities. One straightforward possibility is that difficulty might arise at the stage of establishing meta-control. The participants recruited in this study showed

unexpectedly high error rates even on repetition trials in Fake Rare conditions (around 10% in this study compared to ~5% in Experiment 1, 3, and 5). The only differences from previous behavioural experiments are the adoption of EEG and the insertion of voluntary trials. At this point, the exact reason for such differences on group level is still unclear. It is surprising to see the null results given that outwardly the study was very similar to previous studies.

In terms of voluntary choice, a consistent pattern of higher voluntary switch rate was seen again both in real and fake instruction conditions. First, a strong repetition bias away from pure randomness was observed in every instruction sequence type, which is consistent with past studies of voluntary switching (e.g., Arrington & Logan, 2005; Yeung, 2010). Despite the repetition bias, the influence of meta-control still remained. It is likely that meta-control slightly changed the tendency of the repetition bias by modifying the most recent active task in accordance with the instruction (e.g., participants should predict task B in a frequent switch sequence when following consecutive trials of task A). A similar notion of balance between randomness and more controlled task selection can be seen in other studies (Arrington & Logan, 2005).

Both fake and real instruction conditions did show a similar pattern of higher voluntary switch rates in frequent switch than rare switch sequences. Voluntary switch

rates as reflecting meta-control between frequent and rare switch sequences were stronger in real instruction conditions (7.4% higher with real instructions vs. 4% higher with fake instructions). Similar patterns were also found in Experiment 5. These results are also reminiscent of a more pronounced switch frequency effect on switching error costs found with real instructions than with fake instructions. Such differences between real and fake instructions on voluntary switch rates can be explained by other studies suggesting that even though task choices are made in a top-down fashion, voluntary switching at the same is also sensitive to exogenous influences (Arrington, 2008; Fröber & Dreisbach, 2017; Yeung, 2010). In real instruction conditions, practice effects and task strength due to practice might also contribute to the voluntary switch rate effect, which makes the effect manifest in real instruction conditions. The lessened effect of the free choice bias in fake instruction conditions can be explained by Dreisbach & Haider (2006). Dreisbach and her colleagues suggested that global control influences tend to be weaker (e.g., switch expectancy of 75% in a block vs. cued on a single trial), because people cannot engage in preparatory activity as much as they can on single trials.

Voluntary switching was also found to predict EEG alpha power, though in a mixed way. In the final analysis, in the no reward condition, higher pretrial alpha power predicted voluntary switching in Fake Frequent sequences and voluntary task

repetition in Fake Rare sequences, but this finding was not observed in reward trials. This result is partly consistent with the prediction from the control status theory that higher alpha power reflects a relaxed attentional filter that enables efficient task switching. Also, higher alpha power was not found in Fake Frequent conditions than Fake Rare conditions in the first place, therefore, it is hard to clarify the mixed results here. Overall, the present findings do not provide strong evidence suggesting the association between alpha power and control status. However, before any conclusion is reached, note that the current results still need to consider the null behavioural results of switching error cost in fake instruction conditions.

The null alpha power results in the fake instruction

In the previous EEG study without free choice trials (Experiment 4), higher alpha power was found in frequent switch sequences (with both fake and real instruction conditions). In the current study, this pattern was replicated only in the real instruction conditions but not in the Fake instruction condition. One obvious cause of this failure to replicate is the unclear behavioural effect of instruction in the matched-frequency Fake Frequent and Fake Rare sequences. As mentioned previously, if meta-control was not established in the first place, the attentional filter mode would not differ between instructions and be reflected in alpha power. The consistent pattern

of higher alpha power in Real Frequent than Real Rare sequences observed in both EEG studies to a certain degree adds evidence that alpha power does reflect a relaxation of attentional filter and can be explained in terms of being in different control states.

The above discussion mainly focuses on instruction-related alpha power results. Despite an unclear association between switching error costs effect and alpha power in fake instruction sequences, the overall reduced alpha power by reward incentives was replicated again. This finding confirms the connection between reduced alpha power and reward, which suggests that alpha power here also reflected general task preparation, such as task engagement or cognitive effort (e.g., Macdonald, Mathan, & Yeung, 2011). Together, considering the evidence of some replications and null results on instruction effect, the present findings provide mixed evidence that alpha power reflects distinct control modes.

Conclusion

This study was based on the experimental design used in the last study to reveal meta-control influence on voluntary task switching. In addition, another aim was to search for evidence of meta-control both on cued and voluntary trials. Lastly, I examined the robustness of alpha power as an index of control status while

participants had a certain degree of control over task choice. A clear switch frequency effect was consistently observed in real instruction conditions as expected. Nevertheless, the previous finding of different switching error costs in fake instruction sequences was not replicated in the current study. There were corresponding null findings of alpha power in the fake instruction sequences. However, clear instruction influence on voluntary switch rate was observed in both real instruction and fake instruction conditions. These findings together provide limited evidence of alpha power links to meta-control, but this might be due to a failure to replicate the main behavioural results to establish a strong meta-control influence on task switching.

Interim summary*: instruction studies (Experiments 1-6)*

In this series of experiments, I sought to provide evidence of meta-control in task switching with a novel instruction-based design. To show meta-control in task switching processes, participants received different instructions regarding switch probability, but nevertheless carried out the task sequences with exactly the same switch frequency in the critical Fake Frequent and Fake Rare conditions. With this novel design, dissociation of expectancy-based control from experienced-based control becomes possible. In the first three behavioural experiments, the aim was to employ this design and to establish a robust behavioural index of meta-control. Collectively, Experiments 1-3 showed that instruction alone can lead to modulation of switch costs according to expected switch frequency but, less expected, that this effect was restricted to error costs of switching. To further test this effect, reward incentives were used to encourage attention to instructions and fast and accurate responding in order to detect the instruction effect on RTs. The reward manipulation was effective in reducing both RTs and error rates. Importantly, error measures alone were still sensitive to the instruction manipulation. Moreover, the results from Experiments 2 and 3 indicated that the error rate effects only existed in the motivated trials when there was a reward contrast. When there was a reward contrast, participants might adopt a strategy: They could be relatively more relaxed in no reward trials, while

emphasizing fast and accurate behaviour simultaneously in reward trials. Thus, in situations with response speed pressure and false instructions, inevitable errors were likely on trials that were cognitively demanding, i.e., switch trials when they were unexpected. Based on these three studies, a robust behavioural index was established.

Further evidence of meta-control was found in the first EEG experiment, in which meta-control was proposed could operate on motor preparation level, an abstract level of preparation, or both. The experiment contrasted two level of preparations relating to general task state, as reflected in alpha power, and task-specific preparation as reflected in motor preparatory potentials, such as LRPs and MRAAs. Indeed, clear motor preparation potentials were observed, but they did not differentiate between the two fake instructions. On the other hand, alpha power was observed to be sensitive to instructions, which I interpreted as reflecting distinct control status that determines the strength of attentional filtering and switch efficiency.

Experiments 5 and 6 extended the findings in the previous studies to show that meta-control states affect voluntary task choice, not just the efficiency of cued task switches. This finding implies that instruction did lead to meta-control signals that guided task selection. These results provide further evidence that free task choice is also influenced by task context and internal high-level task representation. In addition

to the effect on voluntary task choice, pretrial alpha power was not found to predict voluntary switching. Though higher pretrial alpha power was found to precede voluntary switch in no reward trials, this pattern was absent or even opposite in reward trials. At this point, the association between alpha power and voluntary choice is still not very clear. However, at least, the evidence of meta-control biasing free choice could be supported.

Overall, these experiments provided robust evidence for the hypothesis that simple instruction about switch frequency is sufficient to induces meta-control states that exert global influence on task switching performance. Meta-control could in principle operate on a task-shielding mechanism by adjusting an attentional filter. The strength of task shielding could be more or less focused on task-related dimensions (odd/even or low/high) according to current requirements.

Implications for studies manipulating switch probability

The results collected from Experiments 1 to 6 have implications for task switching studies concerning switch probability. This line of studies mainly address the relationship between task preparation effects and the probability of a task change, since the contribution of a preparatory component in task switching research has played a central role in the theoretical debate (e.g., Karayanidis et al., 2010; Kiesel et

al., 2010). Some studies have suggested that sequence contexts with different switch frequency could promote adoption of a response strategy (e.g. Monsell and Mizon, 2006). These strategies could be adaptive in that strategically staying in a neutral state after a response could allow for more efficient task switching (e.g., in a frequent task switch sequence). Other studies have proposed a mechanism these effects. A flexible task shielding mechanism regulates cognitive control on the basis of information provided by requirements of the task to be performed (Fischer, Gottschalk, & Dreisbach, 2014; Luria & Meiran, 2005). Some studies further suggested a global version of task shielding that can be initiated prior to performance rather than being activated locally after experiencing conflict (Dreisbach & Haider, 2009). From this perspective, the role of instructions can be treated as setting parameters to tune task shielding (to deploy attention on now-relevant task dimensions and prevent interference from irrelevant dimensions) in accordance to task requirements (switching tasks frequently or rarely).

This proactive form of adjustment has been proposed to be functionally similar to reactive control. Aarts and Roelofs (2011) adopted probabilistic cues in a Stroop task and found that both the anticipation of upcoming conflict and experienced conflict can trigger similar sequential behavioural adjustments and produced comparable activation patterns in the anterior cingulate cortex (ACC). Furthermore, in

some models regarding the relationship between the hierarchical structure of prefrontal region and cognitive control, ACC has been proposed as the apex of the hierarchy of control (e.g. Holroyd & Yeung, 2012), in particular in terms of selecting and maintaining sequence information. All in all, these studies all imply a distinctive level of control signal may be required for choosing among plans in a sustained way throughout a sequence to ensure a completion of a high-level behavioural goal. In other words, this line of studies suggests cognitive control can be nested into a multiple-level structure, in particular for situations involving complex actions over long time windows. Moreover, from the information theory perspective, the information required for selecting an action can be quantified according to the purpose of control, from sensorimotor control to the highest level of branching control (Koechlin & Summerfield, 2007). Specifically, in the current studies, in addition to the mechanism responsible for online adjustment of switching processes, an extra source of information may be required for updating switch probability. Meta-control seems to mainly apply as a higher-level parameter that sets the balance between different task control states, such as shielding and flexibility.

Conclusion

The primary aim of the first project was to test the core hypothesis of

meta-control in task switching with a novel design. The main behavioural findings are that error costs of switching are sensitive to meta-control (instruction) and that this effect is contingent on reward incentives. Moreover, it seems that meta-control affects trial-by-trial processing on a relatively abstract task level instead of directly operating on a motor level of preparation, as evidenced by the EEG studies. The notion of task shielding or control status was proposed as a possible candidate mechanism of the meta-control influence. In short, meta-control affects task-level processing globally and tries to trade off efficient task performance against efficient switching.

Compared to the large number of studies concerning the context of switch frequency, a few studies have investigated different parameters of sequence-level processing on switch performance. Sequence-level control might act akin to task-level control as studied in traditional task switching, with repetition of sequences leading to improved performance whereas switching of higher-order sequence information might lead to costs (and interact with task-level effects). As a result, the above reasons prompted me to conduct another project in which shorter trial sequences were used to investigate sequence transition effects at the level of sequences and their influences on task-level performance.

Chapter 6

The impact of sequence transitions on switching processes

Introduction

In the task switching literature, there are mounting studies implying that sequence-level processing modulates task-switching performance (e.g., Lien & Ruthruff, 2004; Schneider & Logan, 2006). The general finding is that the structure of sequences above the single-trial level can affect task-switching performance. For instance, in a study by Schneider & Logan (2006), participants were asked to remember short sequences of trials prior testing (e.g., an ABA task sequence) and later performed these sequences rather than just being cued for the upcoming trial(s) of a single task. This design creates a contrast between single-trial transitions (i.e., traditional 'switch' and 'repeat' trials) with transitions between sequences (e.g., successive sequences might be ABA-**A**AB, so that the marked trial involves a task repetition but sequence switch). The results indicated that at points where both task transition and sequence transitions occur, the switching cost is primarily determined by sequence transition. Performance on the first trial of a sequence tends to be slower than the following trials but could be faster when the same sequences repeated, regardless of whether the task is the same as on the previous trial (e.g., comparing

ABB-**A**BB and ABA-**A**BA sequences). This implies that when initiating a sequence, sequence-level processing may involve forming a high-level representation (an ordered list of tasks), thus helping task to retrieve on each trial and somehow modify the task preparation or task interference from the last trial.

The high-level sequence representation may involve stepping through the representation to perform the sequence (Anderson, Bothell, Lebiere, & Matessa, 1998). When retrieving sequence representations, task-level processing may be vulnerable to influence from sequence-level processing. This possibility is rooted in studies that manipulated different task strengths (e.g., Yeung & Monsell, 2003), which suggest that task switching costs partially result from differential activation of competing task sets in working memory. Thus, introducing sequence representations might modify the contents of working memory by modulating task-set activation, which then in turn affects switching costs. Moreover, this modulation might be more disturbing at the start of a sequence, when the sequence representation has just been established, compared to subsequent positions that require only accessing the content of representation. For example, Lien and Ruthruff (2004) found that task-switching costs at the first position of a sequence are eliminated or reduced when reaching a sequence transition point.

The modulating effect on switching costs occurring at first positions (T1) of sequences is referred to as the chunk point hypothesis (Schneider & Logan, 2014). However, despite this emerging evidence supporting the modulation effect at T1, these studies did not examine other processes that could also contribute to such effects. For instance, restart costs are usually observed in paradigms with intermittent instructions between sequences of trials (of the same task), in which responding on the first trial of sequences in explicitly cued-repetition trials requires extra time relative to repetition trials that were not immediately preceded by a task cue (Poljac, Koch, & Bekkering, 2009). This extra time has been proposed to reflect a compensatory process for memory decay of the previous task cue (Altmann, 2002). Past studies on hierarchical task structure often use intermittent instructions that increase the time interval between sequences, thus creating the possibility of a restart cost instead of or in addition to any need to build high-level representation of the upcoming sequence. My first aim was to contrast the restart cost account with the sequence effect discussed above. To test this, I will contrast sequences preceded by instruction vs. no instruction. These conditions have the same length of time interval to match for effects of memory decay. The only difference is the possibility of building a sequence representation in preparation.

Recent work has suggested that the T1 modulation effect could relate to implicit and explicit learning that emphasizes the role of attention mechanisms in cognitive sequences (Cushman & Morris, 2015; Savalia, Shukla, & Bapi, 2016). In Experiment 4, the instruction effect on alpha power was suggested to relate to an attentional filtering mechanism that regulates the task shielding. Similarly, Posner and Petersen (1990) postulated attentional networks not only related to orienting and maintenance of vigilance but also higher-order executive or organizational processes. As task instructions are delivered, a task-set should be instantiated and maintained in order to aid in the configuration of downstream moment-to-moment processes. This speculation can be supported by recent imaging studies. For instance, Dosenbach and his colleagues (2006) found sustained activities in the dorsal anterior cingulate cortex (dACC) and anterior insula during several types of cognitive tasks for around 4 minutes, and on this basis, they proposed that these regions formed the network of a task-set system. These findings suggest that attention mechanisms would be critical for engaging and maintaining sequence representations. This hypothesis would be in contrast to the memory mechanism behind the restart cost. If the modulation effects on switching costs were caused by the time gap between sequences for reactivating sequence representations, modulations of switching cost should be found in every condition regardless of whether an instruction is presented in the gap. On the other

hand, if instructions engage attention in building sequence-level representations, the prediction was that modulation of task switching performance by sequence transition will only exist in conditions with instructions but not in a contrasting no instruction condition.

The second aim of the experiments reported in this chapter and Chapter 8 was to extend this prior work on sequence switching, to look at hierarchical sequence effects on performance beyond the first trial of a sequence. Both meta-control and hierarchical control theories suggest that the role of high-level representations is to guide task selection on each action throughout a sequence. This implies that control operations should be sustained throughout sequences of actions, and do not only operate on the first trial where the modulation effect has primarily been studied. However, previous studies have been limited in their ability to study these sustained effects because they have manipulated task organization in only pairs of tasks (Luria & Meiran, 2003), via implicit structure learning through spatial or temporal variations in the presentation of the task stimuli (Lien & Ruthruff, 2004), or even through directly instructed sequences (Schneider & Logan, 2006). A methodological challenge in these studies is that the effects of sequence transitions are often confounded with differences in switch probability beyond the first trial of a sequence. Without matching switch probability beyond first trials, task transition effects might mainly

reflect local switching effects instead of sequence transition influences. The present experiments aimed to control for these possible confounds to investigate lasting influences of sequence-level representations.

In addition to the questions regarding sequence representation influence beyond first positions, I tested another key prediction that average performance across the trials of a sequence should be better if the same sequence task is repeated than if the sequence structure is switched: Switching hierarchical control structures should be more time consuming and less effective than retaining an existing hierarchical control structure. To measure this sustained effect of control throughout a sequence, I developed a design that controlled for local switch probability across trials within a sequence, enabling me to study differences on switch performance that can then be attributed to the instructed sequence structure. Specifically, this was achieved using explicit instructions about the switch frequency within a sequence rather than the specific order of tasks required (e.g., Schneider & Logan, 2006). For example, the participant might be instructed that the upcoming sequence of four trials would involve a single task switch, rather than being cued to perform an ABBB (or AABB, AAAB, etc.) task sequence. Similar to Experiments 1-6, the role of switch frequency here was to help participants to either prepare one of tasks. In addition to testing the

T1 sequence transition effect, I could also test the instruction influence beyond first trials.

There are reasons to expect that this form of partial task cueing may produce more effective preparation than explicit task cueing. For example, a recent study using the voluntary task-switching paradigm found that self-organized task sequences might be advantageous (in terms of cognitive effort) over conditions with externally cued task order (Kiesel & Dignath, 2017). This notion is in line with the idea of meta-control that a high-level process globally determines task order and preparation for the tasks (de Jong, 1995; Luria & Meiran, 2003). Thus, to deliberately encourage a sense of self-organized task sequence, Experiment 7 used instructions for upcoming sequences that were only partially informative in allowing planning the tasks within a sequence.

Experiment 7

Methods

Participants

Seventeen students from the Oxford community took part in this study (11 female;

Mean age =21.9 years, SD =4.16). All of them self-reported as neurologically healthy and not colour-blind. They participated in exchange for payment or course credit. Informed consent form was signed before the start of testing.

