DISSECTING PROACTIVE CONTROL PROCESSES IN TASK-SWITCHING: A MODEL-BASED NEUROSCIENCE APPROACH

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B Psychology (Hons I)

Submitted in total fulfillment of the requirements for the degree of Doctor of Philosophy

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April, 2013

Declarations

Statement of originality

The thesis contains no material which has been accepted for the award of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. I give consent to the final version of my thesis being made available worldwide when deposited in the University's Digital Repository, subject to the provisions of the Copyright Act 1968.

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Elise Mansfield

Publications

Publications arising from this thesis

Karayanidis., F., **Mansfield, E. L.**, Galloway, K. L., Smith, J. L., Provost, A. & Heathcote, A. (2009). Anticipatory reconfiguration elicited by fully and partially informative cues that validly predict a switch in task. *Cognitive, Affective and Behavioral Neuroscience, 9*, 202-215.

Mansfield, E. L., Karayanidis, F. & Cohen, M. X. (2012). Switch-related and general preparation processes in task-switching: Evidence from multivariate pattern classification of EEG data. *The Journal of Neuroscience, 32,* 18253-18258.

Mansfield, E. L., Karayanidis, F., Jamadar, S., Heathcote, A., Forstmann, B. U. (2011). Adjustments of response threshold during task switching: A model-based functional magnetic resonance imaging study. *The Journal of Neuroscience, 31*, 14688-14692.

Mansfield, E. L., Karayanidis, F. Heathcote, A. & Forstmann, B. U. (submitted). Individual differences in strategic adjustments of response caution: Combined evidence from diffusion MRI and electrophysiology. *Cerebral Cortex.*

Conference presentations arising from this thesis

Mansfield, E. L., Karayanidis, F. Galloway, K. L. & Smith, J. L. (2008) Identifying components of task-set reconfiguration using ERP and BESA. *Human Brain Mapping, Melbourne, Australia.*

Mansfield, E., Smith, J., Galloway, K. & Karayanidis, F. (2008). Ready….Set….Switch: B. Source analysis of ERP components of task-set reconfiguration. *Australasian Society for Psychophysiology, Brisbane, Australia.*

Smith, J. L., **Mansfield, E. L**., Galloway, K. L & Karayanidis, F. (2008). Identifying components of task-set reconfiguration using ERP and BESA. *International Organization for Psychophysiology, St. Petersburg, Russia.*

Mansfield, E. & Karayanidis, F. (2010). Investigating top-down control in task-switching: ERP evidence from a voluntary task-switching paradigm. *Australasian Society for Psychophysiology, Newcastle, Australia.*

Mansfield, E. L., Forstmann, B. U., Jamadar, S. & Karayanidis, F. (2011). A multi-component model of reconfiguration processes in task-switching: Converging evidence from ERPs, fMRI and DTI. *Australasian Society for Psychophysiology, Melbourne, Australia.*

Karayanidis, F., **Mansfield, E.** & Cohen, M. X. (2011). EEG spatial multivariate pattern analysis reveals distinct switch-related vs.task-related preparation in cue-target

interval. *International Conference on Cognitive Neuroscience, Mallorca, Spain.*

Mansfield, E. L., Forstmann, B. U., Jamadar, S. & Karayanidis, F. (2011). Preparatory adjustments of response threshold in task switching: A model-based fMRI study. *International Conference on Cognitive Neuroscience, Mallorca, Spain.*

Mansfield, E., Karayanidis, F., Jamadar, S., Heathcote, A. & Forstmann, B. (in press). The role of cortico-basal ganglia networks in adjusting response threshold during task-switching. *Australasian Cognitive Neuroscience Society, Sydney, Australia.*

Mansfield, E., Karayanidis, F. & Cohen, M. X. (in press). Components of preparatory control revealed in the alpha band using a novel pattern misclassification approach. *Australasian Cognitive Neuroscience Society, Sydney, Australia.*

Mansfield, E., Karayanidis F., Heathcote, A. & Forstmann, B. (in press). Fronto-striatal involvement in strategic adjustments of response caution: A combined DWI and ERP study. *Australasian Cognitive Neuroscience Society, Brisbane, Australia.*

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Statement of Contribution

I attest that Research Higher Degree candidate Elise Mansfield made the following contributions to each of the papers that are submitted as part of her PhD thesis. Papers are listed below in the order they appear in this thesis, followed by an outline of co-author contribution.

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E.L. Mansfield collected approximately half of the data, analysed the ERP data and was involved in manuscript preparation. F. Karayanidis contributed to research design and took the lead role in manuscript preparation. K. L. Galloway contributed to data collection. J. L. Smith contributed to data analysis and manuscript preparation. A. Provost contributed to data analysis. A. Heathcote contributed to data analysis and manuscript preparation.

Mansfield, E. L., Karayanidis, F. & Cohen, M. X. (2012). Switch-related and general preparation processes in task-switching: Evidence from multivariate pattern classification of EEG data. *The Journal of Neuroscience*, *32,* 18253-18258.

E.L. Mansfield collected approximately half of the data and took the lead role in manuscript preparation. F. Karayanidis contributed to research design and manuscript preparation. M. X. Cohen performed data analysis and contributed to manuscript preparation.

Mansfield, E. L., Karayanidis, F., Jamadar, S., Heathcote, A., & Forstmann, B. U. (2011). Adjustments of response threshold during task switching: A model-based functional magnetic resonance imaging study. *The Journal of Neuroscience, 31*, 14688-14692.

E.L. Mansfield contributed to research design, collected most of the data, conducted the fMRI data analysis and took the lead role in manuscript preparation. F. Karayanidis contributed to research design and manuscript preparation. S. Jamadar contributed to data analysis. A. Heathcote contributed to data analysis. B. U. Forstmann contributed to data analysis and manuscript preparation.

Mansfield, E. L., Karayanidis, F. Heathcote, A. & Forstmann, B. U. (submitted). Individual differences in strategic adjustments of response caution: Combined evidence from diffusion MRI and electrophysiology. *Cerebral Cortex.*

E.L. Mansfield contributed to research design, collected most of the data, conducted the diffusion MRI data analysis and took the lead role in manuscript preparation. F. Karayanidis contributed to research design and manuscript preparation. A. Heathcote contributed to data analysis. B. U. Forstmann contributed to data analysis and manuscript preparation.

Acknowledgements

This thesis was supported by an Australian Postgraduate Award and University of Newcastle Vice Chancellor's Award for Outstanding RHD Candidate.

First of all I would like to thank my supervisors, Associate Professor Frini Karayanidis and Professor Birte Forstmann for their generous guidance and unwavering patience. I look forward to many more years of collaboration with you both. I would also like to thank Emeritus Professor Pat Michie for insightful comments regarding my work and Professor Andrew Heathcote for his assistance with cognitive modeling.

I am grateful to all members of the Functional Neuroimaging Laboratory, past and present, for their support. In particular I would like to thank Sharna Jamadar and Janette Smith for their excellent training, Tony Kemp and Gavin Cooper for technical assistance and Michael Player and Kasey Galloway for assistance with data collection. I would also like to thank fellow PhD students Lisa Whitson, Dearne Sanday and Alex Provost for their support and encouragement throughout my candidature.

I would like to extend a special thanks to all of the participants who gave their time and brains to contribute to my research. I also thank the radiographers at the John Hunter Hospital for assistance with MRI acquisition.

I dedicate this work to my wonderful friends and family who supported me throughout the journey.

Table of Contents

Abstract

Cognitive control processes support purposeful, goal-directed behaviour in the presence of conflicting demands from our environment. Given advance information, this type of control can be engaged in anticipation of a change in behaviour. The cued-trials task-switching paradigm can temporally dissociate proactive and reactive cognitive control processes involved in switching between sets of abstract task rules. Typically, there is a performance cost for switch relative to repeat trials, which is attributed partly to proactive control processes required to prepare for a switch in task and partly to reactive control processes required to deal with between-task interference. Despite two decades of research into preparatory processes in task-switching, the cognitive processes and neural substrates that support proactive control remain underspecified. This thesis uses a model-based neuroscience approach to define the temporal and spatial characteristics of cognitive processes that contribute to proactive control in task-switching. Using converging evidence from ERPs, a novel multivariate pattern misclassification analysis of EEG data and cognitive modeling, we showed that a switch-specific preparation process is temporally and spatially distinct from more general task preparation for both switch and repeat trials. Consistent with a conflict control mechanism, we show that this switch-specific preparation process is linked to a right inferior frontal source and is related to upward adjustment of response caution in anticipation of more difficult switch trials. We also used fMRI- and DWI-based analyses to examine the neural basis of these cue-related adjustments in response caution, showing that distinct cortico-basal ganglia networks are associated with the ability to flexibly adjust response caution in anticipation of easy or difficult decisions, as well as intrinsic tendencies to set overall response caution high or low. We discuss implications of these findings for our understanding of the organization and timecourse of cognitive control mechanisms.

Abbreviations

Neuroanatomical	
ACC	Anterior cingulate cortex
CPJ	Caudate-putamen junction
DLPFC	Dorsolateral prefrontal cortex
IFC	Inferior frontal cortex
IFG	Inferior frontal gyrus
IFJ	Inferior frontal junction
IPL	Inferior parietal lobule
IPS	Intraparietal sulcus
PFC	Prefrontal cortex
PPC	Posterior parietal cortex
Pre-SMA	Pre-supplementary motor area
SPL	Superior parietal lobule
STN	Subthalamic nucleus
VLPFC	Ventrolateral prefrontal cortex

Other	
BESA	Brain Electrical Source Analysis
BIS	Barratt Impulsiveness Scale
BOLD	Blood oxygenation level dependent
CNV	Contingent negative variation
CSD	Current-source-density
CSI	Cue-stimulus interval
C-T interval	Cue-target interval
dB	Decibel
dHb	Deoxygenated haemoglobin
DMC	Dual mechanisms of control
D-Pos	Differential switch positivity
DWI	Diffusion weighted imaging
EEG	Electroencephalogram
EMG	Electromyogram
EOG	Electrooculogram
EPI	Echo planar imaging
ERP	Event-related potential
Hb	Oxygenated haemoglobin
FA	Fractional anisotropy
fMRI	Functional magnetic resonance imaging
FSL	FMRIB Software Library
HRF	Haemodynamic response function
LPC	Late positive component
MRI	Magnetic resonance imaging

R-C interval	Response-cue interval
ROI	Region of interest
RT	Reaction time
R-T interval	Response-target interval
SPM	Statistical Parametric Mapping
S-R priming	Stimulus-response priming
TBSS	Tract-Based Spatial Statistics
TMS	Transcranial magnetic stimulation
T-R mapping	Target-response mapping
WM	White matter

Chapter 1: The structure and organization of cognitive control processes

1.1 The unity and diversity of cognitive control

Decades of research have led to the development of comprehensive models of cognitive processes required to perform simple everyday tasks, such as word reading and object perception. However, the complex and constantly changing demands of our environment necessitate more than just these basic processes in order to achieve adaptive goal-directed behaviour (Miyake, Friedman, Emerson, Witzki, Howerter & Wager, 2000). Higher-level *cognitive control* processes are required to co-ordinate and control these lower-level cognitive processes, allowing for adaptation to changing environmental demands. More specifically, cognitive control processes enable us to develop plans for action, monitor their execution, and adjust or alter them to accommodate changes in the current context. While there is general agreement on the importance of these cognitive control processes for efficient everyday functioning, there is still a lack of agreement as to how these control processes operate, limiting our understanding of the way in which goal-directed behaviour is achieved (Jurado & Rosselli, 2007).

Early models of cognitive control proposed a unitary control centre, located somewhere in the prefrontal cortex, that is responsible for the co-ordination of all lower-level processing. For example, Baddeley and Hitch's (1974) influential model of working memory included a 'central executive' that co-ordinated processing in two lower-level sub-systems: the visuospatial sketchpad and phonological rehearsal loop. Similarly, in Norman and Shallice's (1986) model of information processing, a Supervisory Attentional System (SAS) controls planning and decision-making, as well as overcoming overlearned tendencies. Therefore, in both these models, cognitive control was conceptualised as

somewhat of a ‘homunculus’, somehow making all of the important strategy selections and decisions that lead to purposeful, goal-directed behaviour.

It has since been argued that these models do not adequately explain the diversity of complex control strategies that contribute to goal-directed behaviour (Baddeley, 1996; Stuss, Shallice, Alexander & Picton, 1995). This is supported when examining individual differences across different tasks designed to measure cognitive control processes. For example, in both healthy young adults (e.g. Lehto, 1996) and brain damaged adults (e.g. Duncan, Johnson, Swales & Freer, 1997) scores across different cognitive control tasks are often not correlated. In addition, studies that have used exploratory factor analysis show that a number of separable factors, rather than a single factor, are needed to explain variance across a range of tasks (Burgess, Alderman, Evans, Emslie & Wilson, 1998). This separability of cognitive control processes is further supported by evidence from lesion studies (Stuss & Alexander, 2000; Stuss et al., 2002) and neuroimaging (Koechlin, Corrado, Pietrini & Grafman, 2000) indicating that different regions of the prefrontal cortex are associated with different cognitive control functions. It has also been suggested that neural models of cognitive control processes must also take into account connectivity between the prefrontal cortex and posterior as well as subcortical regions (Collette & van der Linden, 2002; Royall et al., 2002). For example, Miller and Cohen (2001) proposed that the PFC biases activation in other brain regions to ensure environmental input is converted to appropriate output. According to this model, the PFC is not involved in establishing mapping between input and output – it is instead involved in a more modulatory sense, co-ordinating activity along pathways that are responsible for input-output processing. These models suggest that efficient functioning relies on the integrity of the whole brain, and not just the prefrontal cortex (Zelazo & Muller, 2002).

Other evidence indicates that while cognitive control can be fractionated into several distinct sub-components, there is also some commonality across these components (Miyake & Friedman, 2012). For example, Miyake et al. (2000) used a confirmatory factor analysis, which involved extracting shared variance amongst tasks selected to measure the same underlying cognitive control process. Three processes - shifting between cognitive sets, updating of working memory, and inhibition of prepotent responding - were clearly distinguishable, but still showed moderate correlations with each other. Similarly, Fournier-Vicente, Larigauderie and Gaonac'h (2008) also used confirmatory factor analysis to show that five processes - verbal and visuospatial storage and processing, strategic retrieval from long term memory, selective attention and set shifting - were distinguishable, but also showed moderate relationships with each other. Therefore, while this approach provides evidence that cognitive control can be fractionated into distinct components, it also shows that there is still a common underlying mechanism or mechanisms, suggesting that cognitive control is characterized by both diversity *and* unity.

While these approaches have furthered our understanding of the structure and organization of cognitive control processes, the nature of processes contributing to the unique and shared variance across these tasks remains underspecified. Miyake et al. (2000) argued that the source of the commonality across cognitive control tasks may be the ability to actively maintain task goals and context information and use this to bias lower-order cognitive processes. They further suggested that another process that might explain the commonality is an inhibitory mechanism that involves suppression of irrelevant information or cognitive sets. Alternatively, Salthouse (1996; 2005) suggested that reasoning ability may underlie all areas of cognitive control. To better understand how

these cognitive control processes are both related and distinct, the mechanisms that underlie performance on tests of cognitive control must be further broken down.

1.2 Proactive vs. reactive cognitive control processes

While historically, much of the investigation into cognitive control has focused on the structure and organization of these processes, recently attempts have been made to model their temporal characteristics. For example, Braver, Gray and Burgess (2007) proposed a dual mechanisms of control (DMC) model incorporating both proactive and reactive modes of cognitive control (see also Braver, 2012). Proactive control involves anticipatory goal maintenance processes that are activated in advance of an upcoming behaviorally relevant target. This preparatory mode of control biases attentional and motor systems towards the relevant target features and response modes, respectively. Therefore, this strategy involves maintaining goal information from the time that a goal is activated until the completion of that goal. The advantage of such a strategy is that plans can be continually adjusted while the goal is active in order to optimize behavioural outcomes. In contrast, a reactive mode of control involves only a transient representation of the task goal that is not maintained, followed by a goal reactivation process that is triggered in response to the target. Therefore, according to this framework, proactive control processes are engaged in anticipation of upcoming conflict or interference, while reactive control processes are engaged to resolve conflict upon its detection.

It is argued that the bias towards either proactive or reactive cognitive control modes varies depending on task parameters. For example, Braver, Paxton, Locke and Barch (2009) used an AX-CPT task in which the letters “A”, “B”, “X” and “Y” were presented in

a continuous stream. Participants were required to make a target response to an "X", but only if it followed an "A" (i.e., an AX trial). All other target combinations – AY, BX and BY – required a nontarget response. An index of context processing based on responses to the nontarget trials was used to determine the degree to which proactive control was engaged. In healthy young adults, adding a penalty incentive manipulation that shifted attention to target information produced a shift towards reactive control. In older adults, a shift towards proactive control was produced when adding behavioral strategy training involving instructions to focus on the classification of the cue. Therefore, it was shown that manipulating the task to induce shifts of attention to either the target or the cue produced biases towards more reactive or proactive response modes, respectively.

In sum, cognitive control processes have received a great deal of interest in recent years, with particular attention paid to their organization and temporal properties. However, one of the challenges facing modeling of cognitive control is the difficulty of isolating key underlying processes within the complex and multidimensional processing required for higher-order control. To tease apart these processes, paradigms must be carefully designed, incorporating conditions that unconfound the operation of multiple control mechanisms. The development of such paradigms can therefore allow for the identification of specific and quantifiable control processes.

1.3 Dissociating components of cognitive control using neuroimaging techniques

The identification of core underlying processes of cognitive control is further informed through the use of neuroimaging methodologies. While behavioral data provides us with an insight into differences in processing demands between conditions, it only

allows us to speculate about the nature of the processes that might be contributing to behavioural outcomes. Neuroimaging methods enable the study of the temporal and spatial dynamics of how these processes are implemented in the brain. The rapid development of new neuroimaging approaches together with the advent of innovative analysis methods have allowed for the examination of cognitive control processes from multiple perspectives, leading to more comprehensive and detailed models.

The temporal characteristics of cognitive processes have been examined using the scalp-recorded electroencephalogram (EEG). This technique provides a window to the timecourse of these processes that would otherwise be unobservable in end-state behavioural measures. Activity time-locked to stimuli or responses can be used to decompose cognitive processes into constituent components. However, while the EEG has very high temporal resolution, it has limited spatial resolution, as the neural sources underlying scalp-recorded activity cannot be reliably inferred.

In contrast, functional and structural magnetic resonance imaging (MRI) provides the high spatial resolution required to be able to isolate the brain regions underlying cognitive processes. Functional magnetic resonance imaging (fMRI) measures haemodynamic changes associated with brain activation, providing spatial resolution in the order of millimeters. However, these haemodynamic changes are very slow, and so fMRI lacks the temporal resolution required to decompose brain activation patterns over time. Structural MRI measures such as diffusion-weighted imaging (DWI) indicate the structural integrity of pathways within the brain. Taking advantage of individual variability in these measures, it has been possible to examine the relationship between the integrity of brain structures and both functional brain measures (e.g. EEG, fMRI) and behavioural outcomes.

Therefore, EEG and MRI approaches provide complementary measures that can contribute to the development of models of cognitive control processes.

More recent approaches have combined formal cognitive modeling of behavioral data with neuroimaging in an approach referred to as 'model-based neuroscience' (Forstmann, Wagenmakers, Eichele, Brown & Serences, 2011b). Forstmann et al. argue that theoretical models can benefit from a reciprocal relationship between cognitive modeling and neuroimaging, as parameters derived from cognitive models can guide the interpretation of neuroimaging data, while neuroimaging data can also be used to constrain cognitive models. This approach also limits speculation about the processes associated with patterns of activation from functional measures or differences in structural brain measures, instead allowing for more specific inferences about brain-behaviour linkages.

1.4 Investigating the components of preparatory control in task-switching

In this thesis, we used the task-switching paradigm to examine the organization and timecourse of cognitive control processes. In this paradigm, participants alternate between two or more simple categorization tasks based on a predictable task sequence (e.g. task A, task A, task B, task B; Rogers & Monsell, 1995) or informative task cues presented in a randomized order (e.g. Meiran, Chorev & Sapir, 2000). Switching between tasks, compared to repeating the same task, is associated with a performance cost, or 'switch cost'. Behavioral studies (see Kiesel et al., 2010, for a review) suggest that at least part of this cost may be attributed to a higher-order cognitive control mechanism engaged to 'reconfigure' the cognitive system and enforce the transition to the new task, and that this

reconfiguration process can be partially completed proactively, that is, in anticipation of target onset (e.g., Rogers & Monsell, 1995).

However, while there is general agreement that preparation to switch tasks requires active reconfiguration, the nature of this process or processes remains unclear. In particular, it remains unclear whether switching between tasks involves preparatory control that is exclusively engaged on switch trials or stronger engagement of preparatory processes also carried out in anticipation of repeat trials. Models that posit the existence of switch-specific preparatory control suggest that this preparation involves both inhibition of irrelevant task information and retrieval of the relevant task information from working memory (e.g. Rubinstein, Meyer & Evans, 2001). The cued-trials variant of the task-switching paradigm used in this thesis allows proactive control processes contributing to switch and repeat task preparation to be clearly isolated from reactive control processes and differentiated. Therefore, this paradigm appears particularly suited to investigating the organization and temporal properties of cognitive control processes.

1.5 Overview of the thesis

This thesis aims to define the processes involved in preparation for a switch in task, with two primary objectives: a) To determine whether switching between tasks entails qualitatively distinct preparation specifically related to the signal to switch (which we refer to herein as switch-specific preparation, for simplicity), and b) To define the nature of switch-specific preparation. In isolating and defining switch-specific component(s) of preparation, we can further inform debates about the organization and temporal dynamics of cognitive control.

Chapters 2 and 3 provide more detailed background to topics relevant to this research. Chapter 2 presents an overview of the behavioural and neuroimaging methodologies used in this thesis and how they have been applied previously to investigate cognitive control processes. Chapter 3 gives a review of key behavioural and neuroimaging task-switching studies that have contributed to the development of current theories on the nature of cognitive control processes elicited in this paradigm. It is concluded that while behavioural and neuroimaging evidence have added to our understanding of the temporal and spatial dynamics of preparation for a switch in task, the specific mechanisms by which switch preparation occurs have still eluded us.

We developed a new paradigm that was designed to distinguish switch-specific preparation from task updating and task readiness processes and combined this with an approach that used converging evidence across multiple methodologies. This allowed us to take advantage of the strengths of each methodology to build a more comprehensive picture of the nature of preparation for a switch in task. All experimental chapters have used this task-switching paradigm and so the Methods sections show some overlap. In Chapter 4 (Karayanidis et al., 2009), we combined ERPs with cognitive modeling of behavioural data and found evidence for switch-specific preparation that produces a behavioural advantage even when the upcoming task is not specified. Chapter 5 (Mansfield, Karayanidis & Cohen, 2012) presents a multivariate pattern analysis of EEG that provides converging evidence for switch-specific preparation that can be temporally and spatially dissociated from task readiness processes on both switch and repeat trials. The fact that this switching process was elicited even without foreknowledge of an upcoming task and was associated with a generator over right inferior frontal cortex suggested that it may reflect suppression of the previous task.

However, we also found evidence that response caution was increased in anticipation of a more difficult switch trial, suggesting an alternative explanation for the switch-specific component of preparation (Karayanidis et al., 2009; Chapter 4). In Chapter 7 (Mansfield, Karayanidis, Jamadar, Heathcote & Forstmann, 2011), we use fMRI to further examine the nature of these adjustments, finding a large overlap with networks shown to adjust response caution in response to speed vs. accuracy instructions in two-choice decision-making. In particular, we showed that increasing response caution was associated with activation in the STN, an area thought to slow the output of the basal ganglia under conditions of increased conflict. Therefore, we suggested that switch-specific preparation may involve a conflict control mechanism. However, using a combination of structural measures from diffusion-weighted MRI and functional measures from ERPs in Chapter 8, we showed that the striatum, rather than the STN, may carry out this anticipatory change in threshold. We also showed that networks associated with individual differences in preferences to adopt an overall more risky or more cautious strategy overlap with those associated with trial-by-trial adjustment of response caution, further informing neural models of the speed-accuracy tradeoff. Chapter 9 discusses the implications of the findings presented in this thesis as well as future directions. Taken together, these findings highlight the value of using paradigms that are designed to target specific cognitive control processes, along with an approach that takes advantage of the strengths of a number of neuroimaging modalities.

Chapter 2: Inferring Cognitive Processes from Behavioural, Electrophysiological, Haemodynamic and Structural Measures

As noted in the previous chapter, combining evidence across multiple behavioural and neuroimaging methodologies has the potential to clarify and extend on current models of cognitive control functions, by providing a multidimensional picture of these processes. However, to understand how each methodology contributes to this picture, the strengths and limitations of each must first be considered. In this Chapter, I examine the basis and assumptions of each of the methodologies used in this thesis. This is followed by examples of how these methodologies have previously been applied to uncover the spatiotemporal characteristics of cognitive control processes.