Apparatus and stimuli

Participants were tested individually. The experiment was programmed in Matlab Psychtoolbox. The stimuli were presented on a 17-inch CRT display with a resolution of 1280 * 1024 pixel and a refresh rate of 75 Hz. The screen was located centrally on a desk in front of the participants at a viewing distance of approximately 50-60 cm.

The experimental task extended the standard task-switching approach used previously, in which a low/high or odd/even judgment had to be made on each trial. The critical new feature of this experiment was that blocks were divided into sequences of four trials, before each of which there was an instruction indicating the number of task switches that would be required in the upcoming 4-trial sequence. Target stimuli were the numbers from 1-9 except 5, displayed in the middle of each white frame (Figure 6.1). The cue to indicate the required task was the colour of frame preceding the target digit. For half of the participants, a blue frame cued the low/high task and a red frame cued the odd/even task; for the other half of participants this mapping was reversed. Responses were recorded with a standard QWERTY-keyboard, using “f” and “j” as

response keys with the left and right index fingers. The mapping between response keys and tasks was counterbalanced across participants. The "f" and "j" keys were mapped to odd/even and low/high responses, respectively, for half of participants and vice versa for the other half. All stimuli were displayed in Courier font with a size of 42 on a lighter grey background (RGB code, [168,168,168]). The content of the instruction presented during the testing was in Arial font.

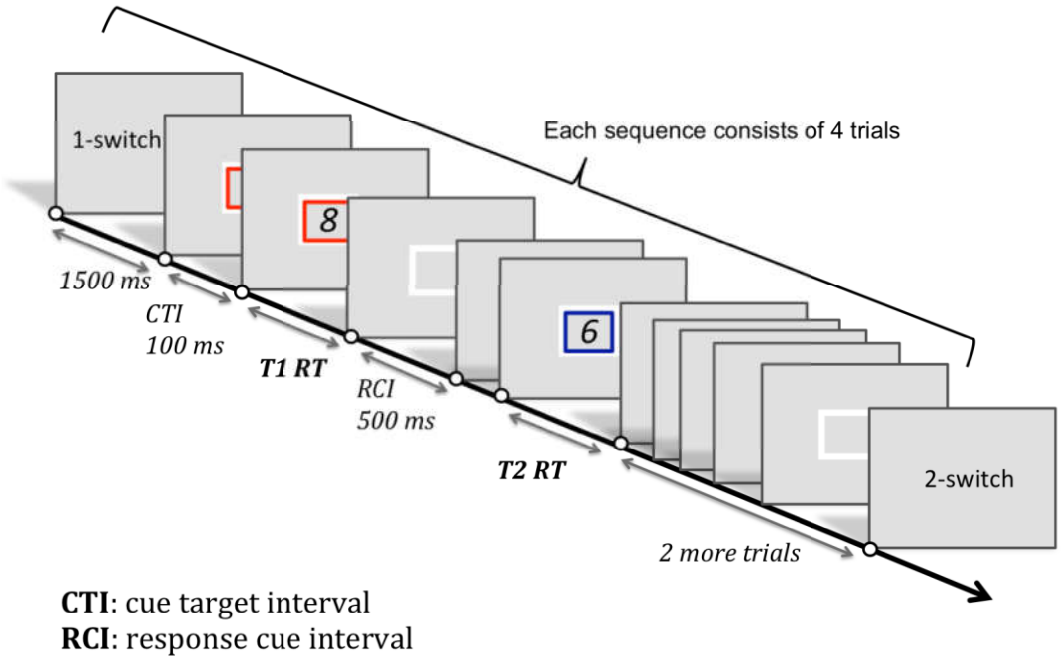


Figure 6.1. *An example of a sequence of events in the task-switching task in short chunks for Experiment 7. This example is from the instruction condition. In the No Instruction condition, the instruction image (e.g., 1-switch) was replaced by a white frame in the center of the screen and without any texts. T1RT: mean RT of first serial position. T2RT: mean RT of second serial position.*

Design and procedure

Participants were required to perform task-switching trials in short sequences of four trials with different instructions delivered prior to each sequence. Prior to each sequence in half of the blocks, participants were told the switch frequency regarding the upcoming sequence and could utilize this information to effectively predict the tasks for the upcoming sequence. Specifically, the instructions indicated that there would be either one or two task switches in the sequence (Figure 6.1). Prior to sequences in the other half of blocks, no information about switch probability was provided. There was a matched inter-trial delay, but the screen remained blank for this period.

The particular set of sequences presented to participants was constrained in order to match the probabilities of sequence and task transitions for the first 3 trial positions of the 4-trial sequences. Thus, in the 1-Switch sequence, task switches only occurred at the 2nd or 3rd position (ABBB or AABB sequences). In the 2-Switch sequence, the task switches could either occur at 2nd and 3rd positions or 3rd and 4th positions (ABAA and AABA sequences). With these constraints, the actual switch probability (50%) on the first and second position were matched across all instruction conditions. The only difference was the instructed switch probability provided by the instruction. As a result, any difference on switch efficiency could be attributed to the instruction rather than

actual switch frequency. Participants were not told about these constraints.

The experimental task consisted of 10 blocks. In 5 blocks, information about sequence type was presented prior to each sequence (Instruction block). In the other 5 blocks, no such information was presented (No Instruction block). The order of these blocks was randomly assigned. Each block consisted of 132 trials in which, after the first 4-trial sequence that was randomly chosen, the remaining 32 sequences were constrained to contain equal numbers of observations for the factorial combination of sequence transition and task transition for 1st and 2nd positions. Thus, there were 16 sequence repetitions and 16 sequence alternations in each block. For the sequence repetitions, 8 sequence pairs were 1-Switch to 1-Switch (labeled as 1-1) and another 8 pairs were 2-Switch to 2-Switch (2-2). Similarly, for the sequence alternations, there were 8 pairs of 2-Switch to 1-Switch (2-1) and another 8 pairs of 1-Switch to 2-Switch (1-2). Simultaneously, at the task transition level, each sequence transition contained equal numbers of task repetition and task switch trials in the 1st position (T1) and 2nd position (T2) within the four-trial sequence. With the above constraints, all possible designations of the odd/even and low/high tasks as A or B yielded only four task-specific sequences: [AABB], [ABBB], [AABA], and [ABBA].

In Instruction blocks, information about sequence type was delivered at the beginning of each short sequence for 1500 ms (see Figure 6.1). Then a white

rectangular frame appeared together with a colour cue, followed 100 ms later by a target digit in the center of the frame until the participant's response (or a timeout period of 5 seconds). A 500 ms interval followed each response before the next cue of the sequence (T1-T3) or the next instruction (T4). The procedure for the No Instruction blocks was almost identical, except that the image of sequence type information was replaced by an image of white frame for the same interval of 1.5 seconds. At the end of each experimental block, participants were given short break and feedback regarding their performance of previous block. The whole experiment lasted about 70-80 minutes.

Before the experimental blocks, participants began with four short practice blocks. In the first two practice blocks, participants were familiarized with both tasks separately (16 trials each). In the third practice block, they practiced both tasks mixed in short sequences in random order, which introduced task switching. In the final practice block of 40 trials, short sequences were introduced with switch frequency information. During this practice, participants were told to use the switch frequency to perform the task more efficiently. To proceed to the next practice block or the formal testing session, accuracy had to exceed 90%. The whole practice session lasted about 15-20 minutes.

Preprocessing and data analysis

The first sequence in each block cannot be defined in terms of sequence transition type and was removed from analysis. Thus, all analyses focused on trials after the first sequence of each block. Analyses of mean RTs excluded error trials. The remaining data were analysed by repeated measures ANOVAs separately for the RTs and the error rates with relevant factors. Corresponding analyses on median RT data mirrored the mean RT results. For all reported results, the alpha level was set at .05. I report on partial eta squared as an index of the effect size.

Results

Switch performance within sequences

Mean RTs and error rates for each sequence type are shown in Figure 6.2. My first analysis assessed the impact of instructions on performance within sequences, testing the key prediction that instructions would improve performance. Of particular interest was the performance of all trials within the sequences. A repeated measures ANOVA was conducted with factors of Instruction (No Instruction, Instruction), Sequence Type (1-Switch, 2-Switch), and Position (1, 2, 3, and 4) respectively for mean RTs and error rates. Not surprisingly, the factor of Position was reliable, $F(3, 48) = 32.9$, $MSE = 196{,}025$, $p < .01$, $\eta_p^2 = .67$, which was primarily driven by noticeably prolonged RTs at

the first positions for both sequence types regardless of the instruction (i.e., a typical restart cost, Altmann, 2002). RTs of 2-Switch sequences were slower than 1-Switch, $F(3, 48) = 73.5$, $MSE = 106{,}053$, $p < .01$, $\eta_p^2 = .82$, simply reflecting the increased rate of occurrence of task switch trials.

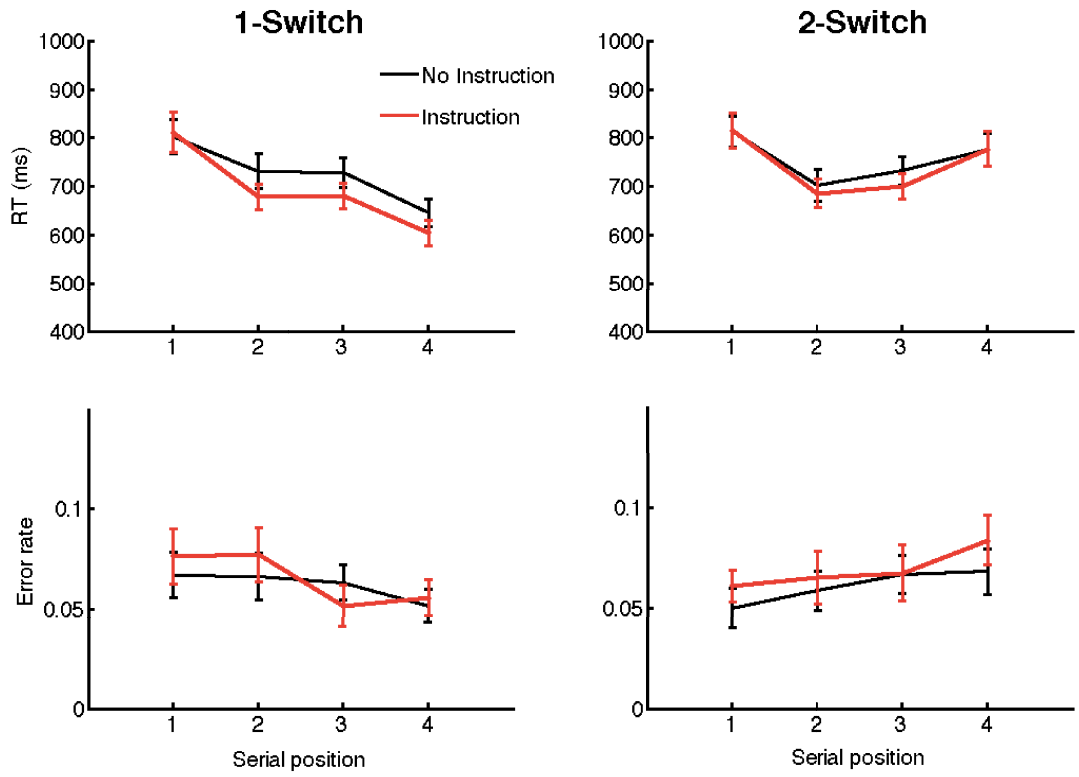


Figure 6.2. *Experiment 7: mean RTs and error rates as a function for sequence type and serial position. No Instruction refers to the condition where no sequence information was provided, whereas in the Instruction condition participants were told whether the upcoming sequence would involve 1 or 2 task switches. Error bars indicate standard errors of the means.*

Finally, the interaction between sequence type and position was reliable, $F(3, 48) = 38.1$, $MSE = 95{,}269$, $p < .01$, $\eta_p^2 = .71$, reflecting decreased RTs in the last position of 1-Switch sequences, which were always task repetitions. However, the key main effect of interest – the effect of Instruction – was not reliable, $F(1, 16) = 2.9$, $MSE = 33{,}182$, $p = .11$, $\eta_p^2 = .15$, which suggested no overall RT benefit of providing instructions regarding switch frequency. However, there was a significant interaction between Sequence Type and Instruction, suggesting a more noticeable RT benefit in 1-Switch sequences than 2-Switch sequences, $F(1, 16) = 6.3$, $MSE = 7{,}849$, $p = .02$, $\eta_p^2 = .28$. To explore this interaction, follow-up pairwise contrasts were run and revealed a reliable instruction RT benefit on the 2nd, 3rd, and 4th positions, all $p < .05$, in 1-Switch sequences. In 2-Switch sequences, only the 3rd position showed a marginally significant RT instruction benefit effect, $p =. 06$.

Error rates for the four positions and the two sequence types were quite similar, such that the ANOVA revealed no reliable main effects of Instruction, Sequence Type, or Position, Fs > 2.4, $ps > .15$. Even though the factor of Instruction was not significant, there was a trend that error rates are numerically higher in the instruction conditions. In this analysis only the interaction between sequence type and position reached significance, $F(3, 48) = 6.7$, $MSE = .005$, $p < .01$, $\eta_p^2 = .30$. This interaction was caused by the pattern of larger error rates at the first two positions in 1-Switch

sequences but pronounced errors in the last two positions in 2-Switch sequences. Overall, there were no clear RT and error rate differences between No Instruction and Instruction conditions.

Sequence transition effects

To examine whether performance differed between repeating vs. switched sequences, RTs and error rates across the four sequence positions were averaged as a single index and entered into a repeated measures ANOVA with within participant factors of Instruction (No Instruction, Instruction), Sequence Transition (sequence repetition, sequence alternation), and Sequence Type (1-Switch, 2-Switch). Here, Sequence Transition relates to the type of sequence (1 vs. 2-switch), not the particular ordering of tasks required. For example, ABBB-AABB is considered a repetition of a 1-switch sequence. For the mean RT analysis, the only reliable main effect was that of Sequence Type, $F(1, 16) = 71.1$, $MSE = 55{,}164$, $p < .001$, $\eta_p^2 = .82$, indicating overall longer RTs in 2-Switch than 1-Switch sequences, as described above, but there was no reliable effect of Sequence Transition, $F < 1$. Instruction did not show a significant effect, $F(1, 16) = 2.8$, $MSE = 19{,}721$, $p = .11$, $\eta_p^2 = .15$. The research interest concerning factors of Sequence Transition and Instruction did not reveal a reliable interaction, $F < 1$. A two-way interaction between Sequence Type and Sequence Transition was

detected, $F(1, 16) = 13.9$, $MSE = 12{,}159$, $p < .01$, $\eta_p^2 = .47$, see Figure 6.3. This interaction further interacted with the factor of Instruction, $F(1, 16) = 4.7$, $MSE = 4{,}950$, $p < .05$, $\eta_p^2 = .23$. To clarify this interaction, separate two-way repeated measures ANOVAs were conducted for the No Instruction and Instruction conditions. A reliable interaction Sequence Type and Sequence Transition was found in No Instruction condition, $F(1, 16) = 12.0$, $MSE = 16{,}313$, $p < .01$, $\eta_p^2 = .43$, but disappeared in Instruction condition, $F(1, 16) = 1.4$, $MSE = 796$, $p = .26$, $\eta_p^2 = .08$. This was mainly driven by the fact that an opposite sequence transition effect in No Instruction sequences, particularly a sequence switching cost in 1-Switch sequences but a sequence repetition benefit in 2-Switch sequences. The remaining two-way interactions were all Fs < 1. Overall, from the above statistical results, there are two main findings. First, there is no clear sequence switching effect. Secondly, the three-way interaction indicates sequence transition effect seems to depend on sequence type.

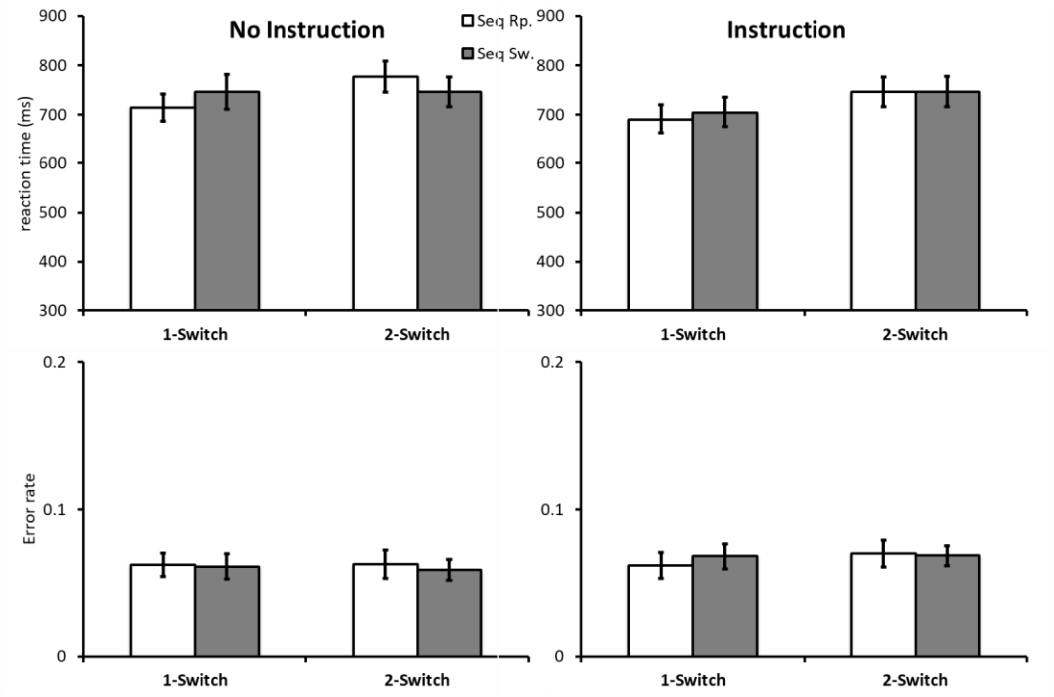


Figure 6.3. *The effects of sequence transition in Experiment 7. Mean RT and error rate for average performance across positions within a sequence, as a function of sequence transition, sequence type, and instruction. Error bars indicate standard errors of the means. No Ins: No Instruction conditions. Ins: Instruction condition. Seq Rp.: Sequence repetition. Seq Sw.: Sequence switch.*

For the error rate analysis, the same ANOVA was conducted. No significant main effects or interactions were observed, all Fs < 2.4, ps > .15. This was consistent with the observation depicted in Figure 6.3 that the error rates of each condition were similar in magnitude, with the weak trends that were apparent being generally consistent with the RT patterns described above.

The above analysis relates to repetitions of sequence type (1-Switch or 2-Switch).

To explore possible sequence transition effects further, I investigated the sequence transition effect for sequences with both the same instruction and identical elements. For example, one might predict better performance in sequences that follow another sequence with identical elements (e.g., AABB --> AABB) than sequences that follow another with different elements (e.g., AABB --> ABBB), even if they contain the same number of switch trials in each case. This hypothesis implies that participants retain exact sequence information from the previous sequence until the next instruction onset and beyond. To test this possibility, a repeated measures ANOVA was performed with within-participant factors of Content (Identical elements vs. Different elements), Instruction (No Instruction vs. Instruction), and Position (Position 1-4) on the data from all sequences separately. Consistent with the main pattern depicted in Figure 6.4, the main effects of Position, $F(1, 16) = 44.7$, $MSE = 128{,}236$, $p < .01$, $\eta_p^2 = .74$, and Instruction, $F(1, 16) = 2.7$, $MSE = 17{,}635$, $p = .12$, $\eta_p^2 = .14$, were all replicated as already described. However, when comparing the data between identical elements (left column) and non-identical elements (right column), the RT pattern looks quite similar, $F < 1$. The rest of the interaction effects were all not reliable, $Fs < 1.2$, $ps > .30$.

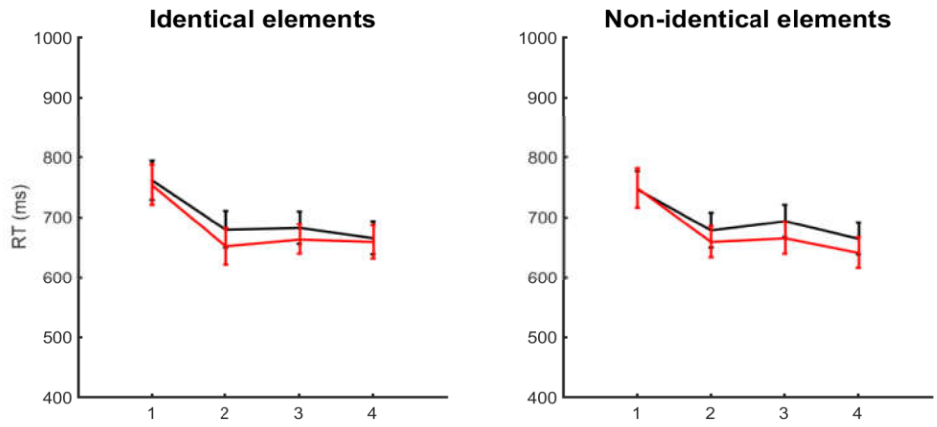


Figure 6.4. *The effects of identical element repetitions in Experiment 7. Mean RT as a function of sequence type, serial position, and repetition type. The figures in the left column represents the data from two consecutive sequences that repeated the same elements whereas the right column represents the data where sequence elements did not repeat. For each figure, error bars represent standard errors of the means.*

Switch performance of T1

Previous studies have observed modulation of switching costs at 'chunk points' where sequence transitions occur (Schneider & Logan, 2014). To examine these effects in the present data, I compared performance on the T1 position of sequences across those involving the same instructions or different instructions. In this analysis, T1 RT and accuracy (excluding the first sequence of each block) were averaged and entered into a repeated measures ANOVA with within participant factors of Instruction (No Instruction, Instruction), T1 Task Transition (T1 repetition, T1 switch), Sequence Type

(1-Switch, 2-Switch), and Sequence Transition (Sequence repetition, Sequence switch). Of the main effects, only the effect of T1 Task Transition was reliable, $F(1, 16) = 18.3$, $MSE = 337{,}088$, $p < .01$, $\eta_p^2 = .53$. As expected, RTs were longer when T1 involved a switch away from the task performed in the last position of previous sequence, as compared to task repetitions (Figure 6.5). The main effect of Sequence Transition was not reliable, $F(1, 16) = 1.0$, $MSE = 7{,}288$, $p = .33$, $\eta_p^2 = .06$. However, Sequence Type interacted with Sequence Transition, $F(1, 16) = 9.3$, $MSE = 56{,}819$, $p < .01$, $\eta_p^2 = .37$. This was driven by a sequence switching benefit in 2-Switch, $p <. 05$, but a pattern of sequence switching cost in 1-Switch, $p = .17$. The interaction between Instruction, Sequence Transition, and T1 Task Transition, which was critical to my research interest, was not significant, $F < 1$. For the rest of the interaction terms, only the interaction between Instruction, Sequence Type and Sequence Transition was marginally significant, $F(1, 16) = 4.5$, $MSE = 12{,}611$, $p = .05$, $\eta_p^2 = .22$. From the figure, it appears that this marginal effect was mainly driven by a larger T1 switching cost in the sequence transition condition (1-2) comparing to other sequence transition conditions. Overall, these results do not provide any clear evidence of modulation of task-level switching costs according to higher-order switching at the level of trial sequences.

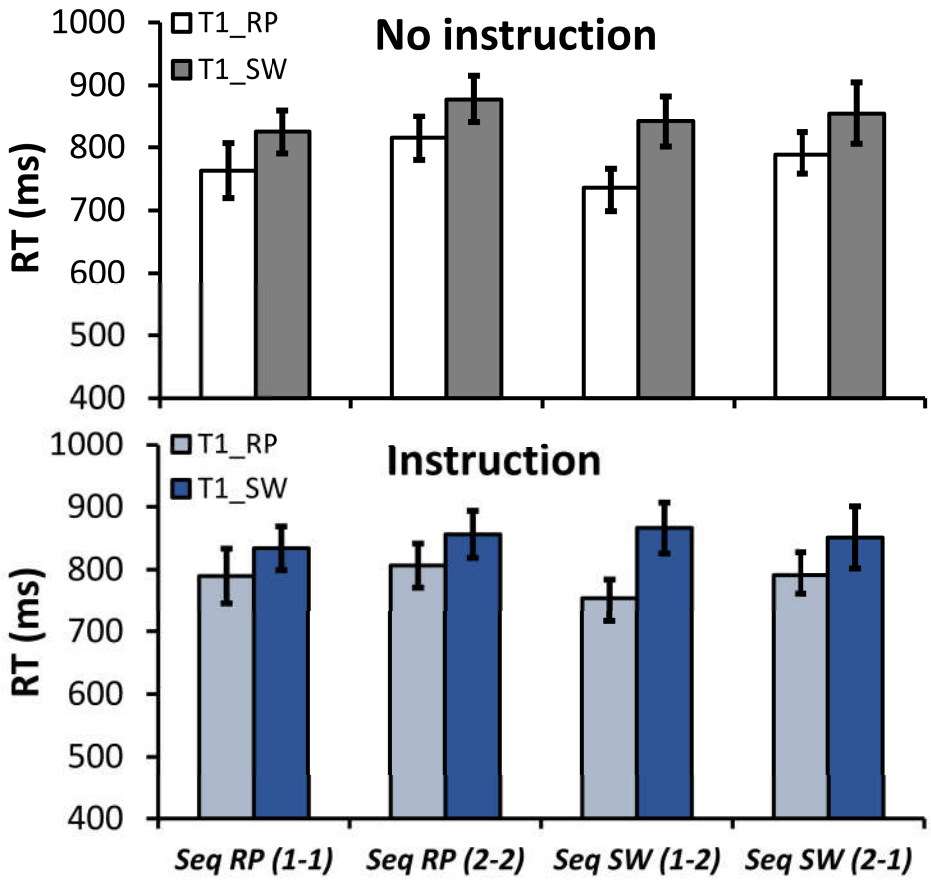


Figure 6.5. *Experiment 7: Mean RT on the first position of sequences (T1) as a function of task transition and sequence transition combinations for the two instruction conditions. Seq SW: Sequence switch. Seq RP: Sequence repetition. The number labels that follow sequence transition indicate the relationship between previous sequence type and current sequence type. For instance, "1-2" represents a sequence switch from 2-Switch to 1-Switch. Error bars represent standard errors of the means.*

Switch performance of T2

As described above, a crucial feature of high-level control is that it should be observed throughout sequential task performance, not only on the first trial of a

sequence. I therefore investigated whether there was a performance benefit to provide instructions about switch frequency on trials within a sequence. This analysis focused on T2, for which task and switch probabilities were matched across all relevant conditions of the analysis. Mean RTs and error proportions were drawn from 2nd positions of every sequence and were examined by repeated measures ANOVAs with the following factors: Instruction (No Instruction, Instruction), Sequence Type (1-Switch, 2-Switch), and T2 Task Transition (T2 repetition, T2 switch). An overall RT Instruction benefit was apparent on T2, $F(1, 16) = 4.5$, $MSE = 48{,}005$, $p < .05$, $\eta_p^2 = .22$. However, although mean RT was reliably greater on T2 switch trials than on T2 repeat trials, $F(1, 16) = 63.0$, $MSE = 720{,}700$, $p < .01$, $\eta_p^2 = .80$, the critical interactions between Instruction and T2 Task Transition and between Instruction, Sequence Type and T2 Task Transition were not reliable, $F(1, 16) = 1.4$, $MSE = 2{,}452$, $p = .26$, $\eta_p^2 = .08$, $F(1, 16) = 1.5$, $MSE = 3{,}711$, $p = .23$, $\eta_p^2 = .09$, respectively. From Figure 6.6, there are numerical differences whereby RTs and switching costs are highest in the 1-Switch No Instruction condition. Relating these observations to the statistical results, the average time costs incurred by task switch in 1-Switch and 2-Switch in Instruction condition were similar in magnitude (132 ms vs. 139 ms), as well as the No Instruction condition (171 ms vs. 130 ms, $p = .72$). In general, from these results, the most reliable finding is the main effect of Instruction even though it

does not interact with T2 Task Transition. This provides evidence that instruction (high level sequence representation) guided task selection beyond first positions.

In the mean error rate analysis, only the main effect of T2 task transition was reliable, $F(1, 16) = 20.3$, $MSE = .037$, $p < .01$, $\eta_p^2 = .56$, with participants making more errors on switch trials than non-switch trials. There was, however, a marginal interaction between Instruction and T2 Task Transition, $F(1, 16) = 4.0$, $MSE = .007$, $p = .06$, $\eta_p^2 = .20$. This effect was driven by a diminished switching error cost of task switching in 2-Switch sequences without any instruction (bottom two panels of Figure 6.6), a result that was unexpected and that has no clear explanation.

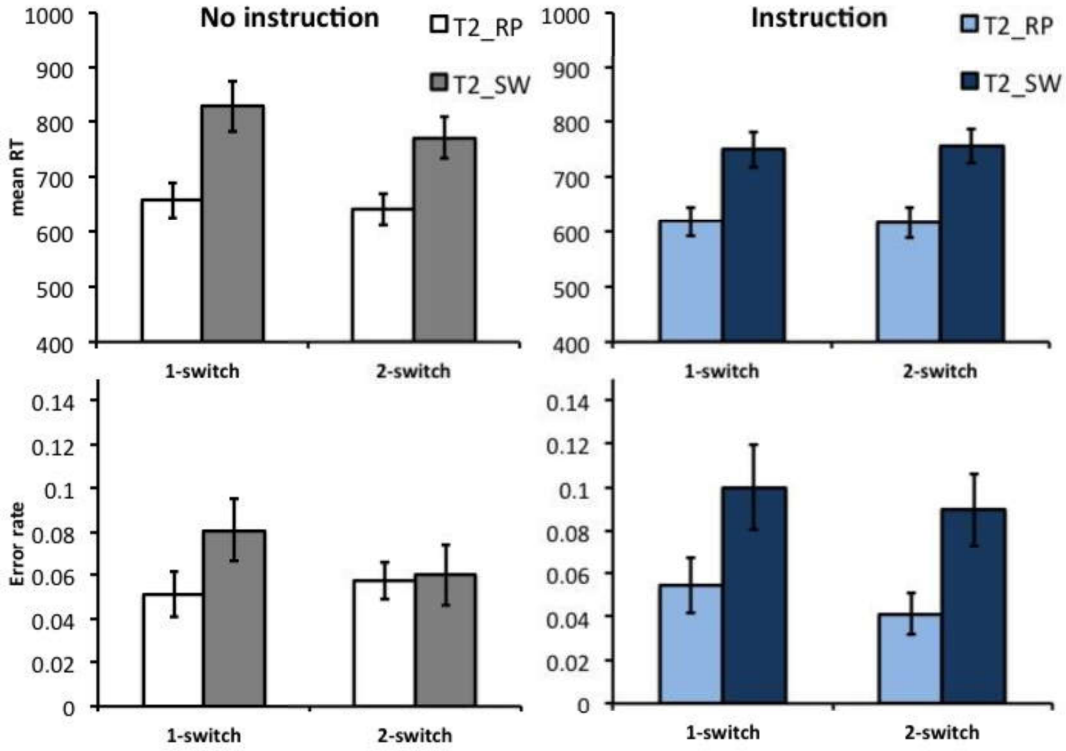


Figure 6.6. *Experiment 7: Performance of the second position (T2) for the two instruction conditions as a function of task transition and sequence type. T2_RP: task repetition occurs at second serial position. T2_SW: task switch occurs at second serial position. Error bars represent standard errors of the means.*

Discussion

The primary aim of this study was to examine the effect of sequential control on task switching performance. In the current study, I tested whether sequential control modulation can be found on first positions and even the 2nd positions. In addition, another interest was whether repeating or switching sequences will produce a cost or benefit that is similar to the traditional "switching costs/repetition benefit" at the task level. I explored these questions using a novel type of sequence information—an instruction about the frequency of task switches in a 4-trial sequence. To distinguish the modulating effects of instructions from restart costs (e.g., Altmann, 2002), I contrasted performance with and without instructions. Finally, to observe the instruction effect beyond the first trial, I carefully matched the switch frequencies of the first and second positions of every sequence to the same probability (50%). Thus, any change in switching performance found beyond first positions can be attributed to the influence of instruction.

To summarize the key results of this experiment, an instruction effect was observed overall but only in 1-Switch sequences not in 2-Switch sequences. There was no evidence suggesting that repeating or switching sequences was similar to task level transitions—there was no reliable cost of switching sequence type (instruction). This was true even when sequences with identical task elements were repeated. For the interaction between sequence and task levels, the sequence modulation effect on first trials of sequences was not clear. However, a robust RT instruction benefit was found on second serial positions.

Instruction effect

First, regarding the instruction effect found in 1-Switch sequences, one possible explanation relates to the notion of meta-control. In the absence of instructions, participants could adopt a flexible (high switch probability) control status allowing efficient switching. If so, there would not be much difference between 2-Switch sequences whether instructed or not. But 1-Switch sequences could benefit from instruction because the instruction could allow participants to adopt a different control status (low switch probability or strong goal shielding). The inclusion of No Instruction conditions was mainly designed to differentiate between sequence control and restart costs. Despite a similarity of methods for these two effects, the underlying mechanisms

are quite different. More specifically, the reduction in switching costs (or, equivalently, the loss of task repetition benefit) on T1 may be due to a compensation on RTs for the memory decay (e.g., Altmann, 2002) or an attentional mechanism involving during sequence transition points (e.g., Savalia, Shukla, & Bapi, 2016).

The effect of sequence level processing on T1

In contrast to previous studies (e.g., Lien & Ruthruff, 2004; Schneider & Logan, 2006), in the current study T1 transitions were not clearly affected by sequence-level processing. Instead, as shown in Figure 6.6, T1 performance was mainly determined by the sequence type per se. Importantly, this effect also interacted with instruction, although in a marginal way. The pattern of a smaller T1 switching cost in the Instruction condition is consistent with the prediction that the effect observed here was not caused by a time gap between sequences (restart cost). This implies the results were caused by sequence-level control and its interaction with task transitions at the single trial level.

Transition effects at the sequence level

In the context of hierarchical task structure, a straightforward question is whether repeating the same sequence representation would produce benefits. This notion is very

similar to the task switching costs on the task level. If we treat action sequences as a higher-level task-set, one might expect a cost when sequence structure changes and corresponding benefits when sequence structures repeat. However, I did not find any costs or benefits at the sequence level. One possibility is that task sequences in general do not operate similarly to low-level tasks in terms of the need for reconfiguration or the possibility of interference when sequence structure switches. In particular, Lien and Ruthruff (2004) proposed a dual-route model to explain the loss of the benefit of repeating cognitive operations (at a sequence transition point) from one task element to the next. They suggested that sequence-level processing primarily relied on a processing route that is distinct from single-trial level task processing. People may deliberately prepare for all elements belonging to the upcoming sequence. Because this advance preparation involves several task elements simultaneously, mental operations from the previously performed task cannot be simply carried over to next trial altogether. Accordingly, if the content of sequences was not specified clearly in advance—which was true in the present study because sequences were defined abstractly in terms of the number of switches required rather than a unique sequence of task elements—no mental operations could be reapplied to next sequence and sequence repetition benefits (and sequence switching costs) would be lost.

T2 performance

The motivation to focus on switch performance on second position was to avoid the possible confounding factors related to the restart cost and observe lasting effects of sequence-level structure. First, a clear overall benefit of instruction effect was found. This suggested the participants did use the instruction to predict the next task based on switch probability. Another finding is no clear sequence-level effects on T2, with similar RTs in the contrast between task repeats and task switches on T2 for each sequence type. These findings may reflect the ambiguity of sequence elements. Due to the nature of the instruction, a rough sequence can be planned during instruction stage (e.g., an example of 1-Switch sequence: AABB) but the correct task elements can only be confirmed after the first position (e.g., ABBB). Thus, a clear instruction benefit might still be expected but the content of sequence representation occasionally needed to be updated when the originally expected sequence does not match the one experienced. If participants actually performed the tasks from a sequence list that was created during instruction stage and stored in their working memory (e.g., Schneider & Logan, 2006), more errors would be expected if they encountered unexpected sequences. This speculation could be partially supported by the fact that slightly higher error rates were found in Instruction conditions (Figure 6.2).