2.1 Behavioural measures and cognitive modeling

Measurement of overt behaviour, including the speed and accuracy of responding, allows inferences to be made about the duration of cognitive processes, the conditions under which certain processes are activated, and the effects of interference and task difficulty on task performance (Coles, Smid, Scheffers & Otten, 1995). Behavioral models provide a framework for the timing and sequencing of mental processes, allowing for an examination of unobservable cognitive processes on the basis of observable behavioural data. For example, the Donders method (1969) involves subtracting an experimental condition from a baseline condition with the assumption being that these two conditions differ on only a single process. The difference in RT between these two conditions is assumed to reflect the duration of this process. For example, when subtracting RT from

simple and choice response conditions, it is assumed that the sensory and motor components common to the two conditions would cancel out, and the difference would reflect the time consumed by the choice process. Donders therefore conceptualised RT as a composite measure of multiple serial processes. However, while this model represented an elegant way of indentifying differential processing between two conditions, it has been criticized for ignoring the possibility that the addition of a new process in an experimental condition may change the nature of the existing processes (Coles et al., 1995). Therefore, a difference in reaction time between conditions cannot be assumed to arise solely from the addition of a single process that is related to the additional task requirement.

Sternberg's (1969) additive factors logic model assumes that differences in behavioural performance between experimental conditions arise from differences in the duration of one or more processing stages. Like the Donders method, Sternberg's model assumes that processes can only occur serially. However, the duration of these processing stages is assumed to be related to the experimental manipulation of 'factors', for example stimulus quality and stimulus-response compatibility. The duration of these processes can therefore be determined using factorial designs, with main effects indicating that factors affect distinct processes (i.e., additive processes), and interaction effects indicating that multiple factors may influence the same process. However, again, the assumptions behind this model are not consistently met. Differences between conditions may involve more than simply a change in the duration of one or more processing stages, as there may also be accompanying changes in other processes that are presumed to be 'unaffected'. In addition, the model relies heavily on the assumption of a single instance of information transfer between serial stages of processing. However, it has been shown that when a stimulus display consists of more than one response-signifying element, this assumption is violated.

For example, using an Erikson flanker task in which target size, stimulus-response compatibility and flanker congruence were varied, Ridderinkhof, van der Molen and Bashore (1995) found that two factors could influence the same stage of processing. Thus, both of these early models rest on strict assumptions that are not consistently met, presenting difficulties for unambiguously interpreting changes in overt behaviour.

Importantly, these behavioural models infer underlying, unobservable processes on the basis of end-state measures, rather than directly measuring the underlying processes themselves. Formal cognitive models address this problem by isolating and quantifying latent cognitive processes that contribute to end-state performance. These models derive parameter estimates that represent latent measures of processes that contribute to explicit performance measures (i.e., RT and accuracy). Numerous cognitive models have been developed with the aim of directly measuring components of cognitive processing, including selective attention (e.g. Nosofsky, 1986), memory storage and retrieval (e.g. Jacoby, 1991; Shiffrin & Steyvers, 1997), and response caution and bias (e.g. Brown & Heathcote, 2008). These models vary in their specificity, with some targeting processes that are exclusive to a particular domain and others targeting more general processes that apply across several domains (see Table 1.1 for examples of these models).

Table 1.1: Examples of formal cognitive models and the domains to which they have been applied (Adapted from Forstmann, Wagenmakers, Eichele, Brown & Serences, 2011b).

Model	**Domain**
ACT-R (Anderson & Lebiere, 1998)	General
DDM (Ratcliff & McKoon, 2008)	Two-choice decision making
GCM (Nosofsky, 1986)	Categorization
LBA (Brown & Heathcote, 2008)	Two-choice decision making
MPT (Batchelder & Riefer, 1980)	General
PDP (Jacoby, 1991)	Memory
REM (Shiffrin & Steyvers, 1997)	Memory

The diffusion model (e.g. Ratcliff, 1978) was developed to derive estimates of decision and nondecision components of responding in two-choice decision making paradigms. Figure 2.1 presents a conceptual illustration of the diffusion process using an example from the lexical decision task. Two response thresholds (corresponding to correct and incorrect responses, respectively) represent the criterion amount of response evidence required to make a response decision. Evidence for each response option begins to accumulate stochastically from a start point that is set between these two response thresholds and a decision is made when evidence has accumulated to a point where one of the response thresholds is reached. The decision time is determined by both response threshold, the amount of evidence that is required for a response to be selected, and drift rate, the efficiency of evidence accumulation. The remainder of RT is subsumed by nondecision time, which includes processes that are not directly related to the decision process, such as stimulus encoding and response execution.

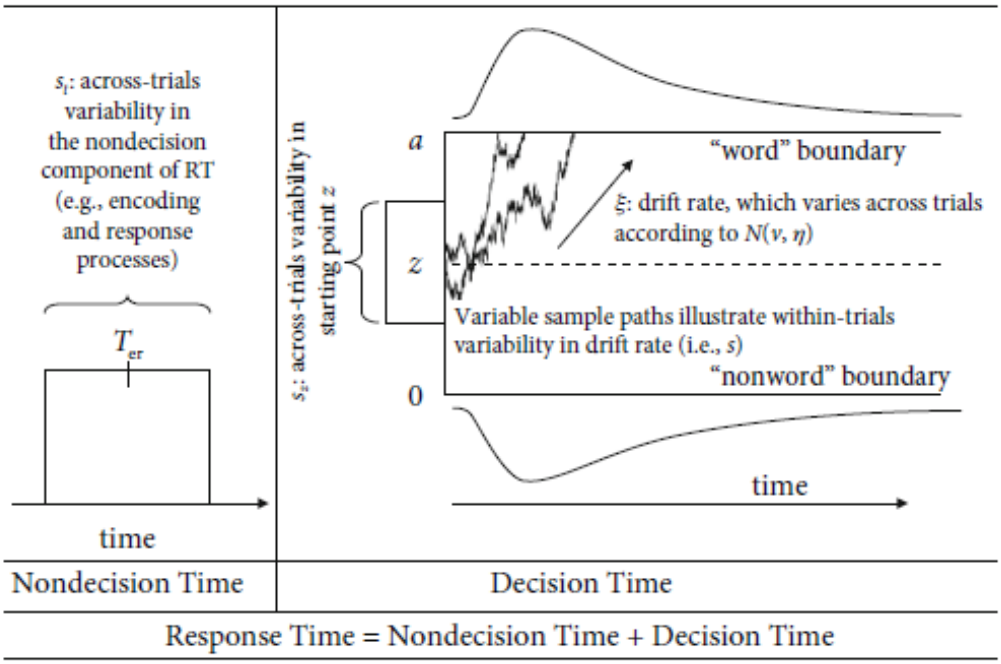


Figure 2.1: Illustration of the diffusion process as applied to a lexical decision task (Adapted from Wagenmakers, van der Maas & Grasman, 2007).

Ratcliff and McKoon (2008) explain how the diffusion model can account for the effects of various experimental manipulations on two-choice decision making. This study used a simple motion discrimination task in which participants are asked to judge the primary direction of movement (right or left) in an array of dots. Changes in RT and accuracy associated with changes in the emphasis of task instructions (either to respond more quickly or more accurately) were entirely accommodated by shifts in response threshold. In contrast, changes in behaviour according to the difficulty of discrimination (i.e., the proportion of dots moving in a single direction) could be explained by differences in drift rate. Therefore, the model was able to provide a fine-grained account of the

unobservable cognitive processes contributing to condition-related differences in observable performance.

To fit the diffusion model, the full distribution of both correct and incorrect responses is required. This presents a problem for paradigms in which error rates are very low, as this does not provide an accurate enough estimate of the response time distribution for error trails. Recently, Wagenmakers, van der Maas and Grasman (2007) formulated a simplified version of the Ratcliff (1978) diffusion model, known as the EZ-diffusion model. This model does not attempt to account for the full distribution of error RTs and focuses on extracting the most psychologically relevant parameters of the diffusion model – response threshold, drift rate and nondecision time. In this thesis, we apply a slightly modified version of this model, the EZ2-diffusion model (Grasman, Wagenmakers & van der Maas, 2009) to the cued-trials task-switching paradigm, to decompose the component processes contributing to performance on this task.

In sum, cognitive modeling offers insight into the nature of processes that contribute to a behavioural outcome. However, it offers only theoretically plausible explanations about how these processes are organized temporally. Electrophysiological techniques allow direct measurements of the timecourse of differences in processing, and can therefore show whether processes are carried out proactively, based on internal goals or plans, or reactively, based on external stimuli. When used in conjunction with formal cognitive modeling, electrophysiology has the potential to enhance our understanding of how cognitive processes are strategically controlled in the service of behavioural goals.

2.2 Electrophysiology

2.2.1 Event-related potentials

Event-related potentials (ERPs) are scalp-recorded voltage changes that show the timecourse of neural activity time-locked to stimuli or responses, with millisecond resolution. ERPs are derived from the ongoing EEG by averaging over multiple instances of the same stimulus type. By using signal averaging procedures, electrical activity associated with sensory or cognitive processes linked to that stimulus type are retained, while EEG activity that is not time-locked to this stimulus (i.e., noise) is averaged out (Coles & Rugg, 1995). The resulting ERP waveform consists of a time-varying series of deflections that can be mapped to specific sensory and cognitive processes.

The high temporal resolution of ERPs offers one main advantage – the ability to determine the effect of specific experimental manipulations at different stages of processing (Luck, 2005). However, while ERPs offer precise temporal resolution, their spatial resolution is limited. Scalp-recorded ERPs represent the summation of activity of large neuronal populations that may be anatomically distinct or distributed across a large number of locations within the brain (Picton et al., 2000). It follows that ERP activity recorded at a particular scalp location may be produced by an infinite number of generator configurations and is therefore not necessarily related to neuronal activity directly below that location (Coles & Rugg, 1995). A further issue that limits the spatial resolution of ERPs is volume conduction, which refers to the fact that electrical activity spreads as it travels through the brain, leading to activity being detected at scalp locations far from its original source (Luck, 2005). For these reasons, ERPs cannot be reliably mapped to specific neural generators.

Variations in the timing and engagement of cognitive processes across experimental conditions can be measured in the ERP waveform by examining latency and amplitude measures, respectively (see Figure 2.2a). Latency is measured as the time delay (in ms) between stimulus onset and the onset or peak of an ERP deflection. Amplitude is measured as the maximum or average amplitude (in μV) of a deflection within a pre-defined time-window of interest. For example, an ERP peak that differs only in amplitude between two conditions indicates a difference in the extent of engagement of this process (Otten & Rugg, 2005). Inferences about the functional equivalence of processes can be inferred on the basis of scalp topography (see Figure 2.2b). While ERPs do not offer high spatial resolution, a difference between conditions in the scalp topography of an effect implies that these conditions are associated with distinct configurations of underlying neural generators, suggesting that these processes are functionally distinct (Otten & Rugg).

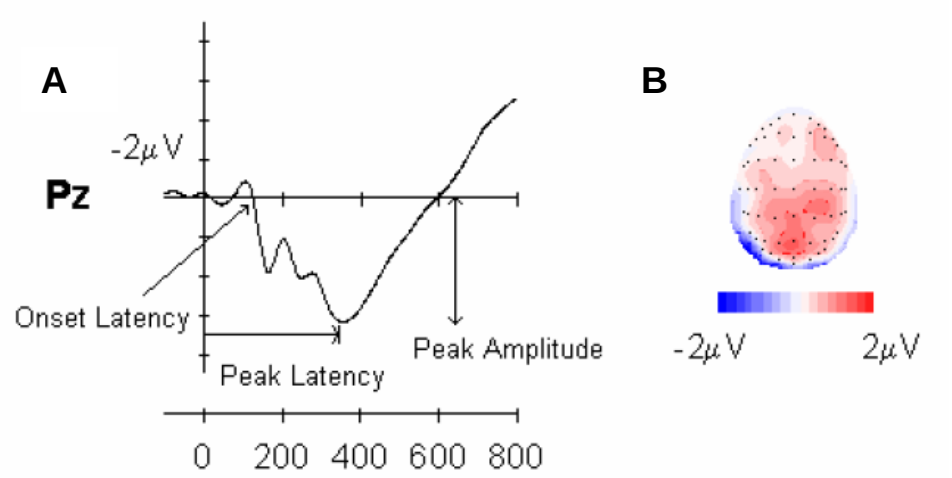


Figure 2.2: A: Hypothetical example of an ERP waveform recorded at the midline parietal site Pz (negative voltage is plotted above baseline). B: Hypothetical scalp topography.