Limitations on task design

Although the present results provide some hints of sequence-level structure effects, the overall weak benefits of instruction and weak T1 and T2 switch modulation effects raise concerns over the effectiveness of the instructions used. Past studies have suggested increasing preparation time is sufficient to reduce switching costs (e.g.,Meiran, 1996). Some also suggest prior knowledge regarding what is likely to occur may facilitate the reconfiguration process (Kleinsorge & Gajewski, 2008) and may bias the control state that can change task switching efficiency (e.g., Goschke & Bolte, 2014). However, previous studies have found sequence structure effects with the same inter-sequence interval of 1.5 s. As a result, I shifted to the possibility that the instructions used in the current study were too abstract, without enough specific details, to allow representation of an effective sequence structure. The experiments in the next chapter therefore used instructions that specified exactly where in the sequence a switch would occur.

Conclusion

To conclude, Experiment 7 aimed to test meta-control effects by focusing on the impact of high-level sequential structure on switch performance. To quantify the meta-control influence, there were three main indexes: T1 switching costs, T2 switch

performance, and overall sequence-level performance. The last two measures have been largely neglected in past research. Analysis of switching costs on T1 revealed very limited evidence of sequence influence on switch performance: I did not replicate previous observations of reduced task-level switching costs across sequence-level transitions. To differentiate meta-control effects from restart costs, I investigated the influence of sequence transition beyond the first position in a sequence. The high-level influence of instructions was found on T2. Moreover, I also tested whether the performance across the trials in a sequence would benefit when sequence structure repeated and incur a cost when sequence structure changed. This simple and straightforward idea has not been seriously tested before, and in the present experiment there was little evidence of sequence-level switching costs. However, because the current study has some limitations in the clarity and usefulness of the instructions, these indexes provide limited evidence supporting the instruction benefits and no clear sequence transition effect on task level processing.

Chapter 7

Evidence of meta-control in sequential task structure

Introduction

Experiments 8 and 9 reported in this chapter re-examined the hypothesis formed in the previous study, with a modified design that aimed to increase participants' use of sequence information. In Experiment 7, participants were encouraged to form high-level sequence representations based on switch frequency information. Although this information is potentially helpful (as shown in Experiments 1-6), at the same time it also leaves ambiguity about the particular task sequence required. Perhaps after anticipating a task sequence incorrectly, participants gradually switched from proactive preparation using the switch frequency information provided to a more reactive strategy by preparing tasks only after cue or stimulus onsets when the required task became unambiguous.

One obvious way to address this issue is to instruct the task sequence explicitly prior the beginning of a sequence (as done in Schneider & Logan, 2006; Mayr, 2009). However, this design might at the same time impose a considerable load on working memory, particularly if longer sequences are used. Moreover, the research in this thesis aims to investigate preparation that is abstracted away from the level of specific tasks,

and instead aims to induce and study more sustained modes of control at the level of task sequences. Therefore, in Experiments 8 and 9 I decided to directly instruct participant regarding the switch position of sequence, without indicating the specific tasks required. With such a design, one could expect that meta-control will be involved in monitoring task selection at least until the position of switch.

Based on a very similar experimental design to Experiment 7, the hypotheses for Experiment 8 were almost identical. First, I expected a benefit of instructions that would be seen not only task switch trials (the ones that are instructed) but also other trials within sequence. Second, if sequence representations are highly activated in response to an instruction (Dosenbach et al., 2006), I predict a diminished switching cost at the first position of a sequence whenever there is a sequence boundary. This prediction is in line with the notion that the meta-control signal is highly activated during the first trial due to the need to scheduling tasks within sequences (Schneider & Logan, 2006). Third, from the meta-control point of view, if sequences act like higher-level task sets, then one would expect repetition benefits and switching costs at the sequence level.

As in Experiment 7, to address the potential confounding of restart costs, sequence transitions were studied both with and without instructions. Even though no instruction was delivered in no instruction condition, participants might still encode the sequential

structure implicitly. Thus, the prediction was any effects induced by meta-control should exist in the instruction conditions but not in the No instruction condition, or that such effects would be more pronounced in the instruction conditions than no instruction conditions.

Experiment 8

Methods

Participants

Twenty participants (12 female; Mean age =19.1 years, SD =0.8) were recruited for this study from the Oxford University community. They were given written informed consent before participating. All participants had normal or corrected-to-normal visual acuity and self-reported normal colour vision. Participants received £8/h or course credits per testing session.

Apparatus, design and procedure, and stimuli

Participants were tested individually. The methods and procedure were very similar to those in Experiment 7. The key difference in this study was that there was always one task switch in each 4-trial sequence, and instructions given prior each

sequence specified the position of this switch. Participants were required to perform task switching in short sequences of four trials. In half of the blocks, instructions about switch position were given prior to each sequence while in the other half of blocks, no such information was provided. Instructions (validly) indicated that the task switch would occur at position 2, 3 or 4 in the sequence equiprobably. The instructions were presented for the participants as images depicted in Figure 7.1: The four trials were depicted as coloured circles with the position of the switch indicated by the colour change. The colours used in the instructions (yellow and black) were distinct from those used to cue tasks on individual trials (red and blue), such that the instructions provided no information about the specific tasks required (which would be unpredictable on the first trial, but predictable thereafter based on the instruction). Participants were encouraged to use the information to improve their performance. In No Instruction blocks, trials were similarly presented in 4-trial sequences, with 1.5 second inter-sequence intervals, but this period was filled with a blank screen.

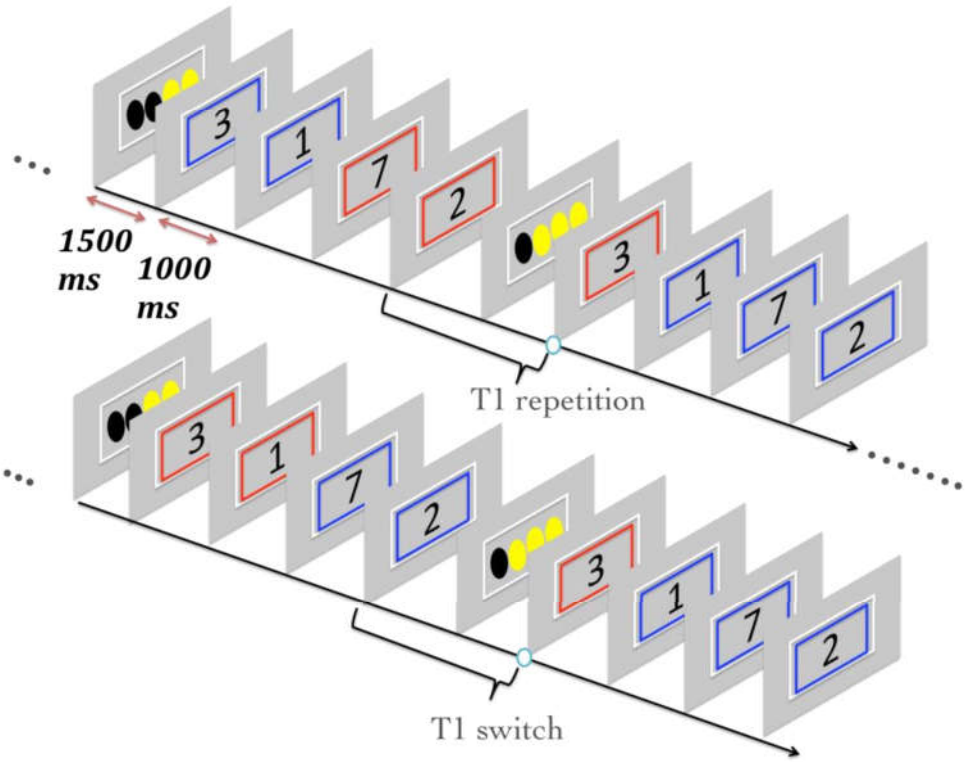


Figure 7.1. *Procedure of Experiment 8. Examples of task repetition and task switch at the first trial position of sequences. The two examples are from the Instruction condition, in which visual instruction was delivered prior to each sequence. T1: first serial position.*

There were 10 experimental blocks, with random ordering of the Instruction and No Instruction blocks. Each block contained 25 sequences for a total of 100 trials. At the end of every experimental block, participants were given a short break and feedback regarding their performance of previous block. The whole experiment lasted about 70-80 minutes.

Before the experimental blocks, all participants began with four short practice

blocks. During the first two practice blocks, participants were familiarized with both tasks separately (16 trials each). In the third practice block, they practiced task switching in short sequences. The final practice block introduced instructions before each sequence. To proceed to the next practice block or to the formal testing session, participants were required to perform at 90% accuracy in the block. The whole practice session lasted about 15-20 minutes.

Preprocessing and data analysis

The first sequence of each block, for which sequence transition cannot be defined, was removed from analysis. Analysis of the mean correct RTs and error rates used repeated measures ANOVAs. Median RT data was also checked and yielded very similar to those reported below for mean RTs. Again, for all reported results, the alpha level was set at .05 and partial eta squared was used as an index of the effect size.

Results

Switch performance within sequences

The first analysis focused on the effect of the instruction manipulation by directly contrasting performance between the Instruction and No Instruction blocks. As depicted in Figure 7.2, considerable improvement can be seen in each sequence type

when instructions were provided. To confirm the observation, separate repeated measures ANOVAs with factors of Instruction (No Instruction, Instruction) and Position (1-4) were applied to the data from each Sequence Type separately (i.e., for each possible location of task switches in the sequence). The analyses of mean RT data revealed main effects of Instruction, all $F(1, 19) > 4.7$, $p < .05$, $\eta_p^2 > .20$, Position, all $F(3, 57) > 47.8$, $p < .01$, $\eta_p^2 > .72$, and a reliable interaction between the two factors, all $F(3, 57) > 3.3$, $p < .05$, $\eta_p^2 > .15$, for all three switch-position sequences. Planned comparisons between the two instruction conditions for each position revealed an evident benefit at every position in Switch at 2 sequences (*t*-tests > 2.4, $p < .03$, with instruction RT benefits of 44, 130, 84, 61 ms for each position). For Switch at 3 and 4 sequences, no consistent benefit from the instruction was observed for the first trial position, $p > .82$, but instruction condition benefits were reliable for the other trial positions 2-4, all $p < .05$.

For the error rate data, the instruction effect was almost reliable in Switch at 1 sequence, $F(1, 19) = 4.3$, , $MSE = .004$, $p = .052$, $\eta_p^2 = .19$, but not in the other two sequences, both, $F < 1.7$, $p > .21$, although the overall trend is still in line with predictions. No other effects were significant. In general, the main findings here are that there is an overall benefit of instructions and that this benefit persist even after the switch when only one switch can happen. For instance, in Switch at 2 sequences, after

the second trial (the switch) instruction benefit can be found on trials 3 and 4. Similarly in Switch at 3 sequences, the benefit can be found on the last trial.

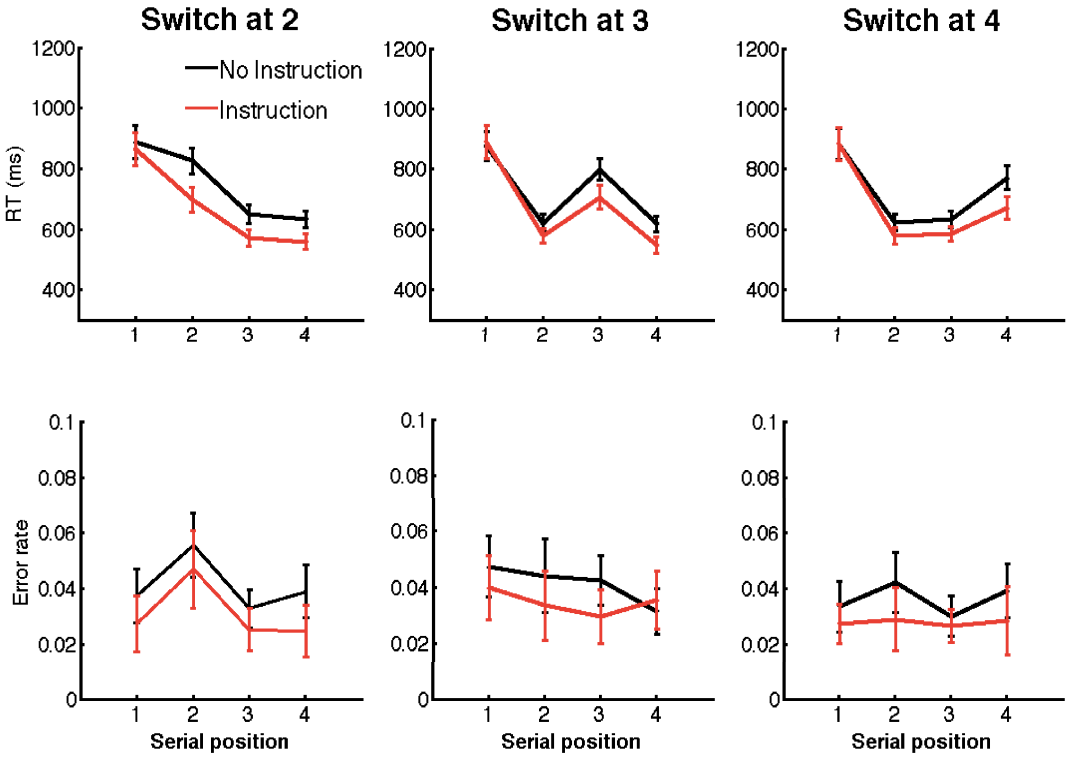


Figure 7.2. *Performance for each sequence type in Experiment 8. Mean RT and error rate as a function of instruction and serial position. Error bars denote standard errors of the means.*

Sequence transition effects

If sequence representations carry over from the last sequence to the next one, performance in sequences that repeat the last one should be better. To examine the effect of sequence transitions on overall performance, I compared RTs and error rates in

sequences where switch position was the same as (sequence repetition) or different from (sequence switch) the sequence just completed.

First, 3 parallel repeated measures ANOVAs with factors of Sequence Transition, Instruction, and Position were applied to the three types of sequences. Since the ANOVA results from these three sequences yielded very similar and robust effects, the three types of sequence then were averaged. Next, a repeated measures ANOVA with factors of Sequence Transition, Instruction, and Position were applied to the averaged sequence data (Figure 7.3). First, RTs from sequences with instructions were shorter that those without instruction, $F(1, 19) = 38.5$, $MSE = 453{,}110$, $p < .01$, $\eta_p^2 = .67$. This indicated a successful implementation of the instruction. Moreover, significant main effect of Position was found, $F(3, 57) = 64.7$, $MSE = 886{,}074$, $p < .01$, $\eta_p^2 = .77$. This main effect was mainly driven by first trials of sequences. The interaction between Instruction and Position was also reliable, $F(3, 57) = 7.2$, $MSE = 14{,}246$, $p < .01$, $\eta_p^2 = .28$. This was mainly driven by a smaller differences between No Instruction and Instruction sequences at first trial positions relative to other positions $F(3, 57) = 7.2$, $MSE = 7{,}123$, $p < .01$, $\eta_p^2 = .28$. However, the important main effect of Sequence Transition, which was the main interest here, was not significant, $F < 1$, as can be seen from the Figure 7.3 that the patterns between right and left panels were almost identical. The only interaction involving Sequence Transition was the interaction of Sequence

Transition × Position, $F(1, 19) = 5.0$, $MSE = 7{,}342$, $p < .01$, $\eta_p^2 = .23$. Follow-up pair-wise comparisons revealed that RTs at the 3rd, $p < .01$, and 4th, $p < .05$, positions were faster (by 21 ms and 10 ms, respectively) in repeated sequences than different sequences. Altogether, there were three main findings here: a clear instruction effect was observed, the instruction effect benefited trial positions 2-4 the most, and a small RT benefit of repeating the same sequence was found at trial positions 3 and 4.

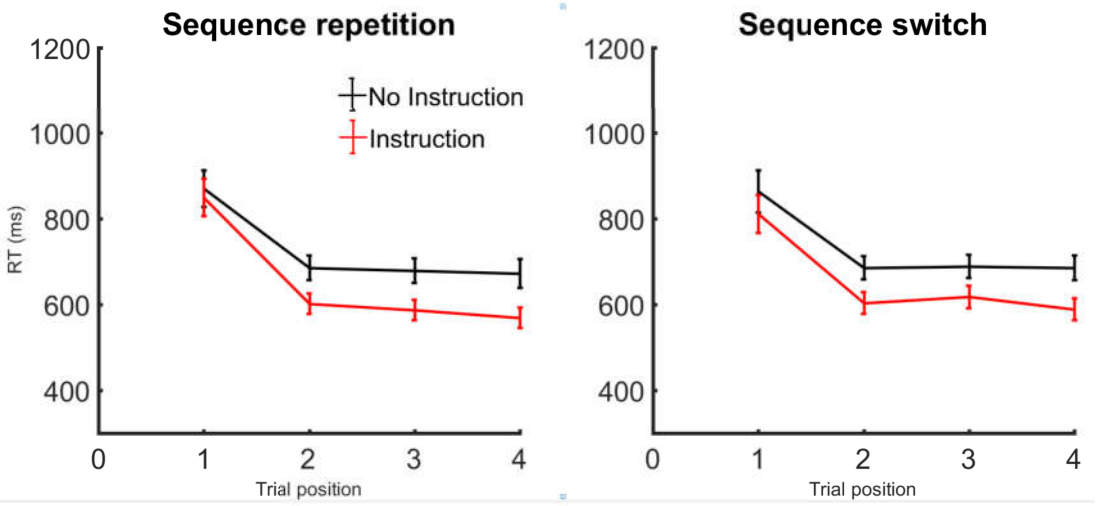


Figure 7.3. *Sequence transition effect in Experiment 8. Mean RT as a function of instruction and serial position. Sequence repetition denotes the same sequence types were repeated but not necessarily repeated the same task elements. Error bars denote standard errors of the means.*

The same procedure performed on the mean RT data was applied to error rate data (Figure 7.4) as well. Again, error rates from the three types of sequences were averaged

and entered into a repeated measures ANOVA with factors of Sequence Transition, Instruction, and Position. Only the main effect of Instruction reached marginal significance, $F(1, 19) = 3.6$, $MSE = .006$, $p = .07$, $\eta_p^2 = .16$, showing a small benefit of providing instructions. There was no significant main effect of Position, $F(1, 19) = 1.7$, $MSE = .002$, $p = .18$, $\eta_p^2 = .08$. Similar to the RT data, Sequence Transition did not affect error rates within sequence, $F(1, 19) = 2.1$, $MSE = .003$, $p = .18$, $\eta_p^2 = .08$. The remaining interactions were all not reliable. Unlike the RT data, the interaction between Sequence Transition and Position was not reliable, $F(3, 57) = 1.2$, $MSE = .001$, $p = .31$, $\eta_p^2 = .05$. Overall, the instruction effect was quite limited in error rates and sequence transition did not affect error rates.

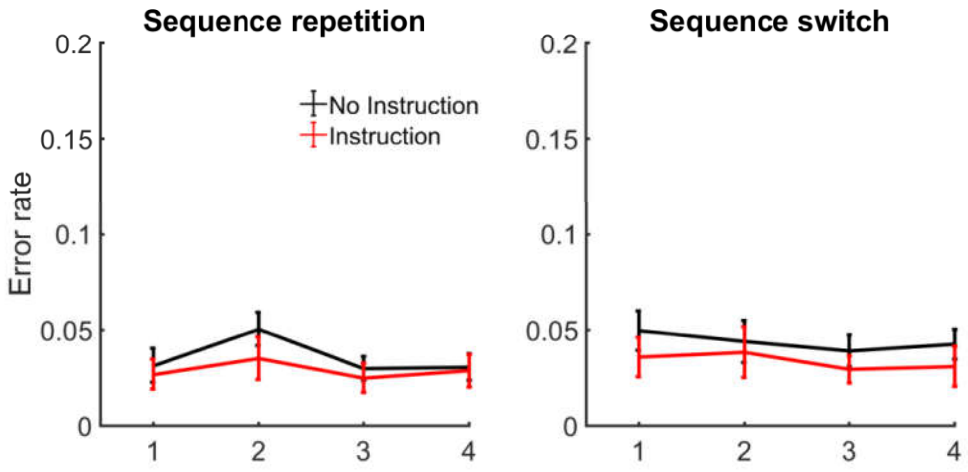


Figure 7.4. *Sequence transition effect in Experiment 8. Mean error rate as a function of instruction and serial position. Sequence repetition denotes the same sequence types were repeated but not necessary repeated the same task elements. Error bars denote*

standard errors of the means.

To further clarify the sequence transition effect, I also compared repeated sequences with the same task elements with those followed by different elements. No main effect of content repetition (i.e., identical vs. different task sequence) was observed, nor did this factor further interact with other factors described in the analyses above. Therefore, it seems that repeating the same task elements did not improve overall performance.

Switch performance on T1

As has been discussed in the introduction, sequence representations might be activated in response to instruction cues. Meta-control might be initiated accordingly around first serial positions and affect task-level processing. To test such transient effects of meta-control, the first trials from each sequence (T1s) were selected and categorised according to their relationship with the final trial of the previous sequence. These trials were then entered to a repeated measures ANOVA with factors of Instruction, Sequence Transition, and T1 Transition (T1 repetition, T1 switch). None of the main effects were reliable: Overall RTs were similar with or without instructions, $F < 1$, see Figure 7.5, for sequence repetitions and switches, $F < 1$, and most importantly,

for trials in which the T1 task repeated vs. switched from the last trial of the previous sequence, $F(1, 19) = 1.5$, $MSE = 106{,}001$, $p = .24$, $\eta_p^2 = .07$. However, T1 Transition marginally interacted with the factor of Instruction, $F(1, 19) = 4.4$, $MSE = 133{,}519$, $p = .05$, $\eta_p^2 = .19$. This interaction indicated that without instruction there was small switching cost, 2 ms, $p = .91$, across sequences; with instructions, there was a switch benefit, 36 ms, $p = .04$. In short, this suggests a T1 modulation effect of sequence-level processing. Follow-up contrasts revealed no significant T1 switching costs in the sequence repetition of No Instruction condition, $t < 1$, however there was a marginal T1 switching benefit sequence repetition of the Instruction condition, $t(19) = 1.8$, $p = .09$. A distinct pattern of T1 switching costs between the two instructions conditions suggests that the need to build a sequence representation, rather than a time gap between sequences, influenced the task level of switch processing. No other interaction terms were detected, all $F < 1$.

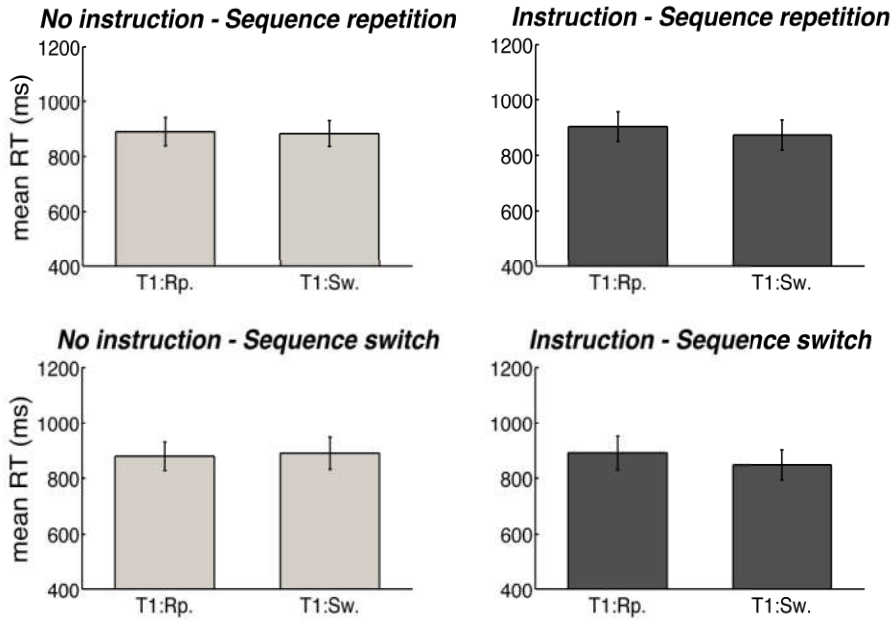


Figure 7.5. *Mean RTs at first serial position (T1) in Experiment 8 as a function of task transition (Switch or Repeat), instruction (No Instruction vs. Instruction, left vs. right panels) and sequence transition (Sequence repetition vs. Sequence switch, top vs. bottom panels) conditions. Error bars denote standard errors of the means. T1:Rp. = task repetition (of the first trial in the current sequence) in relation to the last trial of last sequence; T1:Sw. = task switch (of the first trial in the current sequence) in relation to the last trial of last sequence.*

A corresponding ANOVA on the error rate data (Figure 7.6) revealed that overall more errors were committed in the No Instruction condition in comparison to the Instruction condition, $F(1, 19) = 4.2$, $MSE = .027$, $p = .05$, $\eta_p^2 = .18$. Participants also made more errors in sequences following different sequences as compared to following

the same sequence, 4.2 % vs. 2.9%, $F(1, 19) = 6.9$, $MSE = .063$, $p = .02$, $\eta_p^2 = .27$. Importantly, consistent with the mean RT data, no obvious switching cost was found at T1 positions, $F < 1$. No interactions were reliable, including the interaction between Instruction and T1 transition, $F < 1$.

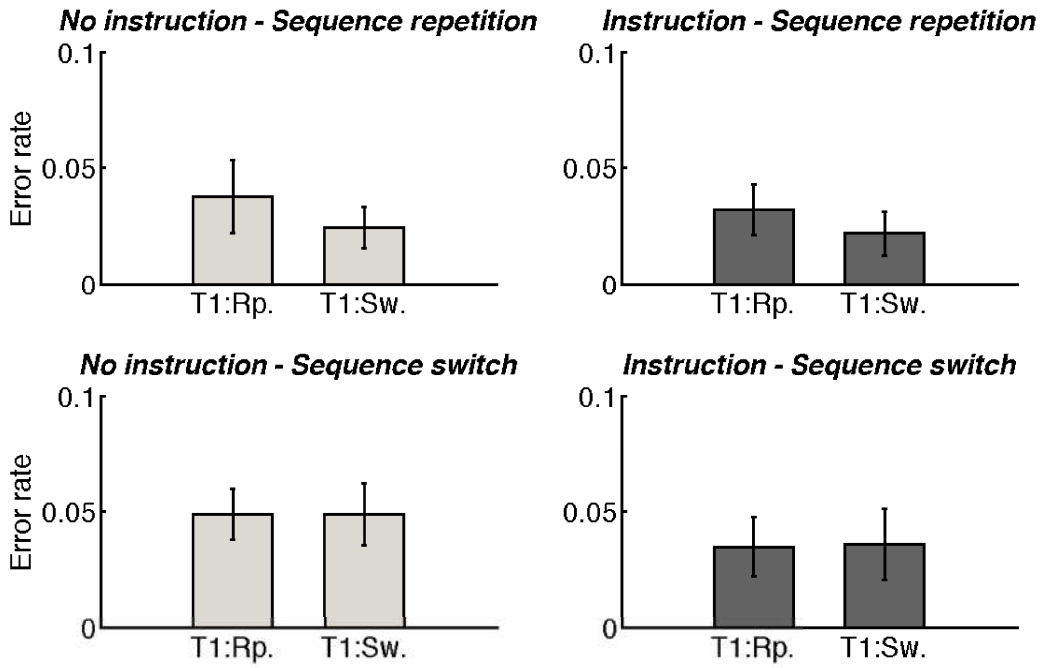


Figure 7.6. *Mean error rates at first serial position (T1) as a function of task transition for both the instruction (No Instruction vs. Instruction, left vs. right panels) and sequence transition (Sequence repetition vs. Sequence switch, top vs. bottom panels) conditions in Experiment 8. Error bars denote standard errors of the mean. T1:Rp. = task repetition (of the first trial in the current sequence) in relation to the last trial of last sequence; T1:Sw. = task switch (of the first trial in the current sequence) in relation to the last trial of last sequence.*

Discussion

The aim of this study was to address issues raised in Experiment 7 and to reinvestigate the influence of sequence representation on task-level processing. To encourage participants to build an effective sequence representation of structure, the current study modified the instructions relative to Experiment 7 to be more transparent. Balancing the requirement of "planning" sequences and avoid ambiguity, the position of the switch trial was always specified. Evidence that participants could implement the instruction comes from the finding of a general improvement in mean RT for every sequence type with instruction compared to a baseline condition with no instructions. Importantly, this improvement was not solely restricted to switch trials, but also distributed across other positions. If participants simply prepared for task switches and ignored information about the overall task sequence, then the performance benefit would only be observed on switch trials. However, this was not observed, suggesting that task sequence representations were maintained and used throughout sequences.

Further evidence suggests the effects of meta-control in this experiment. In particular, disruption of the usual task switching cost on T1 of each sequence was seen for both Instruction and No Instruction blocks, consistent with previous findings about task switching in sequences (e.g., Schneider & Logan, 2006). The reversal of the T1

task switching cost in instruction blocks was striking and unexpected. One interpretation of this is that it relates to the instructions used, in which participants cannot prepare a specific task and in fact must always prepare to switch at some point in the sequence. Perhaps this induces a distributed attention state whereby both task sets are activated (as in previous studies with high switch frequency information). This might lead to the switch benefit observed, as goal/task shielding will be low. Experiment 9 tests this hypothesis.

Experiment 9

The goal of this experiment was twofold. First, I tested the distributed attention hypothesis, which was first proposed in Experiment 4 to explain effects of switch frequency instructions on alpha power and then used to explain the switching benefit observed in the previous experiment. To test whether attention expansion actually operated during sequence transition points, two types of sequences were contrasted in this experiment: one containing no task switches (labeled as One task sequence) and another one with one task switch (labeled as Two task sequence). The hypothesis was that sequence preparation would induce a distributed attentional state only in Two task

sequences but not in One task sequences. Therefore, the prediction was that a T1 switching benefit will exclusively be found in Two task sequences.

Second, I tested for possible effects of positional coding in producing the T1 switching benefit in Experiment 8. The positional-coding model assumes that there is a sequence representation that codes for a series of elements by associating task units and a position code (Henson, 1998; Rosenbaum, Hindorff, & Munro, 1987). Applying the positional code model to the T1 modulation effect, when two consecutive sequences share the same set of positional codes, it is expected that performance will be improved because the codes can be reused across sequences. On the other hand, performance will be worse if they change. Another reason to study this effect was that this positional coding effect was confounded in the previous study (see Mayr, 2009). Because every sequence involved one task switch, T1 task switches always co-occurred with repetitions of T1 positional codes (e.g., AABB -> ABBB) whereas T1 task repeats always co-occurred with changing T1 positional codes (e.g., AABB -> BAAA). As a result, this effect might contribute to the observed switching benefit (actually due to the benefit of repeated positional codes). To test whether the switching benefit on T1 results from positional code effects, a sequence with no task switches was adopted in this study. The use of sequences with no task switches allows me to compare the T1 switching cost effect with and without positional code repetitions.

Methods

Participants

Twenty healthy people were recruited from Oxford community took (11 female; Mean age =24.7 years, *SD* =3.36). All had normal or corrected-to-normal vision and none of them reported colour-blindness. Informed consent form was collected prior to testing. Their time and efforts on participating were in exchange for receiving payment or course credit.

Apparatus, stimuli, and design and procedure

Except where noted below, procedural and experimental details were the same as in Experiment 8. The overall design of Experiment 9 was similar to that of Experiment 8, focusing on the effect of instructions that give advance warning about the location of task switches and task repetitions within a sequence, but do not indicate the particular task sequence required. This experiment differed, however, in that each sequence was just 2-trials long, and some sequences did not include task switches.

Participants were required to perform odd/even and low/high judgment on every trial in short sequences of only two trials. There were two types of sequence used in this study and they were indicated by an instruction delivered at the beginning of each

sequence. The instruction consisted of two circles (see Figure 7.7), with the yellow one indicating the position of the switch trial. There were two types of instruction: 1) Two task sequences (with a black and a yellow circle): both tasks were required in the sequence, with the switch occurring always on the 2nd trial position, 2) One task sequence (with two black circles): the same task was required on both trials of the sequence. Similar to the previous study, on half of blocks, these instructions were given to participants, whereas in the other half of blocks no instructions regarding task sequence were provided. The inclusion of One task and Two task sequences was designed to create different attentional modes—focused and distributed, respectively—that were predicted to interact with T1 task transition types. I tested this by contrasting T1 performance in One task sequences that should induce a focused attentional mode (T1 task repeat: [AA] -> [AA]; T1 task switch [AB] -> [AA]) with T1 performance in Two task sequences that should induce a distributed attentional mode (T1 task repeat: [AA] -> [AB]; T1 task switch [AB] -> [AB]). Moreover, to test the positional interference hypothesis, I contrasted separate T1 transition pairs with T1 positional interference (T1 task repeat: [AB] -> [BB]; T1 task switch [AA] -> [BB]) against performance on pairs without T1 positional interference (T1 task repeat: [BB] -> [BB]; T1 task switch: [BA] -> [BB]).

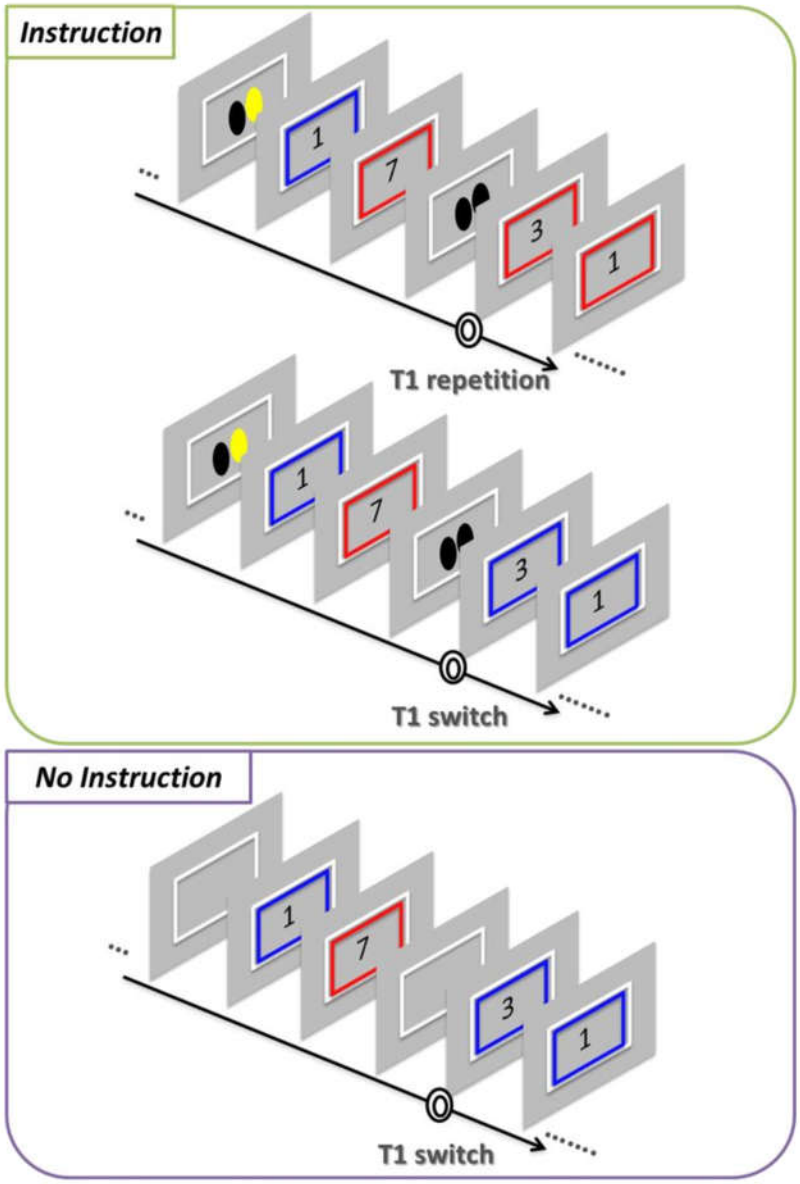


Figure 7.7. *Examples of trial sequences in Experiment 9. In the instruction block, each sequence started with the instruction then followed by two trials. Each trial at first position (T1) can be defined in terms of its task transition (repeating or switching tasks from the last trial of the previous sequence) and sequence type (One task sequence: no distributed attention vs. Two task sequence: distributed attention). The image with two*

different coloured circles served to provide information regarding the upcoming sequence. The yellow circle indicates the location of switch of the two trials within sequence. In No Instruction condition, the design and procedure were almost identical except no information regarding task content was provided for upcoming sequence.