However, it is also important to note that ERP peaks overlap in time, such that voltage recorded at a given time point reflects the summation of many of these overlapping peaks (Luck, 2005). This can make it very difficult to determine which ERP peak is being modulated by an experimental manipulation. ERP peaks can be distinguished from ERP 'components' that are reliably elicited under specific conditions and show a characteristic scalp distribution (Donchin, Ritter & McCallum, 1978). These components can therefore be used as markers for cognitive processes elicited under these conditions (Otten & Rugg, 2005). In paradigms targeting cognitive control, two widely studied components are the contingent negative variation (CNV), a stimulus-preceding negative component, and the P300, a stimulus-elicited positive component.

2.2.1.1 The CNV

The CNV is typically elicited in an S1-S2 paradigm, where the first stimulus (S1) predicts the onset of a second stimulus (S2) which requires a motor response (Birbaumer, Elbert, Canavan & Rockstroh, 1990). In the interval between S1 and S2, a slow negative component is elicited over fronto-central sites, showing a ramp-like morphology that reaches its maximum at S2 onset. Therefore, the CNV has been interpreted as an 'expectancy' component. The fact that it is also elicited even when a motor response is *not* required to S2 suggests that this expectancy is not entirely motor-related but may instead represent a more general anticipatory reallocation of attention (Birbaumer et al.). The CNV is also affected by experimental manipulations of response certainty. For example, a larger CNV is elicited when S2 involves a choice rather than a simple motor response (Kakigi, Matsude & Ueda, 1985). In addition, a larger CNV is also found when the motor response required is specified at S2 onset, relative to when it is specified at S1 onset (Van Boxtel &

Brunia, 1994), suggesting that this component is affected by the predictability of the response required to S2.

2.2.1.2 The P300

The P300 is a stimulus-elicited positive component that occurs approximately 300-400 ms after stimulus onset. This component is typically elicited in 'oddball' paradigms, in which participants respond to a target stimulus type that is less frequent than a standard or non-target stimulus type. In this task, the amplitude of the P300 depends on the probability of the attended stimulus type, with higher amplitudes elicited to rarer stimulus presentations. In contrast, the latency of the component is affected by the difficulty of the discrimination between the two stimulus types, with more difficult discriminations leading to longer latencies. A dominant explanation of the functional significance of the P300 component continues to be that it reflects a kind of context updating in response to relevant incoming information from the environment (Donchin & Coles, 1988, but see also Verleger, Jaskowski & Wascher, 2005).

2.2.2 Oscillatory activity

Another technique that is used to examine processes leading up to a behavioural outcome is EEG spectral power analysis. This technique measures the oscillatory properties of neuronal activity, which reflects rhythmic changes in the depolarization of membrane potentials of large neuronal populations. Neurons oscillating in synchrony are associated with more effective information transfer than neurons not oscillating in synchrony, as rhythmic synchronization between neurons results in strong input to target cells (Klimesch, Sauseng & Hanslmayr, 2007; Ward & Doesburg, 2009). Oscillations in EEG are

characterized by their frequency (cycles per second, *Hz*) and amplitude (how far from a starting point the oscillation reaches in the peak of its cycle).

The EEG signal can be decomposed into several frequency bands, ranging from 0 to 80 Hz. Within each frequency band, changes in neural 'activity' are measured by changes in oscillation amplitude. Spectral power is an index of amplitude and is thought to represent the amount of energy in an oscillation (Ward, 2003), with increased power reflecting increased synchrony of oscillations. Spectral power can be obtained by transforming the EEG signal into the frequency domain using the Fourier transform. However, this technique does not inform on changes in the spectral power within each frequency band over time. Temporal information can be obtained using a wavelet transformation, which involves the original EEG signal being convolved with a scaled version of a mother wavelet function. This produces a wavelet with coefficients that quantify the similarity between the original EEG time series and the mother wavelet function (Herrmann, Grigutsch & Busch, 2005). Therefore, wavelet transformation provides time-varying measures of power within each frequency band.

One frequency band that appears to be closely related to higher-order cognitive control functions is alpha (8-12 Hz). This rhythm has been shown to be associated with top-down attentional control processes, in particular the suppression of distracting or conflicting information (Cooper, Burgess, Croft & Gruzelier, 2006; Cooper, Croft, Dominey, Burgess and Gruzelier, 2003; Klimesch et al., 2007; Min & Herrmann, 2007; Min & Park, 2010). For example, Cooper et al. (2003) found increased alpha activity on a task that involved answering questions about a sequence of imagined stimuli, compared to a task which involved answering questions about presented stimuli. As internally-directed attention requires more effortful suppression of distracting information than does

externally-directed attention, it was argued that this increased activity in the alpha band reflects inhibition. Evidence has also shown alpha activity associated with anticipatory inhibition of irrelevant input. For example, Min and Park (2010) used a paradigm in which participants indicated whether the dimension of a target feature (i.e., shape or color) was the same on two successive trials. Within the pre-target interval, increased alpha power was observed over posterior sites for the shape relative to the color task. As the shape task showed both slower reaction times and decreased accuracy relative to the color task, this increase in alpha power was interpreted as indexing increased top-down preparation to suppress the salience of the target color. Thus, alpha activity appears to be closely linked to an inhibitory control mechanism.

2.2.3 Electrophysiology: Conclusions

As discussed in the previous two sections, electrophysiological measures provide information about the timecourse and relative activation of processes leading up to a behavioural response. Following decades of research, commonly observed components in ERP waveforms and frequency bands within the EEG can now be confidently related to specific cognitive processes. Therefore, these measures have given us extensive insight into both the characteristics and temporal dynamics of the cognitive processes that lead to a behavioural outcome. However, these techniques do not allow for reliable localization of the neural sources associated with these processes. Electrophysiological recordings are also more sensitive to activity occurring at the cortical surface than to activity originating from sources deep within the brain. Further, some subcortical structures do not show the open field configuration that is necessary to produce activity at the scalp (Horovitz, Rossion, Skudlarski & Gore, 2004). Imaging techniques such as functional magnetic resonance

imaging (fMRI) provide high spatial resolution images that allow us to localize the neural regions and networks underlying cognitive processes.

2.3 Magnetic resonance imaging measures

2.3.1 Functional MRI

Magnetic resonance imaging (MRI) produces images of the brain by measuring changes to the spins of nuclei within various tissue types. As hydrogen is abundant across many different tissue types, most MRI techniques measure spins of hydrogen nuclei (Huettel, Song & McCarthy, 2009). The magnetic resonance (MR) signal is produced when nuclei spins are disturbed from a state of equilibrium by the introduction of radiofrequency pulse, which bombards the spin system with electromagnetic waves so that some spins change from low-energy to high-energy states. When the radiofrequency pulse is turned off, the high-energy spins fall back to a low-energy state in order to restore equilibrium. The energy that is emitted as these nuclei return to equilibrium is what constitutes the MR signal. The decay of this signal differs across tissue types, and is described by three time constants – T1, T2, and T2*. Each of these time constants gives rise to a different type of image. In fMRI, both T1- and T2*-weighted images are commonly acquired. T1-weighting produces anatomical images in which white matter shows the highest signal, grey matter shows intermediate signal and cerebrospinal fluid shows little to no signal. T2*-weighted images are sensitive to the amount of deoxygenated haemoglobin (dHb) in blood, which fluctuates within the brain due to the metabolic demands of neurons. These changes in dHb

form the basis of the blood oxygenation level dependent (BOLD) fMRI, providing an indirect measure of activation within neural regions.

The change in signal produced as a result of changes in metabolic demands within the brain is known as the BOLD haemodynamic response. When neurons become active, the vascular system supplies more oxygenated haemoglobin (Hb) to the activated regions than is required. This excess Hb flushes out dHb from capillaries supporting the activated regions, which produces an increase in signal in T2*-weighted images. Therefore, a signal increase in T2*-weighted images corresponds with an increase in oxygen consumption. These changes are measured within voxels that typically range in size from 1 x 1 x 1mm to 5 x 5 x 5mm. However, despite spatial resolution in the order of millimetres, the temporal resolution of fMRI is limited by the sluggishness of the haemodynamic response. While neuronal responses occur within tens of milliseconds of presentation of a stimulus, the haemodynamic response does not increase above baseline until around 2 seconds post-stimulus, reaching a peak at around 5 seconds post-stimulus. Thus, the haemodynamic response shows a considerable lag relative to stimulus onset, and so fMRI can only distinguish between responses to events that are separated by a few seconds.

2.3.1.1 Frontal, parietal and subcortical activation associated with higher-order cognitive control

The high spatial resolution of fMRI has provided valuable information about the neural underpinnings of cognitive control, showing that these functions are at least partly subserved by a fronto-parietal network that incorporates dorsal and inferior portions of the prefrontal cortex, as well as posterior parietal regions. In particular, the dorsolateral prefrontal cortex (DLPFC) has been shown to play a central role in cognitive control.

Activation in DLPFC is consistently observed when task-relevant information needs to be maintained in the service of behavioural goals (Badre & Wagner, 2004; Hester, Murphy, Foxe, Foxe, Javitt & Garavan, 2004; Fassbender, Foxe & Garavan, 2006; Liston, Mathalon, Hare, Davidson & Casey, 2006). For example, the DLPFC showed greater activation for colour-naming than word-reading in a Stroop task (MacDonald, Cohen, Stenger & Carter, 2000), suggesting that this region is particularly involved in the context-dependent selection of task-relevant information, as well as the suppression of distracting input. The DLPFC may carry out these functions by providing a goal-activation signal that biases activation levels of task-relevant rules 'held' in posterior parietal cortex (PPC; Andersen, 1987; Andersen & Bueno, 2002). The distinction between top-down attentional control in DLPFC and rule activation in PPC was supported in Bunge et al. (2002), who showed that the requirement to select amongst available responses was associated with activation in DLPFC, while the requirement to maintain representations of responses was associated with activation in PPC. Further supporting this model, activation in a DLPFC/PPC network has been found in paradigms requiring top-down selection or maintenance of appropriate response sets (Fassbender et al., 2006; Hester, D'Esposito, Cole & Garavan, 2007).

In contrast, the inferior frontal cortex (IFC) has been shown to play a particularly important role in inhibition (Aron, Behrens, Smith, Frank & Poldrack, 2007; Aron & Poldrack, 2006). The IFC, and especially the right IFC, is frequently activated in tasks that require response inhibition, as such as the go/no-go task and stop-signal task, as well as in tasks that require inhibition of retrieval from working memory (Aron, Robbins & Poldrack, 2004). It has also been shown that lesions of the right IFC (Aron, Fletcher, Bullmore, Sahakian & Robbins, 2003), as well as transcranial magnetic stimulation (TMS) over this area (Chambers et al., 2007) impairs performance on the stop-signal task. It is thought that

the IFC suppresses responses via the hyperdirect cortico-basal ganglia network (Nambu, Tokuno & Takada, 2002). According to this model, the IFC provides input to the subthalamic nucleus (STN), which then provides excitatory input to the globus pallidus, resulting in a blocking of response initiation (Aron et al., 2007; Aron & Poldrack, 2006).

In sum, current evidence suggests that a DLPFC/PPC network is involved in selecting and maintaining task-relevant information while also suppressing conflicting information. In contrast, the IFC appears to be specifically involved in inhibiting responses or cognitive sets in the presence of conflict, possibly via a cortico-basal ganglia hyperdirect pathway. Functional MRI has provided an invaluable insight into the neural regions underlying higher-order cognitive processes. However, the existence of networks that support interaction between these regions cannot be directly inferred on the basis of haemodynamic responses. Diffusion-weighted MRI has provided a new tool to analyse the organization of white matter microstructure that supports communication between brain regions. Therefore, this technique allows for stronger inferences to be made about the existence of neural networks supporting top-down control, on the basis of white matter architecture.

2.3.2 Diffusion-weighted imaging

Diffusion-weighted MRI measures the diffusion properties of water molecules, which varies across different types of neural tissue. When no restriction is placed on the diffusion of water molecules (i.e., within a free medium), they diffuse randomly, in a process known as isotropic diffusion (see Figure 2.3). However, when restrictions are imposed on the directionality of the diffusion process, such as those imposed by the presence of cell membranes or fibers, this results in a process known as anisotropic

diffusion. Anisotropic diffusion occurs in nerve fibers making up white matter pathways within the brain. However, the biophysical underpinnings of anisotropic diffusion within these tracts are still not fully understood. While anisotropy in these regions was initially attributed to increased myelination of nerve fibers, anisotropy has also been shown prior to the myelination of axons, although to a lesser extent (e.g. Takeda et al., 1997; Neil et al., 1998), suggesting that myelination of membranes is not necessary to produce diffusion anisotropy. More recent evidence suggests that anisotropy is associated with homogeneity in white matter structures, in particular the spatial organization of axonal membranes (Basser & Özarslan, 2009; Le Bihan & Johansen-Berg, 2012).