The experimental task comprised 900 trials divided into 18 experimental blocks (50 trials each), of which 9 were No Instruction blocks and the other 9 blocks were Instruction blocks. Block order was randomly assigned for each participant. After excluding the first sequence, there were 12 sequence repetitions and 12 sequence alternations in each block. Each block provided 6 cases of T1 transition pairs (e.g., [XX] -> [*A*A] vs. [XX] -> [*B*B] X 6) for the One task sequence and the Two task sequence. Also, each block provided 3 cases of T1 task transition pairs for the two positional interference conditions (in one condition T1 task transitions were not confounded with the same task in the last sequence whereas in the other T1 pairs there was this confound). Thus, in each experimental block, there were equal numbers of sequence transition and task transitions for the first positions. The number of T1 transitions for testing effects of distributed attention and positional interference were also equivalent.

The timing of instructions and inter-sequence intervals was the same as in Experiment 8. The whole experiment lasted about 70-80 minutes. Participants were

encouraged to use instructions to perform the task efficiently. For the No Instruction condition, they were reminded the task was presented individually even for trials with longer time gap (sequence transition points). Before the experimental blocks, participants began with four short practice blocks as described in Experiment 8.

Preprocessing and data analysis

The first sequence of each block was removed from further analysis because sequence transition type is undefined for these sequences. For analysis of mean RTs, correct trials were included. Data were analysed by repeated measures ANOVAs separately for the RTs and the error rates with relevant factors. Again, for all reported results, the alpha level was set at .05 and partial eta squared was used as an index of the effect size.

Results

Switching performance within sequences

Before addressing the new predictions for this study, I first ran analyses to replicate the key finding from Experiment 8 that instructions would benefit performance overall. Figure 7.8 depicts the switching performance for the two sequence types. These results were analysed in separate repeated measures ANOVAs

for RT and error rates using within participant factors of Instruction (No Instruction, Instruction), Sequence Type (One task sequence, Two task sequence), and Position (serial position: 1-2). From the ANOVA results of mean RT data, a clear overall benefit of Instruction was observed, $F(1, 19) = 6.8$, $MSE = 133{,}938$, $p = .02$, $\eta_p^2 = .27$. Position was highly significant as well, $F(1, 19) = 27.9$, $MSE = 105{,}338$, $p < .01$, $\eta_p^2 = .60$, and this factor interacted with the factors of Sequence Type, $F(1, 19) = 32.2$, $MSE = 141{,}652$, $p < .01$, $\eta_p^2 = .63$, and Instruction, $F(1, 19) = 10.2$, $MSE = 14{,}382$, $p < .01$, $\eta_p^2 = .35$. The first interaction indicates that RTs were slower in the 1st than the 2nd position in One task sequences $t(19) = 6.1$, $p < .01$, whereas this difference was not detected in Two task sequences, $t < 1$. The second interaction suggests the instruction effect was larger at the 2nd position, $t(19) = 3.3$, $p < .01$, than at the 1st position, $t(19) = 1.7$, $p = .10$. No other interaction was detected.

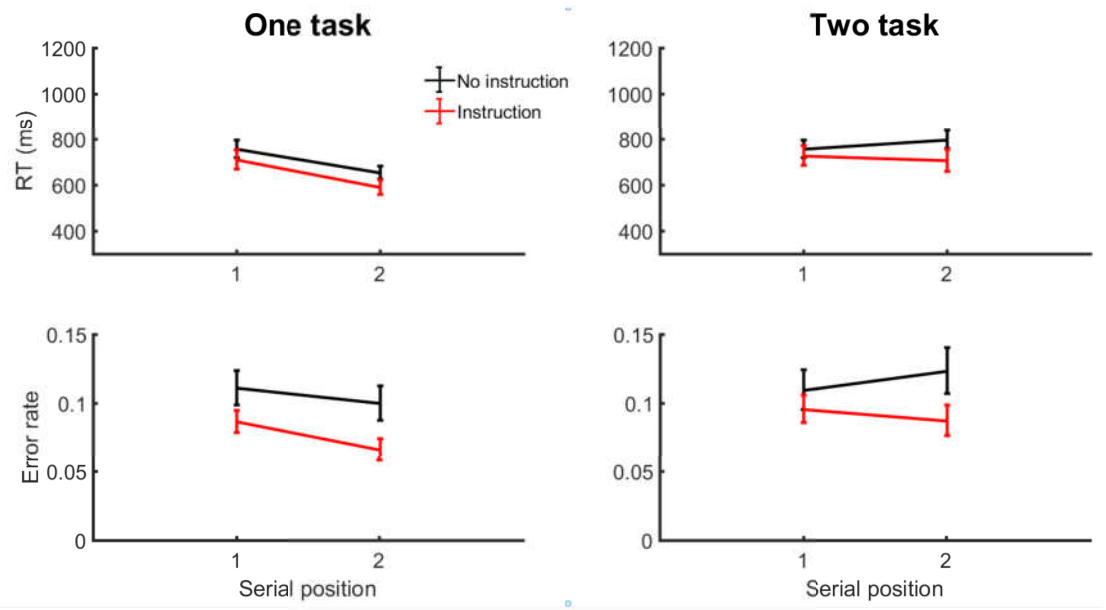


Figure 7.8. *Performance as a function of instruction (No Instruction-black lines; Instruction-red lines) and serial position for the two sequence types in Experiment 9. Error bars of each panel represents standard errors of the mean.*

Corresponding ANOVAs were applied to the error rate data (the bottom row of Figure 7.8). All of the effects were significant except the factor of Position, $F(1, 19) = 2.3$, $MSE = .001$, $p = .14$, $\eta_p^2 = .11$. The main effect of Instruction was highly reliable, $F(1, 19) = 23.0$, $MSE = .031$, $p < .01$, $\eta_p^2 = .55$. In addition, more errors were made in Two task sequences than One task sequences, $F(1, 19) = 24.6$, $MSE = .018$, $p < .01$, $\eta_p^2 = .56$. Like in the RT data, Position also interacted with Instruction, $F(1, 19) = 28.5$, $MSE = .015$, $p < .01$, $\eta_p^2 = .60$, with significant instruction benefits only seen at the 2nd position, $t(19) = 5.8$, $p < .01$. Importantly, this two-way interaction further interacted with Sequence Type, $F(1, 19) = 15.5$, $MSE = .006$, $p < .01$, $\eta_p^2 = .45$. Follow-up

comparisons revealed clear instruction benefit at both 1st and 2nd trial positions for One task sequences, $t(19) > 2.8$, $p < .10$, but only at the 2nd trial position in two task sequences, $t(19) = 5.4$, $p < .01$. Overall, the analyses from error rates and RTs revealed effects of instruction manipulation and sequence type.

Performance on T1

To assess the instruction and sequence transition effects on switching performance at first serial positions (T1), I conducted repeated measures ANOVAs on mean RT and error rate data sets. Three within-participant factors were included: Instruction (No Instruction, Instruction), Sequence Transition (sequence repetition, sequence alternation), and T1 Transition (T1 repetition, T1 switch). In the mean RT data (Figure 7.9), there was a significant main effect of Instruction, $F(1, 19) = 6.2$, $MSE = 90{,}427$, $p = .02$, $\eta_p^2 = .25$, reflecting an overall RT benefit of instructions, and a marginally reliable main effect of T1 Transition, $F(1, 19) = 3.5$, $MSE = 69{,}029$, $p = .08$, $\eta_p^2 = .16$, reflecting a trend towards task-level switching costs even across sequence transitions. Sequence transition did not affect T1 switching performance, $F < 1$. Importantly, T1 Transition interacted with Instruction, $F(1, 19) = 20.7$, $MSE = 124{,}422$, $p < .01$, $\eta_p^2 = .52$, which indicated a marginally significant switching cost in the No Instruction condition, $t(19) = 2.0$, $p = .06$, but no switching cost in the Instruction condition, $t(19) =$

1.6, $p = .14$. No other two-way interactions were reliable, all $F < 1.9$, $p > .18$. The three way interaction between Instruction, Sequence Transition and T1 Transition was marginally significant, $F(1, 19) = 3.3$, $MSE = 4{,}258$, $p = .09$, $\eta_p^2 = .15$.

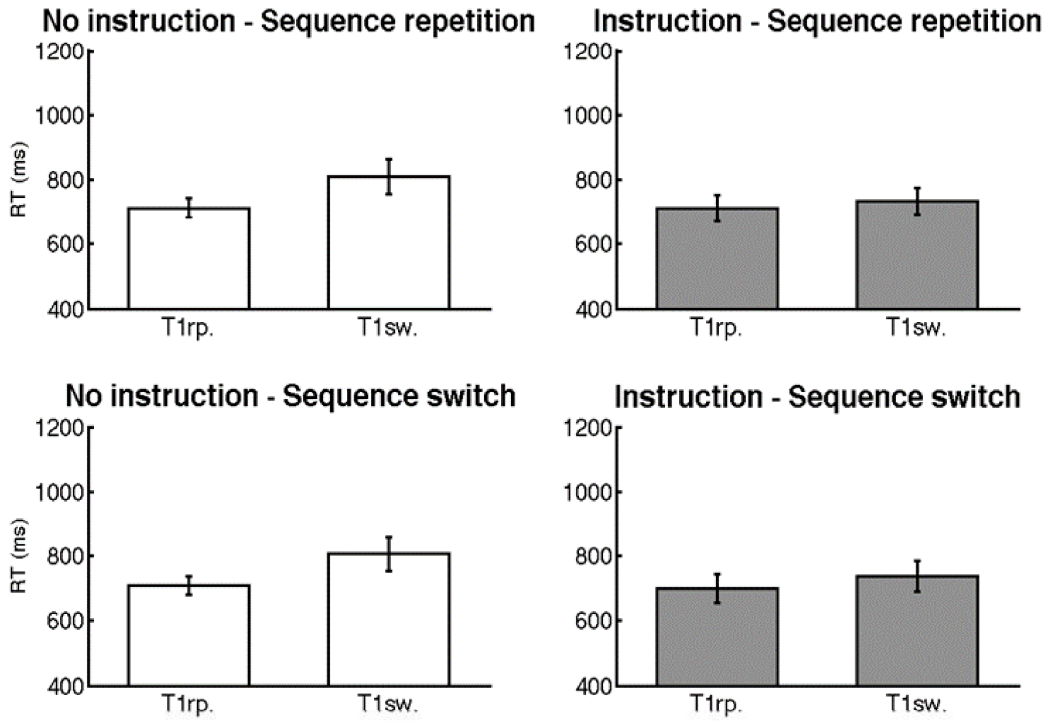


Figure 7.9. *Mean RTs of first position trials (T1) as a function of task transition, instruction condition, and sequence transitions. Error bars indicate standard errors of the mean.*

For the error rate data (Figure 7.10), the only effect that was close to significant was the main effect of Instruction, $F(1, 19) = 3.2$, $MSE = .003$, $p = .09$, $\eta_p^2 = .14$, with somewhat lower error rates overall in Instruction blocks compared to No Instruction

blocks. There was no switching error cost overall, $F < 1$, and switching error costs did not differ reliably between the two instruction conditions, $F(1, 19) = 1.7$, $MSE = .001$, $p = .21$, $\eta_p^2 = .08$. Overall, from these analyses on the T1 performance data, T1 switching costs seems to be attenuated with instruction regardless of the factor of sequence transition. However, this pattern was not noticeable in error rates.

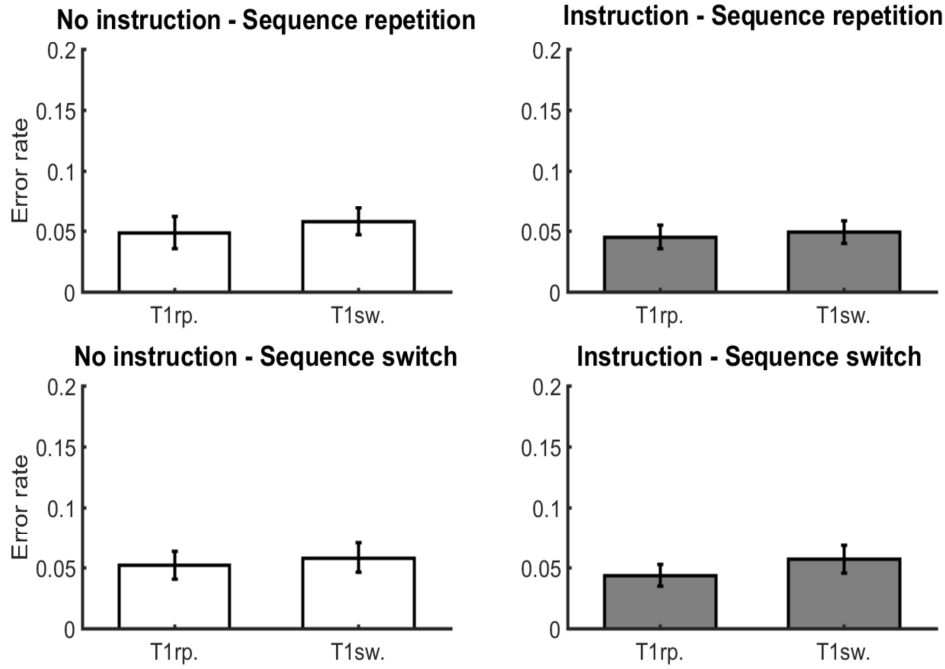


Figure 7.10. *Mean error rates of first position trials (T1) as a function of task transition, instruction condition and sequence transition. Error bars of each panel represents standard errors of the mean.*

Distributed attention status modulated T1 switching costs

Based on the results of Experiment 8, I hypothesised that the T1 switching benefit

occurred because instructions always indicated that task switching would be required in the sequence. This interpretation predicts that T1 switching costs should vary according to whether sequence instructions indicate that task switches will or will not be required. To test this prediction, the T1 data were separated into two groups based on the number of switches required in the upcoming sequence, and then entered into a repeated measures ANOVA with factors of Instruction (No Instruction, Instruction), T1 Transition (T1 repetition, T1 switch), Attentional Status (Distributed attention = Two task sequence, Focused attention = One task sequence). Analysis of the mean RT data (Figure 7.11) revealed an overall RT improvement from instructions, though it was just marginally significant, $F(1, 19) = 3.2$, $MSE = 64{,}196$, $p = .09$, $\eta_p^2 = .43$. Besides the already reported effect of T1 Transition, $F(1, 19) = 19.9$, $MSE = 165{,}926$, $p < .01$, $\eta_p^2 = .51$, RTs of One task sequence were slower in relation to RTs of Two task sequence, $F(1, 19) = 8.0$, $MSE = 4{,}456$, $p = .01$, $\eta_p^2 = .30$. Critically, the factor of Attentional Status also interacted with T1 Transition, $F(1, 19) = 5.2$, $MSE = 6{,}411$, $p = .03$, $\eta_p^2 = .22$. This crucial interaction indicated a reduced switching cost in trials when distributed attention was required compared to trials when distributed attention was not necessary. This pattern is consistent with the prediction that the T1 switching cost was partially caused by an adjustment of attentional status, although in contrast to Experiment 8 there was no consistent difference between switch and repeat trial RT rather than a

switching benefit. Finally, the three-way interaction was not reliable, $F(1, 19) = 3.5$, $MSE = 6{,}617$, $p = .08$, $\eta_p^2 = .51$, although the numerical trend was towards the prediction that the instruction attenuated T1 switching costs. However, any suggestion drawn from this marginal effect needs to be cautious, since the main effect of Instruction was only marginally significant as well.

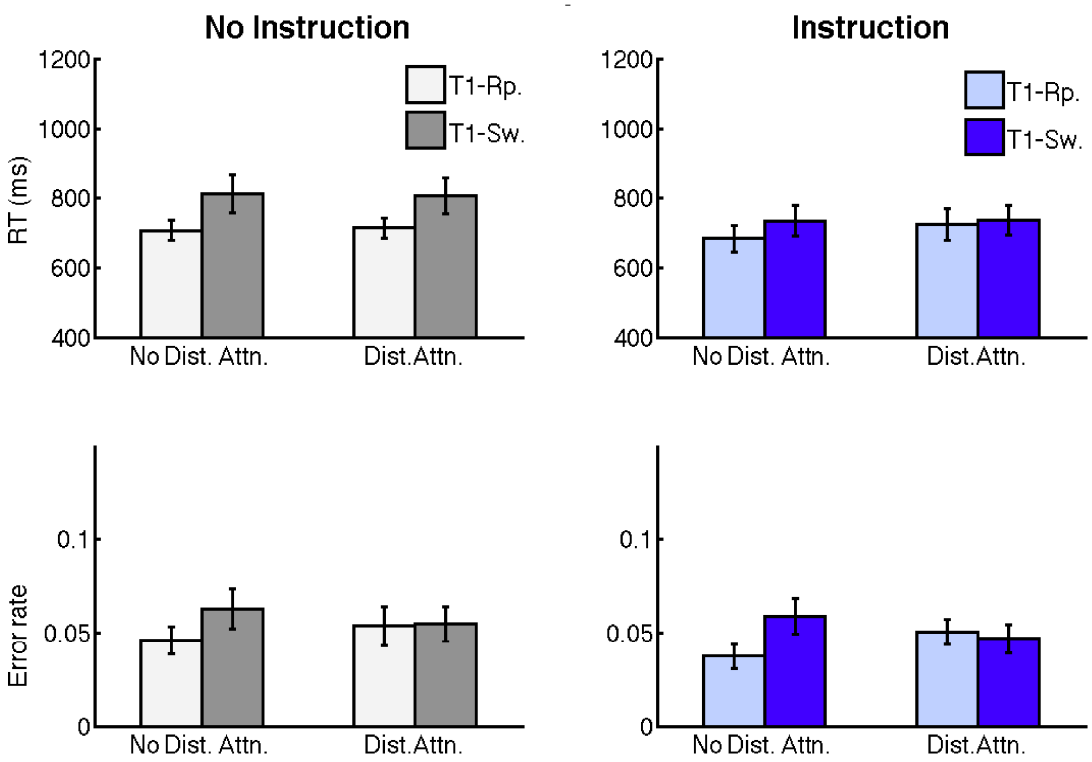


Figure 7.11. *T1 switching performance as a function of instruction and attentional status in Experiment 9. Mean RTs and error rates at first serial positions a function of T1 transition and attention statuses. No Dist. Attn. denotes No distributed attention condition. Dist. Attn. denotes Distributed attention. T1-Rp: task repetition at T1. T1-Sw.: task alternation at T1. Error bars represents standard errors of the mean.*

For the error rate data, a noticeable switching error cost can be seen in some conditions (bottom row of Figure 7.11), which was reflected in the main effect of T1 Transition, $F(1, 19) = 5.5$, $MSE = .003$, $p = .03$, $\eta_p^2 = .22$. No other main effects or interactions were significant, all $F < 3.0$, $p > .10$. To summarize the main results in this section, evidence of attentional status affecting T1 switching costs is not particularly strong, but at least the trends in the data are in line with the prediction.