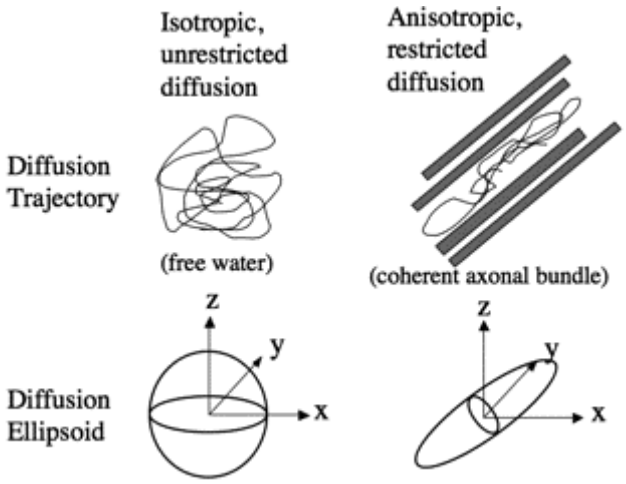


Figure 2.3: Diffusion trajectories and corresponding ellipsoid shapes for isotropic diffusion (left) and anisotropic diffusion (right; Figure adapted from Mukherjee, Berman, Chung, Hess & Henry, 2008).

MRI sequences can be made sensitive to diffusion by adding in magnetic field gradients. These gradients label space along a single direction and measure the

displacement of hydrogen nuclei along this direction over a finite interval. This displacement is calculated by measuring the change in phase that is brought about between a first gradient pulse and a second gradient pulse. This displacement produces a signal attenuation that indicates the relative displacement of nuclei, such that high signal attenuation in the direction of the gradient indicates the presence of more anisotropic diffusion. For each voxel in the resulting images, a diffusion tensor is fit, consisting of a 3 x 3 matrix that fully describes diffusion in 3D space. The principal direction of diffusion can be computed by deriving the eigenvectors and eigenvalues of the tensor. Eigenvalues are ordered $\lambda_1 \geq \lambda_2 \geq \lambda_3$, each of which corresponds to one eigenvector. The eigenvector associated with the highest eigenvalue (λ_1) is the main direction of diffusion. If this eigenvalue is significantly different from the other eigenvalues, then diffusion is anisotropic and is represented as a cigar-shaped ellipsoid in 3D space (see Figure 2.3). In contrast, if all eigenvalues are similar, then diffusion in isotropic, and represented by a sphere shape. Fractional anisotropy (FA) is the most commonly used measure of structural integrity of white matter and is calculated on the basis of all three eigenvalues. FA values range from 0 to 1, with values approaching 1 indicating increased directionality of diffusion (independent of diffusion rate).

However, it is important to point out diffusion-weighted MRI measures only one thing – the displacement of hydrogen. The signal attenuation produced by this displacement is sensitive to not only barriers imposed by microstructure (e.g. cell membranes, microtubules) but also a range of other factors, including temperature and viscosity (Jones, Knösche & Turner, 2013). As our understanding of the true biophysical basis of the signal attenuation is still in development, we interpret changes in FA as reflecting changes in 'structural integrity', in line with current terminology.

2.3.2.1 White matter connectivity in networks subserving higher-order cognitive control

Diffusion MRI has largely been used to examine changes in white matter microstructure across the lifespan, as well as differences in white matter between individuals with various psychopathological disorders and healthy controls. Relatively few studies have used this technique to examine the structural correlates of individual differences in cognitive control in normative samples. These studies have shown that measures derived from diffusion MRI can be used to provide corroborating evidence for neural network models derived on the basis of fMRI data. For example, Aron et al. (2007) showed increased activation in right IFC, pre-SMA and STN for individuals who showed greater conflict-induced slowing on a stop-signal paradigm. Using diffusion MRI, it was shown that these three regions were connected in a 'triangular' network of white matter pathways, further supporting the notion that response slowing is implemented via a cortico-basal ganglia hyperdirect pathway (see also Section 2.3.1.1).

Other studies have shown that measures of structural integrity are correlated with measures of brain function, as well as behavioral outcomes. For example, Forstmann et al. (2008b) found that individuals who showed more proficient response inhibition on a Simon task showed both increased fMRI activation, as well as increased FA in the right IFC. In addition, the extent of fMRI activation in the right IFC showed a positive correlation with FA within this region. Using the Eriksen flanker task, Westlye, Walhovd, Bjørnerud, Due-Tønnessen and Fjell (2009) showed that structural integrity within the cingulate is related to the error-related negativity, an ERP index of conflict-monitoring. In another study examining the structural and functional correlates of conflict-monitoring, Cohen (2011) showed that theta band activity during errors in a modified Simon task was correlated with

structural integrity within the ventral striatum and IFC. Therefore, while this technique is still developing, the available evidence indicates that measures derived from diffusion MRI closely correspond with both individual differences in functional measures (e.g. fMRI, ERPs, EEG oscillations) as well as behavioral outcome measures within normative samples. Thus, it appears that diffusion MRI can further our understanding of the way in which brain regions shown to be important for cognitive control form distributed networks that enable efficient information transfer.

2.4 Bringing it all together: Using multiple methodologies to inform models of cognitive control

As outlined in Section 2.1, observable behavioral measures (RT and accuracy) represent the end-point of a number of transient cognitive processes. Therefore, models of cognitive control based purely on these measures can only speculate about the underlying processes that contribute to a behavioral outcome. Formal cognitive modeling approaches overcome this limitation by extracting a number of latent processes that contribute to these behavioral outcomes. These techniques therefore allow for a finer-grained examination of the strategic processes that may be performed to ensure efficient top-down control of behavior.

These models may be further informed through the use of electrophysiology. ERPs allow for the examination of the relative activation and timing of these processes, and can therefore show whether processes are engaged proactively (e.g. in response to a pre-cue) or reactively (e.g. in response to a target). Examining activity within EEG frequency bands can also lead to a better understanding of the way in which processes evolve in the lead up

to a response. However, while these electrophysiological measures provide a relatively direct measure of neuronal activity, the pattern of activity observed at the scalp can arise from an infinite number of neuronal generator configurations, making it difficult to map scalp-recorded activity to underlying neural structures (Coles & Rugg, 1995). In addition, some neural activity (particularly deep within the brain) cannot be detected using scalp-recorded electrophysiology. Therefore, electrophysiological measures suffer from a lack of spatial resolution that in turn limits inferences about the networks underlying cognitive control processes.

MRI techniques provide a more indirect measure of neural activity and the structures that support it. The haemodynamic response is based on the metabolic demands of neuronal populations, and so the signal derived is indirectly coupled with actual neuronal firing. Thus, while this technique offers precise spatial resolution in the order of millimetres, its temporal resolution is limited due to the lag between neuronal activity and the onset of the response, as well as the slow nature of the response itself. Diffusion MRI can build on inferences made on the basis of functional measures by measuring the strength or coherence of white matter tracts supporting communication between brain regions. However, these measures are also indirect, as inferences regarding structural integrity of white matter tracts are based on diffusion properties of water molecules in tissue.

Recently there has been an increased focus on integrating across behavioural electrophysiological, haemodynamic and structural measures to provide converging evidence for the existence of brain networks that support specific cognitive processes. This approach overcomes the inherent disadvantages associated with using any one technique in isolation. One such strategy involves using measures derived from cognitive modeling to guide the interpretation of neuroscientific data, and vice versa. This ‘model-based

neuroscience' approach limits speculation and allows for more specific inferences about the nature of the processes underlying measures of brain activation (Forstmann et al., 2011b). A key feature of this approach lies in taking advantage of individual differences to increase confidence that a particular cognitive process is related to activation in a specific brain network. Much of this work has focused on examining the neural correlates of the speed-accuracy tradeoff in two-choice decision making (e.g. Forstmann, Brown, Dutilh, Neumann & Wagenmakers, 2010b; Forstmann et al., 2008a). For example, Forstmann et al. (2008a) found that individuals who showed lower response threshold estimates in response to instructions emphasizing speed relative to instructions emphasizing accuracy on a two-choice decision making task showed increased activation in a fronto-striatal network. Therefore, activation in this network could be related to a specific strategic cognitive process, rather than a gross measure of performance.

Another integrative approach involves relating measures of brain structure and function, to build more comprehensive models of the spatio-temporal dynamics of cognitive processes. For example, fMRI activation can be used to guide source modeling of ERPs to more reliably estimate the generator configuration driving activity at the scalp (e.g. Jamadar, Hughes, Fulham, Michie & Karayanidis, 2010). Another approach involves using individual differences to relate the magnitude of fMRI activation to the amplitude of ERP components (e.g. Horovitz, Skudlarski & Gore, 2002; Jamadar et al.; see Gore, Horovitz, Cannistraci & Skudlarski, 2006). As the haemodynamic response is too slow to enable dissociation of processes elicited by stimuli separated by only brief intervals, integrating fMRI activation with ERPs can provide a clearer picture of the timecourse of activation within brain regions. Further, as noted in Section 2.3.2.1, individual differences in diffusion MRI measures of white matter integrity have been related to fMRI activation as well as

electrophysiological measures to identify the structures that underlie these functional outcomes. Examining brain-behavior and brain-brain linkages takes advantage of the strengths of each technique while also overcoming some of their inherent limitations.

Chapter 3: Preparatory processes in the task-switching paradigm: Behavioural, ERP and fMRI evidence

3.1 Behavioural findings in task-switching

The ability to flexibly shift between multiple tasks according to environmental demands has been studied extensively with the task-switching paradigm. In this task, participants rapidly alternate between two or more simple tasks, such as classifying a target digit as odd or even, or classifying a target digit as higher or lower than 5. Task-switching studies typically find a switch cost – slower reaction time and higher error rate for switch as compared with repeat trials. However, while switch cost is an extremely consistent finding, different explanations have been proposed to account for this effect (see Kiesel et al., 2010 for a review). One view suggests that the switch cost reflects time taken to overcome interference from the previously relevant task (Allport, Styles & Hsieh, 1994). Another view posits that switch cost results from an active reconfiguration process that is engaged exclusively on switch trials to shift the system from readiness to perform one task to readiness to perform another (Rogers & Monsell, 1995). This additional process is thought to involve updating the 'task-set' – the set of rules that specify and link attentional and motor processes required for a particular task. Further, it is thought that part of this reconfiguration can be completely *proactively*, i.e. in anticipation of target onset. In this section, I present a selective review of the various processes that are thought to contribute to switch cost, paying particular attention to attempts to isolate anticipatory reconfiguration processes from other processes involved in task-switching. I then examine the question of what a switch-specific reconfiguration process might entail.

3.1.1 Early behavioural models of task-switching: Passive dissipation vs active reconfiguration of task-set

Early evidence for the existence of an active preparatory process when switching tasks was found by Spector and Biederman (1976), who gave participants columns of two digit numbers and instructed them to either add 3 to each digit, subtract 3 from each digit, or alternate between adding and subtracting 3 from successive digits. Participants had to retrieve from memory which task to complete. As expected, participants were slower when alternating tasks as compared to repeating the same task. In a second experiment, participants were given visual cues which indicated which task should be performed. While task switch trials were still slower than task repeat trials, the switch cost was smaller than when visual cues were not provided. This suggested that an active control process may be required on switch trials which may benefit from external cues.

Two decades later, Allport et al. (1994) revived interest in task-switching research when they found evidence that an endogenous reconfiguration process cannot fully account for switch cost. Allport et al. used incongruent Stroop stimuli (e.g. the word *blue* printed in red ink), and two tasks of unequal difficulty – word-reading and colour-naming. These stimuli were presented in lists, with participants either reading the word for every item on the list, naming the colour of the ink for every item on the list, or switching between word-reading and colour-naming. Switch cost was measured by comparing RT for mixed-task lists with RT from single-task lists. Colour naming produced slower RT compared to word reading, indicating it was a more difficult task. Yet, switching from colour naming to word reading produced a greater switch cost as compared to switching from word reading to colour naming. This finding of an asymmetric switch cost between two tasks of unequal difficulty cast doubt over the notion of a switch-specific

reconfiguration process, as according to this view, switching to the easier task should have produced a smaller switch cost due to less effortful switch-specific reconfiguration.

Allport et al. (1994) put forward an alternative explanation for the switch cost – that it is due to continued priming of the previous task-set as well as suppression of the now-relevant task-set – which they termed 'task-set inertia'. The task-set inertia hypothesis is based upon two assumptions: 1) performing a task increases the primacy of the target-response (T-R) mapping associated with that task and may also reduce the level of activation or inhibit T-R mappings associated with other tasks; and 2) the T-R mapping which was active on the previous trial remains partially active at the onset of the subsequent trial. This is assumed to facilitate performance when the same task is repeated on the next trial, but to interfere with performance when the next trial requires switching to the previously irrelevant task. Allport et al. suggested that when two tasks of unequal difficulty are performed, the weaker task (in this case, colour-naming) would require stronger suppression of the stronger task (word-reading). Hence, switching to the stronger task (word-reading) would require overcoming the persisting inhibition of that task. Further evidence for such a process came from their finding that, when participants switched between two tasks that had different T-R mappings (in this case, the word-reading Stroop task and a digit-magnitude task, which involve different stimuli, responses and T-R mapping), switch cost is substantially reduced as compared to switching between tasks that have similar T-R mappings (Allport et al.).

In summary, while early research suggested that switch cost reflected a time-consuming, endogenous process of reconfiguration in anticipation of switch trials, Allport and colleagues' work suggested that switch cost could be accounted for by passive interference processes which affect the level of activation of competing sets of T-R

mappings. On switch trials the previous, now-irrelevant task-set is still partially active causing interference on the current trial. According to Allport et al., this interference can fully account for prolonged RT on switch trials, without any requirement for an endogenous process of task-set reconfiguration (see also Wylie & Allport, 2000).

However, Rogers and Monsell (1995) produced evidence that an endogenous reconfiguration process can help account for at least part of the switch cost. Rogers and Monsell used an 'alternating runs' task-switching paradigm in which subjects alternated between two tasks in a fixed sequence (classifying a letter as a consonant or vowel and classifying a digit as odd or even). A 2 x 2 grid was continuously displayed, with the top two segments corresponding to the letter task and the bottom two segments corresponding to the digit task. The target moved around the grid in a clockwise direction, such that the task sequence was predictable (LLDDLLDDLL; see Figure 3.1). Each target consisted of one character that was relevant to the current task and another character that was not relevant to the current task. On 2/3 of trials, the irrelevant character belonged to the alternative task-set (e.g., if the relevant task was letter, the irrelevant character was a digit). On the remainder of trials, the irrelevant character did not belong to either of the tasks and was therefore neutral. When the irrelevant character was from the alternative task-set, on half the trials it was congruently mapped to the response required for the task-relevant character (e.g., A4 where A and 4 are both mapped to a left hand response), and on the other half it was incongruently mapped to the response required for the task-relevant character (e.g., A5 where 5 is mapped to right hand response). Consistent with Allport et al.'s (1994) task-set inertia hypothesis, switch cost was largest for incongruent trials, suggesting that the previous response mappings caused interference on these trials. However, switch cost was also observed on both neutral and congruent trials, a finding that

is not easily reconciled by the task-set inertia hypothesis, as there should be no carry-over of the previous T-R mappings for these trial types.

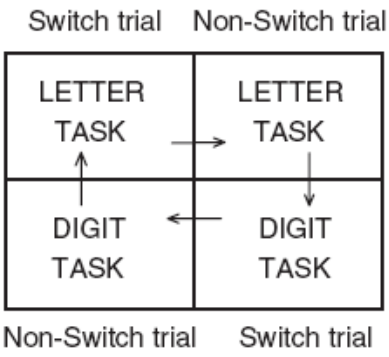


Figure 3.1: Rogers and Monsell's (1995) alternating runs paradigm. The top two segments were associated with the letter task, and the bottom two segments with the digit task. Targets were presented in a clockwise direction around the grid, so that the task sequence was completely predictable (Adapted from Karayanidis, Coltheart, Michie & Murphy, 2003).

Rogers and Monsell (1995) found further evidence that the task-set inertia hypothesis cannot fully account for RT switch cost. In Experiment 6, participants alternated between repeating four trials of one task, and then repeating four trials of the other task. They argued that if there is task-set inertia, then a slowing of RTs should be observed not only for the first trial of a block, but should still be present for the remaining trials in the block. The effect of this interference should also decay over time, such that the greatest slowing should be seen on the first trial of the block, followed by the second and so on. Contrary to this prediction, RT did not differ between second, third and fourth trials in the block but was slower than for the first trial in the block, a finding that was again inconsistent with Allport et al.'s (1994) predictions. Thus, Rogers and Monsell argued that these results are consistent with a process of reconfiguration to the new task-set on the first switch trial of a block that was not required for subsequent trials in that block.

Rogers and Monsell (1995) also manipulated the length of the response-target (R-

T) interval within and between blocks to examine whether the time made available for preparation would affect switch cost. When the R-T interval was varied between blocks of trials, Rogers and Monsell found that switch cost decreased as R-T interval increased up to 600 ms. As performance improved with greater opportunity for preparation, this provided evidence for the existence of a time-consuming, active *preparatory* task-set reconfiguration process. This reduction in RT switch cost with increasing R-T interval was not evident when R-T intervals were randomised within a block of trials, suggesting that this preparation is only carried on when the R-T interval is predictable.

Rogers and Monsell (1995) argued that the operation of this reconfiguration process was akin to Shallice's (1988, 1994) production-system account, in which competition between action sets or schemas is regulated by a top-down control mechanism which ensures that the correct schema is selected in order to achieve the current task goal. However, the fact that a switch cost remained even at the longest preparation interval of 1200 ms (which they termed the *residual switch cost*) suggested that while subjects seemed to be able to partially prepare endogenously before target onset, the remainder of the reconfiguration processes were triggered by the target. The authors argued that these target-triggered or 'exogenous' control processes are activated in order to overcome the prepotent tendency to respond to the target according to the task set which was previously active. Thus, Rogers and Monsell reasoned that task-set reconfiguration is a stage-like process, involving both endogenous and exogenous components.

In sum, while Allport et al. (1994) argue that switch cost is a product of an entirely passive process whereby the previous task-set interferes with the current task set, Rogers and Monsell (1995) argue that switch cost is due to both an endogenous process of reconfiguration in anticipation of a switch in task, as well as an exogenous, target-driven

component of reconfiguration. The following section summarises research aimed at further dissociating these two components by using a cued-trials task-switching paradigm.

3.1.2 Cued-trials task-switching paradigms

The 'alternating runs' paradigm used by Rogers and Monsell (1995) is limited in that passive carry-over effects from the previous trial and active preparation for the upcoming trial cannot be separated within the R-T interval. If active preparation does occur within the R-T interval, then it may be carried out at any time following the response to the previous trial. Paradigms in which tasks alternate unpredictably and a task-indicating cue is presented for each trial allow passive and active processes to be distinguished, as active preparation can only begin after the cue is presented.

Meiran (1996) used a paradigm in which participants were given a 2x2 grid and switched between two tasks – deciding whether a target was presented in the upper or lower half of the grid or deciding whether a target was on the left or right half of the grid. Participants were given explicit cues informing them about which task was required on the upcoming trial. In order to dissociate the effects of active preparation for the upcoming task and passive dissipation of the previous task, The length of the cue to target (C-T) interval was manipulated while the R-T interval was kept constant (see Figure 3.2). When the C-T interval increased (216 to 1716 ms) for a constant long R-T interval (1848 ms), switch cost decreased. Thus, when controlling for the effects of passive dissipation, performance improved with increased opportunity for preparation, supporting Rogers and Monsell's (1995) contention that an active process is responsible for switch cost. Further, switch cost remained in the long C-T interval condition, which again supports the existence of an exogenous, target-triggered component of reconfiguration.

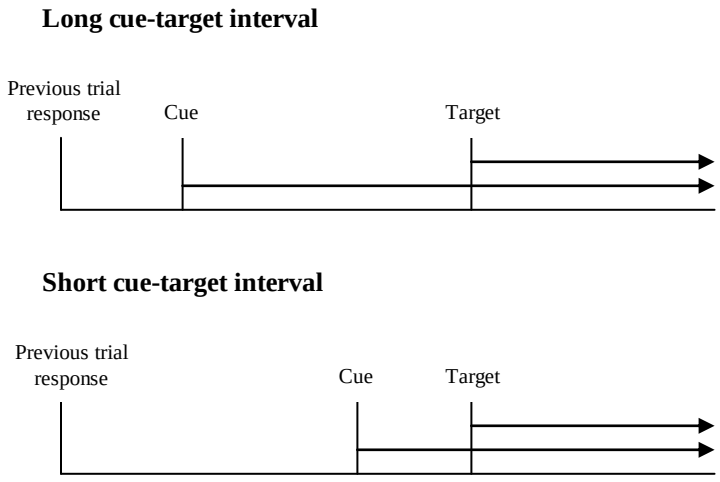


Figure 3.2: Schematics showing manipulation of the C-T interval, controlling for the length of the R-T interval (Adapted from Meiran, 1996).

In a later study, Meiran, Chorev and Sapir (2000) held the C-T interval constant (117 ms) while varying the R-C interval (132 to 3032 ms). Switch cost also decreased with increasing R-C interval. Since the C-T interval was held constant changes in RT switch cost would not be related to active preparation, but rather to increased passive decay of activation of the previously relevant task-set with increasing passage of time. Hence, switch cost is attenuated with both increased time available for preparation and increased time for the previous task-set to dissipate, indicating that both active and passive processes play a role in task-switching. Meiran et al. proposed a multi-component switch cost framework. The first component of the overall switch cost, the preparatory component, explains the reduction in switch cost due to preparation occurring in the C-T interval. The second component is the residual switch cost. A third component is a 'dissipating' component, which explains the reduction in switch cost with increasing R-C interval. Following from this, Meiran et al. suggested that task switch cost should not be interpreted as being representative of the operation of a single process. Rather, switch cost appears to reflect the

operation of a number of different active and passive processes, which can be separated out by manipulating the R-C and C-T interval.

3.1.3 The contribution of cue switching to switch cost

While cued-trials paradigms can help differentiate between the relative role of passive and active processes to task-switching performance, they have some inherent limitations. When each task is mapped to one cue, switch trials involve not only a change in task but also a change in cue, and similarly, repeat trials involve both a repeat in task and cue. Logan and Bundesen (2003) argued that this confound is significant in that switch cost in the cued-trials paradigm may be explained entirely by slower encoding of the cue on switch trials. Thus, there may be no requirement at all for an executive control process on switch trials.

Logan and Bundesen (2003) used a paradigm in which there was a 2:1 cue to task mapping (i.e., two cues were assigned to each task – *high* and *low* for the magnitude task, and *even* and *odd* for the parity task). This produced three possible conditions – *cue repeat*, in which both the cue and task repeated; *task repeat*, in which the cue changed but the task repeated; and *task switch*, in which both the cue and task changed. Results showed only a small task switch cost (*task switch- task repeat*), but a large cue switch cost (*task repeat – cue repeat*), supporting their argument that switch cost in the cued-trials paradigm may be largely attributable to the change in cue on switch trials (see also Mayr & Kliegl, 2003; Schneider & Logan, 2005).

To further tease apart the contribution of cue-retrieval and other processes to switch cost, Arrington, Logan and Schneider (2007) used a paradigm in which participants were required to respond to both the cue and the target. It was argued that any task switch effects

on RT to the cue would reflect cue encoding, whereas task switch effects on RT to targets would represent true switch cost (separate from cue encoding effects). Results showed a true switch cost in target RTs, suggesting that cue encoding cannot completely explain switch cost. Therefore, although it has been shown that cue encoding on switch trials may account for some of the total switch cost, there is still a true task switch cost that is attributable to an active preparatory control process.

3.1.4 Is there a switch-specific reconfiguration process?

While the task-set reconfiguration model assumes switch-specific preparation, that is, a separate process or processes that is engaged on switch trials to prepare for the upcoming task (Rogers & Monsell, 1995), other models have proposed that more general preparation processes occur on both switch and repeat trials. Hence, these models suggest that switch cost arises fully or partially from these processes simply taking a longer time to implement on switch compared with repeat trials. Several lines of evidence suggest that preparation also occurs on repeat as well as switch trials, calling into question the core assumption of the task-set reconfiguration model.

Firstly, it has been shown that repeat trials performed within mixed-task blocks show a performance decrement compared to repeat trials performed within single-task blocks (Kray & Lindenberger, 2000; Kray, Li & Lindenberger, 2002). This difference, termed the *mixing cost,* suggests that preparation for an upcoming task may also be carried out for repeat trials. It has also been found that reduction of RT for both switch and repeat trials occurs with increasing preparation interval. Altmann (2004) found that switch cost only reduced with increasing preparation interval when it was varied within-subjects, while increasing the preparation interval resulted in faster RT on both switch and repeat trials

whether preparation interval was manipulated within or between subjects. Thus, as the reduction of RT for both trial types appeared to be the more robust finding, Altmann suggested that a more general preparation process that is more strongly activated for switch trials may parsimoniously explain switch cost.