Positional interference at sequence transition points

The previous analyses are consistent with the idea that sequence instructions induce an overall attentional mode that affects switching. The final analysis looked for evidence of another kind of sequence-level effect, of positional codes whereby serial position codes and tasks are incorporated into sequence representation. For instance, participants might be slower when a different task appears at T1 than in the previous sequence (e.g., in **A**A – **B**A and **A**B – **B**A trial sequences compared with a **A**B – **A**B and **A**A– **A**B sequences).

Both the mean RT and the error rate data sets were assessed using the same three-way repeated measures ANOVA with within-participant factors of Instruction (No Instruction, Instruction), Positional Interference (No interference, Interference), and T1 Transition (T1 repetition, T1 switch). In the mean RT analysis, the main effects

of Positional Interference, $F(1, 19) = 9.3$, $MSE = 40{,}931$, $p < .01$, $\eta_p^2 = .33$, and T1 Transition, $F(1, 19) = 22.1$, $MSE = 102{,}913$, $p < .01$, $\eta_p^2 = .54$, were both highly significant (Figure 7.12). The interaction between Positional Interference and T1 Transition was reliable, $F(1, 19) = 5.8$, $MSE = 36{,}500$, $p = .03$, $\eta_p^2 = .23$, which suggests that positional interference affected the switching process. This interaction was caused by a manifest switching cost in the no Positional Interference condition but a non-significant cost in the Positional Interference condition (80.9 ms vs. 20.5 ms). Similar to the previous analysis, a marginal two-way interaction between Instruction and T1 Transition was also detected, $F(1, 19) = 3.2$, $MSE = 66{,}990$, $p = .09$, $\eta_p^2 = .15$. The three-way interaction failed to pass the statistical criterion, $F < 1$.

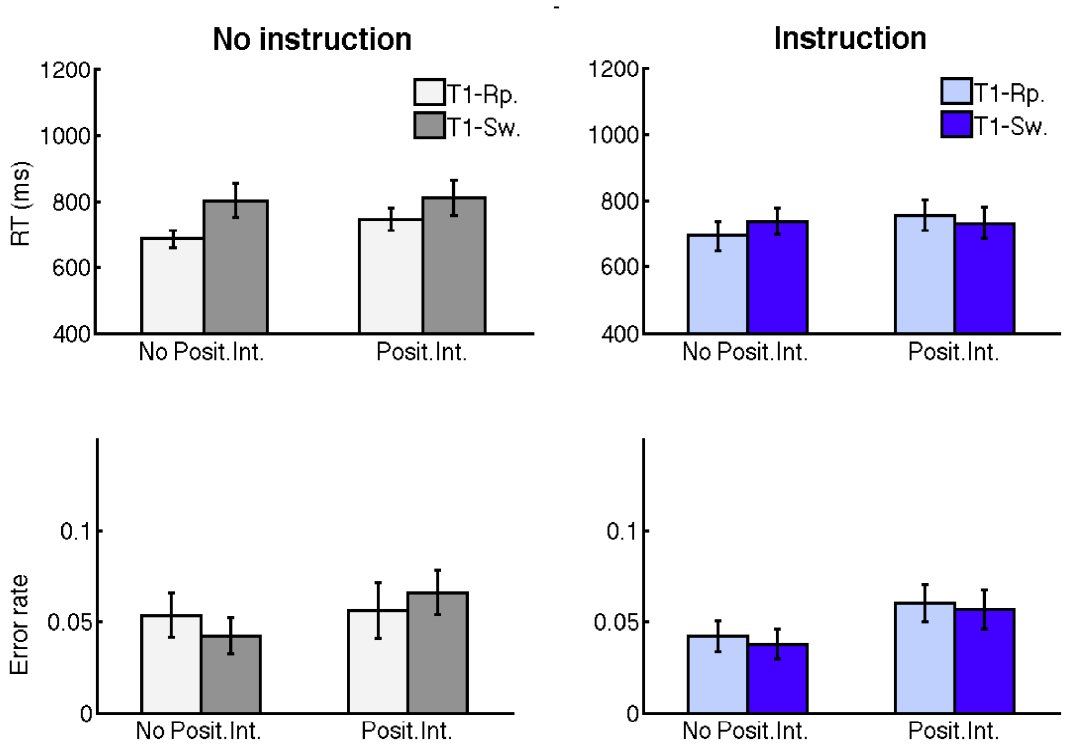


Figure 7.12. *Mean RTs and error rates in Experiment 9 on first position trials (T1) as a function of positional interference and task transition, separately for the two instruction conditions. Posit.: Positional. Int.: Interference. T1-Rp: task repetition at T1. T1-Sw.: task alternation at T1. Error bars indicate standard errors of the mean.*

For the error rate data, only the main effect of Positional Interference was reliable (bottom row of Figure 7.12), indicating that more errors were made when positional interference was present (6%) than when it was absent (4.4%). This sole effect also indicates no clear switching error costs can be observed in general, $F < 1$, and the switching error costs for the two Positional Interference conditions were comparable, which was confirmed by an insignificant interaction of Positional Interference and T1 Transition, $F < 1$. The three-way interaction was not reliable, $F < 1$.

Discussion

The present study explored two possible sources of sequence-level influence on task switching performance. There are three main findings. First, the manipulation of instruction proved to be effective again. Similar to Experiment 8, the benefit of instruction was observed across positions for each type of sequence. Second, reduced T1 switching costs were detected in Two task sequences, in which attentional focus was

hypothesized to be distributed across two task dimensions. Third, the T1 switching cost modulation effect was observed when the positional code was repeated. This finding suggests the role of positional codes in creating sequence representations.

One of the major findings is that T1 switching costs were modulated according to the need for filtering/shielding in the upcoming sequence. The results are in line with my predictions. This finding is reminiscent of the EEG results of alpha power in Experiment 4, which suggested the critical role of attentional status in meta-control. A shift of attention status may be used to adapt to different conditions with differing frequency of switches (e.g., Dreisbach, Haider, & Kluwe, 2002). This implies there might be a mechanism or process that lies behind such variations in cognitive control. When planning a new sequence, the attentional status will change in order to accommodate multiple tasks. If one is told to prepare for a sequence that involves a task switch, it seems that people prepare for both tasks (or, more theoretically, they adopt weaker goal/task shielding) and therefore switching costs are reduced. Here, preparing for both tasks in upcoming sequence can be treated as another example of distributing attention across the tasks. This notion is reminiscent of recent proposals that combine monitoring, attention, and cognitive control into a single framework for sequential control (a review see Desrochers, Burk, Badre, & Sheinberg, 2016). Desrochers et al. (2016) suggested the control of sequences can be divided into two main networks:

schematic (e.g., sequences of procedural movements) and supervisory control. The supervisory control system is mainly in charge of monitoring and keeping track of higher-level task goals. Moreover, the role of attention has been emphasized to not only support schematic control without conscious regulation but also to bias the activity of downstream regions to help obtain task goals. Back to the current study, the role of attention, which is more similar to the supervisory control system, was to provide more or less bias toward task-relevant dimensions according to instructions.

The other major aim of this experiment was to investigate the positional interference account, which proposes that sequence representations code the associations between serial position codes and task elements. Consistent with this theory, switching costs on the first position in the sequence (T1) were modulated by positional interference. This finding suggests the serial code information was incorporated into a sequence representation. The finding raises the question of what exactly is the source of positional interference that contributes to the reduced RT costs reported here and how it relates to meta-control. One theoretical possibility comes from traditional models of hierarchical motor control, which propose that performance costs occur whenever there is a need to re-program a recent action event, task dimension judgment or stimulus-response mapping (Kleinsorge & Heuer, 1999). Moreover, as suggested by Logan (2007), when there is a task structure, the task level switching cost

is determined by the serial positions and task elements together. Accordingly, in this experiment, a positional code and task may be combined when a new sequence representation is formed. In other words, the switching costs at T1s may be a product of the process for disconnecting the associations between task elements and positional codes in order to recombine each of the individual task elements as needed. The source of the positional interference has been further proposed to occur via representation stored in working memory or events traced in episodic memory (Mayr, 2009). However, the current study does not aim to distinguish between the two possibilities. All in all, apparently, the work on assembling the association of the positional codes and task elements itself indicates another level of control, which is needed when tasks are executed in sequences or with a task structure.

General discussion

Experiment 8 and 9 shared a similar aim in creating sequence-level representations and investigated how these representations interact with task-level processing. Some of the findings were observed in both experiments, thus the following key findings are considered and discussed together.

Overall benefit of instruction

Unlike past research that has utilized explicit memorized sequences, the current design focused more on the component of planning in cognitive control. Although there are some dissimilarities between task designs used here and the ones used in past research, the evidence of meta-control influence is coherent in showing reduced switching costs at first serial positions. Moreover, the instruction effect was even distributed across every position of sequences. When retrieving memorized sequences, sequence-level representation may involve retrieving an ordered list of task names, thus making information about upcoming tasks accessible in working memory (Schneider & Logan, 2014). In the current experiment, the role of meta-control was to schedule control resources adjusting switch efficiency in time for the expected switches and repeats.

Switching cost modulation at first positions

One of the main findings is the reduced or even reversed switching cost found at the first serial position of sequences. The attenuated switching cost at first position is consistent with previous studies (e.g., Lien & Ruthruff, 2004; Schneider & Logan, 2006, 2014) and is broadly consistent with motor sequence studies, in which costs and benefits are pronounced at the boundaries of organizational units (Keele, Cohen, & Ivry, 1990). To extend previous findings, a No Instruction condition was included to exclude

confounding effects of restart costs. Indeed, the T1 modulation effect was found specifically in the Instruction condition only. This suggests that the effect found here is dependent on the requirement to build sequence representations which then affects task-level processing, rather than simply being an effect of a gap in time between trials.

There are various possible explanations for the T1 switching cost modulation. One interpretation is that at each sequence transition point—regardless of whether the sequence type repeats or switches—a neutral state must be achieved before adopting a new sequence representation. This interpretation was first proposed by a study by Monsell and Mizon (2006) suggesting that participants tend to reset to neutral state after finishing a task. Also, based on the assumption that only one sequence can be loaded/formed at a time (Oberauer & Bialkova, 2009), previous sequence information may have to be abandoned. Therefore, at sequence boundaries, moving from the task level (just-performed task of the previous sequence) to the sequence level, the system may shift to a neutral state that is not biased toward one task over another. Another similar account is derived from an influential task-switching theory. Some researchers propose task-switching cost is caused by lingering interference from the previously activated task (e.g., Allport et al., 1994). Applying this idea to sequence transition points, the role of meta-control could be to eliminate interference from previously activated task sets in order to impose a sequence structure. This possibility can be

supported by some studies suggesting that stimulus–response variations, which cause interference to the next task, may be selectively shielded through the visual attention system (Steinhauser & Hubner, 2007, 2008; Wendt & Kiesel, 2008). This suggests that task-level processes to a certain degree could be removed strategically as part of sequence-level control.

Lack of sequence transition effects

One of the main purposes for this chapter is to test whether sequences could act like higher-level task sets. The main idea was that if previous sequence is composed of certain numbers of task switches and knowing their positions, meta-control should be tuned to this type of sequence representation. From meta-control point of view, one would expect repetition benefits and switching costs at the sequence level. Thus, two types of sequences were introduced. In both Experiments 8 and 9, sequence transitions did not directly affect performance overall within sequences: Overall performance and switching costs were similar when sequence structures repeated and switched. The absence of this high-level influence cannot be attributed to an absence of meta-control signal. Clearly, the instruction effect was distributed across every position for each sequence, indicating that participants utilized instructions to build a hierarchical structure. One straightforward explanation is that participants always disengaged the

previous sequence representation to create a new one whenever reaching a sequence boundary. There are several possible reasons why they chose not to carry sequence information to the next sequence. First, it is likely that sequence-level processing and task-level processing rely on different processing routes. This idea is similar to the dual-route model proposed by Lien and Ruthruff (2004). In their model, when sequence representations change, elements of the lower level route cannot simply be reapplied. However, this model would predict a loss of task repetition benefits on task level. Another possibility is that only a single sequence representation can be loaded at one time (Oberauer & Bialkova, 2009). Thus, after finishing the last task of a sequence, the best strategy might be to abandon previous sequence and to prepare for next sequence. Testing this possibility might be an important question for future research.

How do positional codes and distributed attention relate to meta-control?

When people try to remember a chunked sequence of elements, they tend to keep elements across chunks while retaining codes of within-chunk positions. One might assume that a sequence representation is composed of ordered elements stored in working memory. The present findings of positional interference indicate sequence representations are built from two components: task elements and positional code, and these two components need to be combined when updating a new sequence.

The idea of combining the positional codes and elements shares much in common with the parameter-remapping model mentioned above (Rosenbaum et al., 1987), according to which sequences tend to be preserved and only be changed only when parameters of the sequence actually need changing. If we assume the parameters and the motor programs in the parameter-remapping model are analogous to the positional code and sequence representation respectively, then the re-parameterization process can be thought as combining positional codes with task elements to generate a sequence representation. A similar account for considering position code and tasks together has also been proposed recently (Desrochers et al., 2016; Desrochers, Chatham, & Badre, 2015). They have found the activities of rostral lateral prefrontal regions ramped up over sequence positions. These activities were suggested to resolve task-position-related interference and at the same time to monitor the task sequence. Desrochers and her colleagues (2016) extended previous work on motor-only sequences by showing that internal position codes are also required in "task" sequences.

Conclusion

Experiments 8 and 9 investigated the impact of sequence representations on switching performance within sequences, focusing in particular on the first serial

positions. In addition to an overall benefit of instructions about positions of task switches within a trial sequence, a reduced switching cost (even, surprisingly, a switching benefit) was detected on the first trial position in a sequence. This effect seems to reflect both distributed attention and positional interference effects. Reduced switching costs the first serial position only existed when a distributed attention status is required because participants expected to perform both tasks in the upcoming sequence. At the same time, the effect when positional codes overlapped between two consecutive sequences. Together, these two findings suggest that attentional status is adjusted when updating sequence representations, and that positional codes are used in building sequence representations. All in all, the two experiments in this chapter not only establish another means to effectively induce sequence-level representations, but also reveal results that are in line with the notion of meta-control. Unlike previous studies inducing hierarchical control with a representation in working memory or implicit learning through temporal and spatial chunking, the contribution of these experiments in showing how these effects can be induced using instructions about abstract properties of upcoming task sequences.

Chapter 8

General discussion

Summary of findings

The main goal of the experiments reported in this thesis was to examine the impact of meta-control signals in task switching processes. Task switching has been proposed as one of the core components of complex goal-directed behaviour, due to its requirement for task coordination (Vandierendonck, Liefooghe, & Verbruggen, 2010). A level of control dedicated purely to switching between tasks or simple actions may not be sufficient for tasks with apparent sequence structure, because a series of simple events is sufficient to elicit a structural representation; often a higher level of control signal (meta-control) might be required to provide contextual information that facilitates the switching process. Motivated by this idea, I conducted two main projects, the first of which focused on testing the switch frequency effect on switching processes and the second on the role of meta-control in hierarchical task structure. In the following paragraphs, I summarise the key findings of each project in turn.

Project 1 findings

In the first project, I began with the switch frequency effect, which previous work

has suggested could exert global influence over the efficiency of task switching. The main hypothesis of this project was that switch frequency effects could be established through an explicit instruction, to induce a tonic and global control state that modulates trial-by-trial switching processes. This hypothesis was tested through a novel design in which pure top-down influences were teased apart from experience-driven adjustment. Specifically, participants' beliefs about switch probability were manipulated in blocks through explicit instruction but objective frequency was matched for a subset of blocks (Fake Frequent and Fake Rare). The prediction was that switch performance would differ between these two instruction conditions, being larger when instructions led participants to believe switches would be rare.

Across the 6 experiments of the first project, I confirmed this prediction, but only in error cost data. Participants made more task switching errors, but were not consistently slowed at switching, when instructed that such switches would occur infrequently. The limitation of this effect to error rates was apparent even when a reward scheme incentivised accurate and fast responding, to encourage participants to make use of the instructions (Experiments 2, 3, 4 and 5). In short, the first three behavioural studies demonstrated behaviourally that instruction induced a meta-control signal that modulated individual switch efficiency (through switch expectancy) as evidenced by increased switching error costs in the Fake Rare vs. Fake Frequent

condition.

This effect was motivation-dependent. The dependence of effect on reward is consistent with the notion that control is weighted in terms of its benefits and costs (e.g., Shenhav, Botvinick, & Cohen, 2013). Reward encouraged participants to allocate more control effort and reduced the overall switching costs accordingly. Furthermore, the engagement of cognitive control differed between frequent and rare switch situations. Frequent switch situations could be perceived as relatively control demanding as they require several task switches. This might deter participants away from choosing task switches and resulted in deploying less control (because the cost of control was high). Actually, this account is in accordance with the task shielding (Dreisbach & Haider, 2009) which predicts a relatively relaxed task shielding in frequent switch conditions.

Experiment 4 used EEG methods to adjudicate between two different interpretations of the instruction effect observed in Experiments 1-3. According to one interpretation, meta-control will enhance motor preparation directly. This was mainly assessed by laterised motor potentials, such as LRP, CNV, and MRAAs. Another interpretation is relatively more global in nature (but not mutually exclusive with the previous one), in which participants can adopt a meta-level set that is either committing less strongly or more strongly to the current task according to current instructions. The meta-level set is related to the hypothesis that task sets serve as attentional filters that

shield the current task from interference but increase the cost of switching tasks (e.g., Dreisbach & Haider, 2006, 2009). Alpha oscillatory power was used to index general task preparation or task focus.

The EEG results indicated that the instruction effect is more likely mediated by meta-level set, rather than in terms of motor preparation. This was evidenced by little evidence of LRP-like effects that differed across instruction conditions, but instead the effects of instruction were only found on alpha power (Frequent Switch > Rare Switch). This finding suggests that instructions prompt the adoption of distinct control modes across blocks but not motor preparation at the individual trial level. Importantly, this pattern was again motivational dependent as were the behavioural results. Divergent views have been proposed about the functional roles of alpha power. One common explanation is that alpha power relates to task engagement (e.g., Macdonald, Mathan, & Yeung, 2011), with less alpha power when engaging a task. Surprisingly, this account is not consistent to what I found in Experiment 4. Instead a more plausible explanation is that alpha power might reflect an adjustment of attentional scope (e.g., Compton et al, 2011), which varies according to the amount of expected conflict. In this study with different switch frequency instructions, attentional scope for filtering relevance of stimuli dimensions needs to adapt flexibly adjusting for different instruction contexts. Relaxing the attentional filter might be helpful for

alternating between tasks more efficiently whereas focusing the filter would be beneficial for repeating the same task. In other words, meta-control via switch expectancy could exert its influence across trials through strategically changing attentional filters as reflected in EEG alpha power.

Another major finding was the effect of participants' subjective belief about switch frequency on voluntary task trials, which was revealed in Experiment 5 and 6. In the last two experiments of the first project, a voluntary task switching procedure was adopted to test whether such meta-control influence could be observed in a free-choice situation. This was introduced to strengthen the idea that the instruction effect here affects voluntary, planned behaviour and not only externally cued or experience-dependent actions. In these experiments, free task choice trials were inserted unpredictably into sequences of cued task switching with different switch frequency instructions. The results showed consistently higher voluntary switch rates with frequent switch instructions than rare switch instruction, both for real and fake instruction conditions, though the difference was more obvious in real instruction conditions. However, this pattern was the same irrespective of reward.

Experiment 6 was designed to compare switch-related EEG potentials between cued and free-choice trials under the influence of meta-control. The behavioural results of task choice were replicated only in no reward trials. The main behavioural index of

the switch error results in fake instructions only reached a numerical trend. Correspondingly, higher alpha power associated with frequent switch instructions was replicated only in the real instruction conditions but not in the fake instruction conditions. The successful replication of the effects in real instruction conditions at least demonstrates the reliability and robustness of two measures: the rate of free choice as a means to see the effect of meta-control and alpha power adjusting for different instructions. The null results of alpha power in fake instructions could be due to the difficulty might arise at the stage of establishing the meta-control.

Project 2 findings

The second project investigated the role of meta-control in sequence transitions and how such transitions affect switching processes. Structure of sequences, which naturally might require meta-control and operate above the single-trial level, can affect task-switching performance. To test these questions, I developed a design that controlled for local switch probability across trials within a sequence. Participants were instructed about the switch position in the upcoming sequence. The main difference from past studies (e.g., Schneider & Logan, 2006) was that instructions provided information about abstract properties of the upcoming sequence (switch frequency or switch location) rather than the specific order of tasks required.

In this project, control operated at high-level of task organisation (sequences of 2 or 4 trials), which could be treated as a mind-set containing task order. Meta-control was induced by instructions about switch frequency (e.g., one switch or two task switches), in which a sequence representation could be built in advance to predict switch probability on each trial to enable more efficient switching. The core hypothesis was that the sequence set should exhibit similar properties as single task set, such that repeating the same sequence should benefit performance. However, repeating or alternating sequences did not affect overall switch performance within sequences. Across Experiment 7-9, I did not find any costs or benefits at the sequence level. The absent sequence transition effect could imply a limitation from the participants that sequence representations have to be built in every sequence and could not be simply carried over from the previous sequence. Instead, significant benefits of instructions about sequence structure were observed not only on switch trials but also across other positions, suggesting the operation of meta-control. As for the sequence transition effect on task-level transitions, I replicated previous findings of reduced task-level switching costs on first trials in a sequence, at least for sequences preceded by instructions. These findings together indicate that sequence representations did interact with task-level switching processes as evidenced by a reduced switching cost, even a slightly switch benefit in Experiment 8, on the first serial positions within a sequence.

In the final study of this project, participants either faced no switch sequences (which should induce a focused attention mode) or sequences with task switches (which should induce a distributed attention mode). The results showed that instruction did improve switch performance overall as compared with no instruction sequences. Like the previous study, smaller switching costs were found exclusively in instruction conditions. Supporting the attentional filter hypothesis, a smaller switching cost was detected in the condition where distributed attention mode was encouraged. I also found evidence for effects of positional interference, where performance is worse when successive sequences require different tasks at a given trial position within a sequence. These results suggest that building a sequence representation involves a need to combine a positional code with task elements. This positional code hypothesis was also supported by finding a reduced switching cost only on trials with interference on positional codes.

Meta-control in task switching and a broader context

Mental flexibility is involved in our daily routines, ranging from tasks as simple as making a cup of coffee to cooking three-course meals for family. Common cognitive theories assume that prefrontal cortex exerts top-down control signals to ensure the success of each task component, such as boiling water. However, success of individual

task components is not enough to perform the whole task efficiently. One also requires a plan that incorporates relevant task components into an overall structure and to know when to switch between these components. Accordingly, the core hypothesis of my thesis was that meta-control would be required in tasks that contain several components, such that there is a higher-level structure that can be represented and used. I focused on switch frequency effects to capture the idea that we are often aware of structure in our environment, even if we cannot predict the specific sequence of tasks and actions required. Here the relevant parameter is the likelihood that we will be able to perform one task uninterrupted vs. being required to switch frequently (adapt to changing demands frequently). Actually, real-world tasks rarely occur equally often. For instance, when preparing a manuscript in different stages, one needs to frequently switch between referring to data and writing, as compared to focusing on writing than checking data at latter stage. When task goals are instantiated with different frequencies, not only the influence of the bottom-up environmental factors would affect task selection, but also switching efficiency will vary. The novel design introduced in Experiments 1-6 controlled for these bottom-up environmental factors, allowing me to investigate meta-control relatively purely.

The EEG results in Experiments 4 and 6 indicate that meta-control did not directly involve motor preparation, which is evidenced by no separation of motor preparation

potentials between different instructions, but instead appears to operate on a more abstract level that I have characterized as an attentional filter. Alpha power may be a marker that tracks fluctuations of the attentional filter. In addition, the attentional filter mechanism may also be deployed during transitions between sequences. Most importantly, systematic study of sequence transition effects in Experiments 6-8 revealed that sequence-level processing is not the same as control applied at the single-task level, such that simply reapplying the same mind set is not possible. The results of absence of sequence level switching costs is consistent with theories suggesting that task and sequence levels rely on distinct processing routes (Lien & Ruthruff, 2004). In traditional task switching studies, task repetitions rely on a fast route whereas task switches use a slow and controlled route. The controlled route is sensitive to the degree of advance preparation, which could derive from task structure (e.g., AB-AB); thus, a reduced switching cost at first positions. This view is also consistent with the idea that when moving toward to a representation that involves several task components, a different type of control signal might be needed and operate in a sustained fashion (e.g., Braver, Reynolds, & Donaldson, 2003; Braver, 2012; Bugg & Braver, 2015; Holroyd & Yeung, 2012; Schneider & Logan, 2006). Again, this implies the prominence of meta-control might be likely in several types of cognitive control settings.

Even though all of the experiments in this thesis were based on the task switching paradigm, the concept of meta-control has also been discussed in theories developed in other research areas. For example, distinct control modes might also exist in goal-directed behaviour (Goschke & Bolte, 2014). Goal-directed behaviour often encounters a dilemma that requires balancing between maintaining task goal and shielding from distracting stimuli vs. flexibly adapting to changes and increasing distractibility. These control states are adaptive and can be biased by internal states, such as positive affect or reward (Frober & Dreisbach, 2016). Similarly, the adaptive gain theory by Aston-Jones and Cohen (2005) proposed task-related utility as a mechanism for switching between an exploitative control mode and an explorative control mode. The critical point is that switching between the two modes takes account of both short- and long-time changes in utility, in which exploration is favored by low long-time utility. Although these two theories do not directly speak to the concept of meta-control, they suggest a type of control signal that operates in a tonic fashion and can modulate individual task processes. For instance, Goschke and Bolte (2014) proposed an updating threshold that regulates global features of the mode of information processing. A high updating threshold prevents distractions and reinforces biasing perceptual processing towards goal-directed information (Goschke & Dreisbach, 2008). On the other hand, a low updating threshold allows potentially

relevant information to gain access to working memory. In short, the threshold mechanism determines the stability of working memory representations, and working memory then directly regulates the rigidity of task sets. From the meta-control view, this updating of threshold can be treated as meta-control signal, and individual task set processing is a lower level that operates under the influence of meta-control.

In the field of reinforcement learning (RL), models of hierarchical reinforcement learning (HRL) have been applied to understand mental flexibility and action selection. The main difference from standard RL is that within HRL there is not only selection of primitive-level actions, but also the temporally extended actions, specified by options (e.g., Botvinick, Niv, & Barto, 2009; Holroyd & Yeung, 2012). With this temporal abstraction, the computational efficiency increases. Since several tasks can be grouped temporally to make exploration easier, this renders HRL able to explain more complex behaviours. For instance, to make a meal for friends, planning might include several sub-goals such as write a shopping list, drive to store, find cooking materials etc., and each sub-goal can be further divided into more details, thus without temporal abstraction that group things close to each other, the search space would be very large and computational efficiency will be low. In one of its extensions, model-based HRL, which can inherit matrices specifying outcomes of primitive-actions and options (sequence of actions) from other situations, the learning system is further proposed to

be capable of planning with options. This option model works somewhat independent of primitive actions. From the meta-control point of view, the option model can be seen as a type of meta-control signal that governs the selection of options. Similarly, in this thesis, different switch frequencies could be applied and then used to regulate switch efficiency.

Overall, based on the main findings of the two projects, there are two main contributions relevant to these broader research questions. One contribution is a methodological improvement. The other one is on the theoretical side. From the first project, the novel task design dissociated pure meta-control from the control at trial-to-trial level or other bottom-up processes (e.g., stimulus associations or practice effects on switching) that are normally confounded with differences in meta-control. The method used in Project 1 introduces a new way of studying meta-control.

The second contribution relates to an extension of past relevant theories. Temporal integration was one of the most emphasized form of hierarchy in early work (Lashley, 1951) as it can be related to the nature of the nervous mechanisms involved. The orderly and timely activation of neurons in neural networks is crucial for the temporal transfer of information in the structuring of behaviour. This idea is conceptually inherited in Fuster's cognit model (e.g., Fuster & Bressler, 2015). This model particularly emphasizes the role of PFC since it not only represents complex

prospective series of goal-directed actions, but also enables their execution proactively under cognitive control. The PFC engages regions that integrate sensory stimuli and motor acts across time. This notion supports a critical role of PFC in motor set and motor sequences, and broadly, in the temporal organization of behaviour. Apparently, meta-control in this thesis is not strongly restricted to temporally integrated actions.

Importantly, meta-control particularly emphasizes the point that cognitive control signals can be multiple layered. The notion of meta-control differs from another line of work, which relatively focuses on rule or policy integration and on the connection to the organisation of PFC. Policy here is defined as the association between an action and an anticipated outcome. Policy abstraction refers to the degree to which a given goal representation forms a generalization over lower-level goal representations. Accordingly, policy abstraction could be treated as a change of rule complexity. The frontal cortex is often proposed to be responsible for learning, storage and/or retrieval of rules for behaviour whereas the other motor related regions, such as dorsal premotor region, are relatively associated with preparation and execution of simple action rules. Growing evidence suggests that when rules are more abstract, the execution of these rules depends on more-anterior portions of the frontal cortex (e.g., Koechlin, Ody & Kouneiher, 2003; Koechlin & Summerfield, 2007; Badre &

D'Esposito, 2009). These theories together advance our understanding of frontal lobe function - regions arrayed along dorsal and ventral anterior-posterior gradients act as coherent functional networks, and this network seems to be capable of supporting increasingly complex action rules.

The meta-control functions studied here are not strongly tied to rule complexity. Instead, meta-control here is more concerned with a set of parameters that govern the order, timing, and transitions of tasks. That is, participants are not required to remember a large number of rules, which could avoid the potential confound of task difficulty or working memory load. Together, this distinction not only relies on the methodological improvement but also strengthens the core features of meta-control, which is a set of parameters controlling how tasks should be performed and scheduled. In addition, contributing to understanding the nature of meta-control, the experiments in this thesis also provide evidence that meta-control is closely dependent on motivational incentives. This again emphasizes the notion that cognitive control interacts with motivation (Botvinick & Braver, 2015). Specifically, motivational incentives have been proposed to mediate the switching between control modes (Goschke & Bolte, 2014).

Limitations and future directions

The meta-control model is not without any limitations. At which level of task structure meta-control is required is not clearly defined. In the series of experiments in the thesis, I only tested high-level processing of sequences beyond the task level. It is not clear that where the meta-control would be situated in task structures that could be defined more than two layers. A similar issue has been raised in research on congruency effects in which the congruency frequency effect could operate at the level of whole lists or single items (Egner, 2014; Schmidt, 2013). To interpret such variations of the results, theories ranging from a generalized conflict model (e.g., Botvinick et al., 2001) to associative learning models (e.g., Schmidt, 2013) have been proposed. Recent research has started to incorporate these views into a coherent one (Egner, 2014). These two views claim that congruency effects operate on stimulus feature to task-set levels. From the hierarchy point of view, stimulus feature can be included in task-set. As a result, Egner (2014) suggested the level of feature abstraction might determine at which level control or learning effects are expressed. For instance, a high-level of abstraction of attentional state could be strategically used to filter features.

There are other theories proposing that the attentional system may be crucial to switching between different control states. Savalia, Shukla & Bapi (2016) suggested that the deployment of attention holds a key to switching between deliberate learning

and automatic learning processes. At the bottom of hierarchy, learning takes place implicitly. However, when proceeding up the hierarchy, the size of sequences increases which then crosses a threshold that determines whether more or less attention is directed toward the sequences. During executing or controlling these sequences at the top of the hierarchy, selecting sequences from middle levels engages attention for goal-directed and model-based learning. Comparing to the alpha results of this thesis, the attentional system has been mentioned as a crucial mechanism that mediates switching between relaxed and focused processing modes. Future studies are needed to investigate whether the size of sequences or the abstractness of tasks (or both) determines the involvement of meta-control. But the problem is that as more practice is gained, executing sequences might gradually become automatic. According to Savalia et al.'s model, the need for attentional deployment might move to a higher level or even not be required anymore. Therefore, it becomes difficult to specify clearly when meta-control is involved. Together, these studies seem to imply two main points. First, effects other than task switching costs, such as congruency and learning effects, could also rely on multiple levels of processing. Second, high-level processing across these domains might share an association with an attentional mechanism that filters stimulus features depending on the size of sequences.

Another main point to be addressed in future research is the degree to which

meta-control can be mapped functionally to the organization of PFC. There is some evidence suggesting that meta-control could depend on anterior regions along the anterior-posterior axis of PFC. In an early study by Braver and his colleagues, sustained activation of anterior PFC was associated with actively maintaining different high-level representations (mixed- or single- task block, Braver, Reynolds, & Donaldson, 2003). Mixed-task blocks can also be conceptualized as requiring maintenance of two sets of stimulus mappings, with attention is directed toward the various mappings as required on the individual task trials themselves. However, as the novel design of the current thesis indicates, these results are likely to be complicated with experience-driven control. It would be interesting to try to replicate Braver et al.'s findings using an instruction design as introduced here. This study would be worthwhile given that the exact functional hierarchy in PFC remains to be determined. The apex of this functional hierarchy in frontal cortex has been proposed to be positioned either on anterior PFC or ACC in different theories (Koechlin, Ody, & Kouneiher, 2003; Holroyd & Yeung, 2012).

Another question for future research is to identify the range of factors that can be used to trigger different meta-control modes. In the experiments studied here, I used instructions to induce meta-control signals. However, in real life the choice of control mode might depend on multiple factors (including experience-based learning,

regularities of an environment, personality dispositions, etc.). The novel experimental design was successful in deconfounding experienced-based learning through matching objective switch frequency but manipulating anticipated switch frequency. However, most cognitive control models would assume a small set of meta-parameters that is used for dynamic regulation of control status of information processing. These parameters could relate to complying internal behavioural goal, motivations or even could be altered through a bottom-up fashion (e.g., salient features). The last point indicates the control status could be conditional to the statistics of the environment. Indeed, Behrens et al., (2007) have demonstrated that information from a relatively local temporal context (e.g., the last trial) should be more influential in a volatile environment, whereas information extracted from a more global temporal context (e.g., a block of trials) should be integrated to guide behaviour in a more stable environment. To test the task volatility in task switching, one could control objective switch frequency but manipulate the variance of switch probability. For example, given the same numbers of task switches, in some blocks, switches could be evenly distributed whereas in a volatile condition, switches occur heavily in the first part of the block but very few could occur in the last part of block. As a result, in the evenly distributed case, instruction of switch frequency is expected to be more informative thus producing stronger effects than should be the case when there is a high variance of switch

frequency. This line of work could help to understand the robustness of meta-control from environmental regularities and possibly constrain the effective time frame of the meta-control in a stream of actions.

Conclusion

Mental flexibility is an essential feature of cognitive control. The task-switching paradigm has provided a valuable tool for studying mental flexibility and control of goal-directed behaviour in situations involving several tasks. The core question of this thesis was whether cognitive control in task switching could be organised hierarchically. Meta-control is proposed as a set of parameters controlling and scheduling actions in a sequence. The series of behavioural studies conducted here demonstrated that switch frequency could be treated as meta-control signal that modulates cognitive control during switching. The EEG results provide insight into the mechanisms by which instructions affected task switching performance, suggesting strategic modulation of attentional filtering (task shielding) that is flexibly tuned to task requirements. Effects were observed both on performance efficiency and biases in voluntary task choice. In a hierarchical task structure environment, benefits of instructions about sequence properties were observed. Also, the task performance was shown to be sensitive to the distribution of attention and associations between tasks and serial position in sequences.

The results from the second project not only provided another means to effectively induce sequence-level representations but also linked to the notion that switching processes (T1) can be modulated by sequence transitions. Overall, in addition to the methodological novelty, the present studies demonstrate the influence of meta-control in task switching processes. In the future, more meta-control parameters remain to be documented and more neuroimaging studies will be required to connect meta-control and the organization of prefrontal cortex.

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