Studies that manipulate task certainty provide further evidence for the existence of general rather than switch-specific preparation. For example, Dreisbach, Haider and Kluwe (2002) used a paradigm in which participants were given probability cues on each trial that specified the probability of repeating the same task vs. switching to a specified task. On each trial, cues predicted an upcoming repeat in task with either 0%, 25%, 50%, 75% or 100% probability, and conversely an upcoming switch to a specific task with 100%, 75%, 50%, 25% or 0% probability. Switch cost were not dependent on these probabilities – instead, when a task was specified with high probability, participants responded faster, regardless of whether cue called for a switch or repeat in task. Thus, predictability about the upcoming task appeared to affect preparation on repeat and switch trials to an equal extent.

Koch (2005) manipulated predictability by comparing switch cost on alternating runs and cued trials paradigms in the same participants. Reaction time was slower on both switch and repeat trials for the cued-trials condition compared to the alternating runs condition. However, there was no corresponding increase in switch cost for cued-trials compared to alternating runs. Thus, again, task predictability did not appear to result in any switch-specific preparation advantage.

Therefore, the effects of preparation interval, as well as manipulations of task predictability have shown that preparation does not appear to be exclusive to switch trials. These findings challenge the notion of a switch-specific task-set reconfiguration process, and suggest that the same general preparation processes are activated for both switch and

repeat trials, but to a greater extent for switch trials.

3.1.5 Evidence for inhibition of irrelevant task-sets in task-switching

Arguments for switch-specific reconfiguration are further weakened by ambiguity about what this process might entail. Rubinstein et al. (2001) proposed that endogenous preparatory reconfiguration may be best conceptualised as a *goal shifting* process, which entails insertion or deletion of goals in working memory. According to this model, one process that could be engaged exclusively in preparation for a switch in task is inhibition or suppression of the now-irrelevant task set, due to the requirement to delete/suppress this task set in order to maximize activation of the now-current task set. Evidence for such a process comes from studies utilizing the backward inhibition paradigm (e.g. Mayr & Keele, 2000; see Koch, Gade, Schuch and Philipp, 2010, for a review). In this paradigm, participants use informative cues to switch between three different tasks (e.g. task A, B and C). When switching back to task A following one intervening trial (i.e., an AB<u>A</u> task sequence), reaction time is slower compared to switching back to task A following at least two intervening trials (i.e., a CB<u>A</u> task sequence). This *n – 2* repetition cost is thought to reflect the need to overcome more recent, and therefore stronger, inhibition of task A when it was performed more recently. However, there is ongoing debate as to the timing of this inhibitory process, as it could be carried out at the level of task-set activation (i.e., when the cue appears), at the level of stimulus processing, or at the level of response selection.

In their recent review article, Koch et al. (2010) argue that inhibition most likely targets response selection (see also Gade & Koch, 2007). Evidence for this comes from Schuch and Koch (2003), in which participants switched between three number-based tasks. On each trial, an auditory go (75%) or no-go (25%) signal was presented

simultaneously with stimulus onset. While the *n – 2* repetition cost was observed if the intervening trial in an ABA sequence was a go trial, this cost was substantially reduced when this intervening trial was a no-go trial. Schuch and Koch therefore argued that response execution on trial *n – 1* is required to produce backward inhibition, suggesting that inhibition acts at the level of response selection and execution.

In contrast, Houghton, Pritchard and Grange (2009) argued that *n – 2* repetition costs can also reflect inhibition in response to the cue. The degree of association between cue and target (referred to as cue transparency) was manipulated, with high transparency cues providing a feature of the target, and low transparency cues having no relationship with target features. Therefore, low transparency cues were designed to elicit more difficult cue-based retrieval of the correct task-set (i.e., biasing attention towards the relevant target feature) relative to high transparency cues. Low transparency cues, but not high transparency cues produced a significant *n – 2* repetition cost, suggesting that when the task is difficult to retrieve on the basis of the task cue, inhibition appears to be required to suppress competing cue-task associations. This finding led the authors to argue that inhibition occurs when conflict is detected at the cue-task translation stage (see also Grange & Houghton, 2010).

Therefore, there is evidence to suggest that inhibition of a previous task-set may be able to occur at the level of response selection/execution or at the level of cue-task translation. The finding that inhibition may occur at the level of cue-based retrieval of the relevant task-set supports Rubinstein et al.'s (2001) goal shifting process, indicating that inhibition of a previous task-set may be part of the top-down preparatory control strategy used on switch trials. However, these behavioral studies provide only indirect evidence that inhibition is carried out as part of preparatory control within the C-T interval (see Koch et

al., 2010). Other methodologies that allow for a more direct observation of the processes occurring within this interval are required to provide stronger evidence that this is the case.

3.1.6 Summary of behavioural findings

A number of theoretical models have tried to account for the behavioural switch cost. At one extreme, models posit the existence of a time-consuming, active reconfiguration process that includes both anticipatory and target-driven components (Rogers & Monsell, 1995; Rubinstein et al., 2001). At the other extreme, it is argued that passive dissipation of activation over time can account for switch cost (Allport et al., 1994). Multicomponent models, like that of Meiran et al. (2000) propose that both active reconfiguration and passive activation processes contribute to the switch cost, depending on task parameters. In addition, paradigms using a 2:1 cue to task mapping have shown that cue encoding may also account for at least part of the switch cost.

While studies have found evidence for an active process of reconfiguration, this process is still not well understood. In particular, it is unclear whether there exists a switch-specific preparation process that is distinct from more general preparation processes engaged for both repeat and switch trials. Behavioural data so far favour the latter, i.e., general preparation processes being engaged more strongly on switch than on repeat trials. However, there is some evidence that inhibition of the irrelevant task-set may be one process that is engaged specifically in preparation for a switch in task.

3.2 Electrophysiological evidence for advance task-set reconfiguration

The excellent temporal resolution of ERPs enables us to examine the timeline of

processes leading up to target onset. Therefore, ERPs have proven an attractive option for the study of preparatory reconfiguration, as they allow for a direct examination of the timecourse and organization of these processes within the C-T interval in cued-trials task-switching paradigms. By examining how ERPs for switch and repeat trials within the C-T interval are affected by task parameters and the opportunity for advance preparation, it is possible to gain insight into the nature of preparatory reconfiguration processes.

Electrophysiological studies of task-switching typically find differential activation for switch as compared with repeat waveforms following the response to the previous target in alternating runs paradigms or following the cue in cued-trials paradigms (Karayanidis, Coltheart, Michie & Murphy, 2003; Hsieh & Chen, 2006; Kieffaber & Hetrick, 2005; Lavric, Monsell & Mizon, 2008; Miniussi, Marzi & Nobre, 2005; Rushworth, Passingham & Nobre, 2002, 2005; Swainson, Jackson & Jackson, 2006; Wylie, Javitt & Foxe, 2003). This differential activation has typically been expressed as either a larger posterior positivity for switch compared with repeat cues (which we refer to as the *differential switch positivity*) or differential modulation of a *slow frontocentral negativity*. It is possible that the recording reference used may influence the relative morphology of these components. Studies that find the differential switch positivity but not the frontocentral negativity tend to use a linked mastoids reference (Goffaux, Phillips, Sinai & Pushkar, 2006; Karayanidis et al., 2003; Nicholson, Karayanidis, Poboka, Heathcote & Michie, 2005; Nicholson, Karayanidis, Bumak, Poboka & Michie, 2006a), whereas studies showing the frontocentral negativity tend to use a common average reference (Astle, Jackson & Swainson, 2006; 2008; Mueller, Swainson & Jackson, 2007).

3.2.1 Differential switch positivity: Evidence from alternating runs and cued-trials task-switching

Karayanidis et al. (2003) systematically examined the ERP correlates of anticipatory control and post-target adjustment in a task-switching paradigm at different preparation intervals. Using Rogers and Monsell's (1995) alternating runs paradigm, Karayanidis et al. reported a negative drift for both switch and repeat trials in ERPs locked to the response to the previous trial. At 200-300 ms post-response, a differential switch positivity emerged over parietal regions and peaked at around 400 ms (see Figure 3.3). At long R-T intervals (600 ms, 1200 ms), this positivity resolved before the onset of the subsequent target, while at short R-T intervals (150 ms, 300 ms) it continued beyond target onset. The authors argued that this differential switch positivity is consistent with Rogers and Monsell's conceptualization of the endogenous, controlled component of task-set reconfiguration.

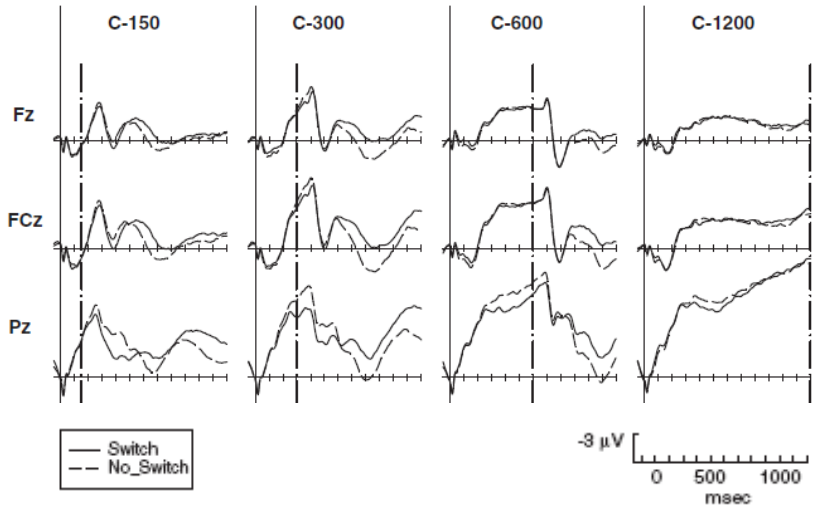


Figure 3.3: Response-locked waveforms from Karayanidis et al. (2003) at electrodes Fz, FCz and Pz, and across the four different R-T intervals (Adapted from Karayanidis et al., 2003).

The differential switch positivity has also been consistently observed in cued-trials task-switching paradigms. For example, Nicholson et al. (2005) used a variant of Rogers and Monsell's (1995) paradigm, with the task cued by a highlight of one of the four task quadrants. They differentiated cue-locked from target-locked effects by independently varying R-C interval and C-T interval to distinguish between passive task-set interference and active preparation for a switch in task. With a C-T interval of 600 ms, there was a greater positive modulation 300-400 ms after cue onset for switch compared with repeat trials, which was similar to the differential switch positivity observed by Karayanidis et al. (2003). With a shorter C-T interval of 150 ms, both the behavioural switch cost and the differential switch positivity were greater than for the longer C-T interval condition. Moreover, a larger switch positivity emerged after target onset and switch cost was greater again when there was no preparation interval, indicating that task-switching performance is facilitated even at very short preparation intervals. Together, these findings support the contention that the differential switch positivity represents active reconfiguration processes that may occur before target onset where subjects are given the opportunity to prepare, or after target onset when there is no opportunity for preparation.

An alternative explanation of this positivity is that it may reflect processing of the change in cue on switch trials, rather than an active reconfiguration process (e.g., Logan & Bundesen, 2003). However, ERP studies that have used a 2:1 cue to task mapping provide evidence that a cue encoding process can be dissociated from this switch positivity (e.g. Jost, Mayr & Rosler, 2008; Nicholson et al., 2006a). For example, Jost et al., (2008) showed that cue switch compared to cue repeat trials showed an increased negativity at fronto-central electrodes at around 300 ms. A significant switch-related positivity was still found between 700 and 850 ms post-cue for switch relative to repeat (cue switch) trials.

Thus, it appears that the switch positivity reflects active reconfiguration, rather than simply processing of a change in cue.

3.2.2 Type of preparation indexed by the differential switch positivity

A number of ERP studies have attempted to define the nature of preparation processes represented by the switch positivity. Rushworth et al. (2002; 2005) distinguished between 'intentional' and 'attentional' set preparation. Intentional set switching is defined as alternation between different rules linking targets to responses (e.g. switching response mappings from square = left and circle = right response, to square = right and circle = left response). Attentional set switching is defined as alternations between attending to different visual features of a target (e.g. attend to colour vs. attend to shape). Most task-switching paradigms require a change in attentional set and a change in intentional set, making it difficult to determine which of these processes is reflected in switch-related preparatory ERP components.

Rushworth et al. (2002) showed that the posterior differential switch positivity was associated with intentional set switching. In this study, a paradigm was used in which the response to hand mapping was switched unpredictably every 7 to 18 trials. When the new 'intentional set' was being initiated, an increased positivity for switch versus repeat waveforms was found early in the C-T interval over frontal areas, and later in the C-T interval over parietal sites. However, Rushworth et al. (2005) found a similar positivity for an attentional set switching task in which participants selected targets according to either their colour or shape. Kieffaber and Hetrick (2005) also found evidence that the differential positivity reflects preparation for the change in attentional set. Participants switched between three tasks – two of these were visual and one auditory – and responded to all of

these tasks using a match/mismatch response. Spatiotemporal principal components analysis revealed three separable components within the time window of the differential switch positivity. Two of these components were associated with switching between sensory features of the stimuli, while the third was associated with switching tasks regardless of task modality. As intentional set was held constant (with all three tasks requiring the same response), the authors argued that this component reflects switches in attentional set. Taken together, this evidence suggest that the differential switch positivity reflects both preparation to change response set, as well as preparation to focus attention on the relevant stimulus dimension.

3.2.3 General updating vs. Switch-specific preparation

As the morphology of ERPs within the C-T interval is similar for switch and repeat trials, it is unclear whether differential activation for switch compared with repeat trials reflects a switch-specific reconfiguration process, or greater activation of the same general task updating process required on all trials. Evidence that repeat trial waveforms also show preparatory activity comes from findings that cue-locked waveforms for repeat trials within a mixed-task block (termed mixed-repeat trials) show a larger positivity than repeat trials in a single-task block (termed all-repeat trials). This effect is similar to but earlier than the switch-related positivity (e.g. Goffaux et al., 2006; Jost et al., 2008). Wylie, Murray, Javitt and Foxe (2009) showed that preparation for mixed-repeat trials involves quantitatively different activation in the same cortical generators as switch trials, suggesting a common preparation process. However, Wylie et al.'s Figure 5 also showed distinct frontal generators for switch as compared to mixed-repeat trials that were distinct from parietal sources activated for both trial types. This finding suggests that although some preparation

processes may be engaged on both switch and mixed-repeat trials, switch trials may also require additional processes to configure the new task set.

Miniussi et al. (2005) found further evidence that the switch positivity does indeed reflect an additional switch-specific preparation mechanism, using a cued trials task-switching paradigm in which subjects switched between a verbal task and spatial task. Task-specific (verbal vs. spatial task) and switch-specific (switch vs. repeat cue) effects were compared within the C-T interval. Relative to repeat cues, switch cues produced an early differential switch negativity that was maximal over frontal sites (280-440 ms), followed by a differential switch positivity that was maximal over parietal sites (440-600 ms). In contrast, anticipating a specific task set was associated with earlier modulation over parietal and then central sites. Thus, switching between tasks and loading the required task-set appeared to be separable processes involving distinct neural mechanisms

Further evidence for a switch-specific preparation process was presented in Nicholson, Karayanidis, Davies and Michie (2006b). Nicholson et al. used a paradigm in which participants switched between three tasks using cues that provided different information about the upcoming target (Figure 3.4). Two of the cues were fully informative, i.e., *repeat* (e.g., repeat task A) and *switch-to* (e.g., switch to task B) cues provided complete and valid information about which task was relevant for the upcoming target. The third cue was partially-informative i.e., the *switch-away* cue specified that the previous task was no longer relevant (e.g., do not repeat task A). However, the relevant task (i.e., whether it would be task B or C) was specified only by the location of the target. Hence, on these switch-away trials, during the preparation interval it was possible to suppress the previously active task but not activate the new task. Cue-locked waveforms showed an early differential switch positivity for both switch-to and switch-away cues but

not for repeat cues (D-Pos1) as well as a second differential switch positivity for switch-to cues only (D-Pos2). As the early positivity occurred for cues that predicted a switch in task with certainty, regardless of whether the upcoming task was specified, this supported the existence of a switch-specific preparation process.

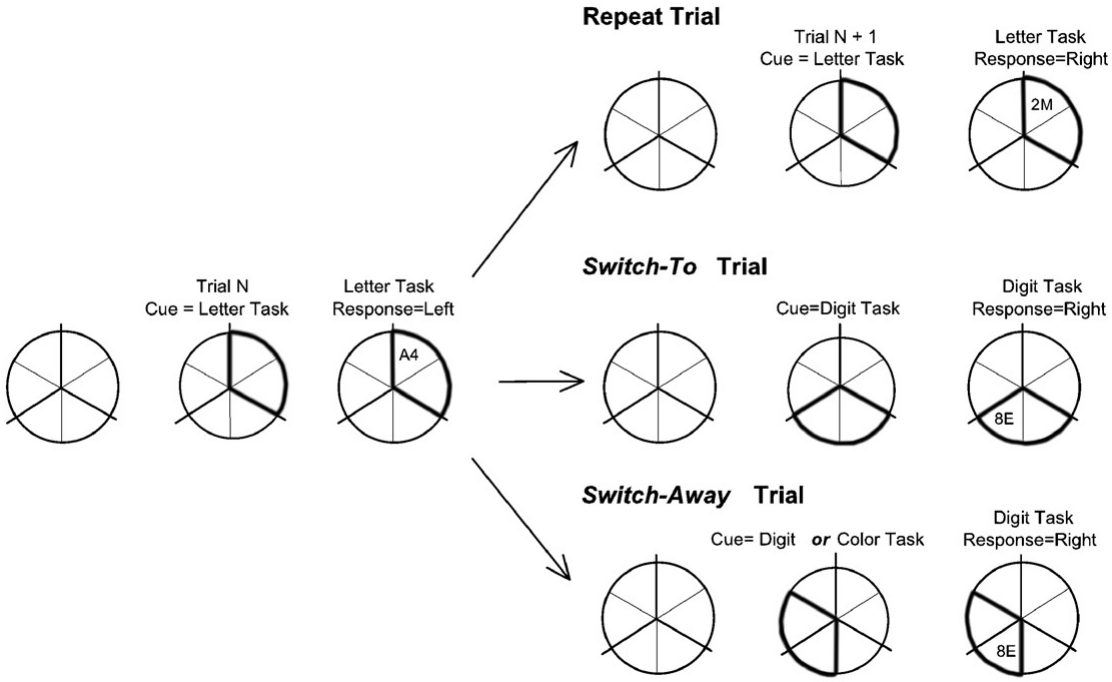


Figure 3.4: The paradigm used in Nicholson et al.'s (2006b) study, showing a trial progression from trial N to trial N + 1. A circle was divided into six segments, with groups of two segments forming three major task segments. Each of the three major segments was associated with a particular categorization task (letter, digit and colour). On each trial, the target appeared in one task segment, which defined which task would be performed on that target. The cue was a highlight of two adjacent segments, and the target appeared in one of the cued segments. *Repeat* cues highlighted the same task segment as on the previous trial. *Switch-to* cues highlighted a different task segment to that completed on the previous trial. *Switch-away* cues overlapped the two task segments corresponding to the two tasks that had not been completed on the previous trial (Adapted from Nicholson et al., 2006b).

In summary, the above ERP studies show direct evidence for advance preparation and additionally suggest that this preparation consists of multiple component processes. There is evidence for a switch-specific preparation process that can be dissociated from task-specific and more general preparation processes occurring on both switch and repeat trials. These findings are not in line with behavioural studies that argued against switch-specific preparation (see Section 3.1.4). In order to reconcile these contradictory findings, researchers have attempted to link switch-related ERP components with behavioural measures, to show that these components are indexing effective preparation.

3.2.4 Linking cue-locked ERP components to behavioural performance

Studies have taken a number of different approaches to the integration of ERP with behavioural data. One approach examines whether variability in preparation-related ERP components can account for individual differences in behavioural outcomes. Using this approach, Kieffaber and Hetrick (2005) examined whether the amplitude of switch-related ERP components was related with behavioural performance using a cued trials paradigm in which participants switched between two visual tasks and one auditory task. The cue-locked differential switch-positivity was inversely related with RT switch cost, but only when switching between the two visual tasks.

Another approach involves partitioning ERPs into ‘fast’ and ‘slow’ trials on the basis of RT, in order to determine whether the efficiency of preparation is reflected in preparation-related components. Lavric et al. (2008) used a cued trials paradigm in which participants switched between a shape naming and a colour naming task. With a C-T interval of 800 ms, they found a differential switch positivity emerging around 500 ms over posterior sites and a concurrent negativity for switch compared with repeat trials over

anterior sites. Behavioural and ERP data were analysed separately for the fastest and slowest third of trials for each participant. Fast responses were associated with smaller RT switch cost as well as larger cue-locked switch-positivity than slow responses, supporting the link between switch-related ERP components within the C-T interval and active preparation to switch task.

Karayanidis, Provost, Brown, Paton and Heathcote (2011) used orthogonal polynomial regression analysis (Woestenburg, Verbaten, Van Hees & Slangen, 1983) to provide more fine-grained evidence linking cue-locked ERPs with behavioural preparation. Single-trial cue-locked ERPs were extracted for each of 10 RT percentiles. As shown in Figure 3.5, the amplitude of the cue-locked posterior positivity varied as a function of RT for switch cues, but not repeat cues. Moreover, although repeat trials also showed a positive peak within the same latency range as the cue-locked positivity for switch trials, the switch positivity was always significantly larger even for the slowest switch trials. This suggests that, regardless of the efficiency of preparation, switch trials still showed an additional preparation process relative to repeat trials. Interestingly, the amplitude of the later pre-target negativity was also inversely related to RT, but this time for both switch and repeat trials. Hence, these findings suggest a dissociation between the cue-locked posterior positivity and the pre-target frontocentral negativity. While the posterior positivity appears to be associated with a switch-specific preparation process, the pre-target negativity reflects a more general preparation process that is common to both repeat and switch trials. These findings provide converging evidence for the notion of a switch-specific preparation process that is distinct from more general task-updating processes.

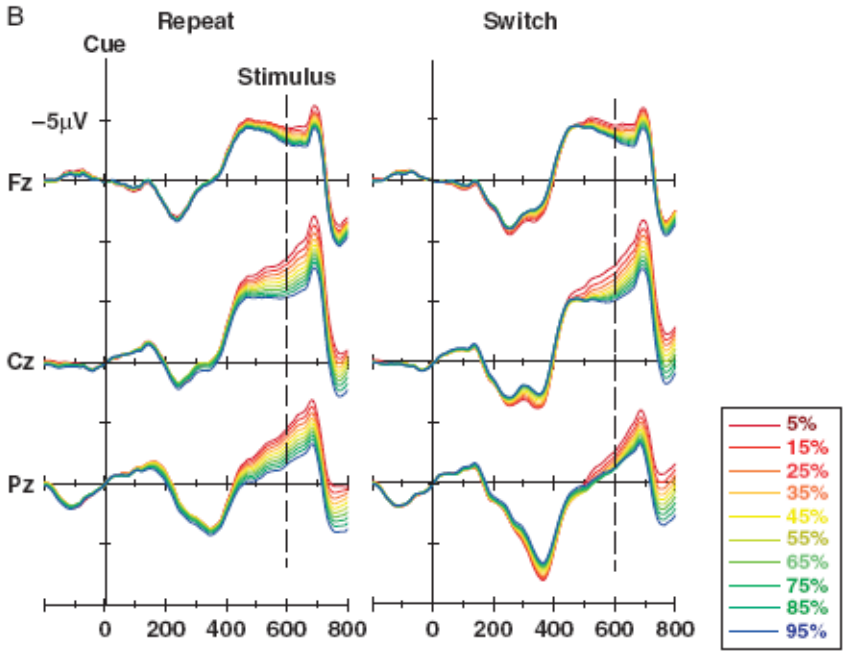


Figure 3.5: Cue-locked waveforms for switch and repeat trials from Karayanidis et al. (2011), at each of the 10 percentiles (Adapted from Karayanidis et al., 2011).

3.2.5 Post-target differences between switch and repeat trials

Target-locked ERPs also consistently show differential activation for switch compared to repeat trials. With the alternating runs paradigm, Karayanidis et al. (2003) showed a large post-target centroparietal positivity that was attenuated for switch compared to repeat trials. Karayanidis et al. (2003) argued that this reflected a negativity for switch compared with repeat trials which was superimposed on the large positivity for both trial types. At long R-T interval trials (300 ms, 600 ms, 1200 ms), this negativity was time-locked to target onset, while at the shortest R-T interval (150 ms), the negativity did not emerge until the differential switch positivity had resolved. Karayanidis et al. (2003) argued that the target-locked differential switch negativity mapped onto Rogers and Monsell's (1995) exogenous or target-triggered component of reconfiguration.

A similar target-locked differential switch negativity has also been reported in cued task-switching paradigms. For example, Nicholson et al. (2005) showed that, at a C-T interval of 600 ms, a centroparietally maximal differential switch negativity emerged at around 100 ms following the target. Consistent with Karayanidis et al.'s (2003) findings, for both no cue and short C-T interval (150 ms) conditions, the differential switch negativity did not emerge until after the differential switch positivity had resolved. This finding has also been replicated in the Switch To and Away paradigm (Nicholson et al., 2006b). Switch-to cues, which specified the required task before target onset, produced a differential switch negativity at target onset. In contrast, switch-away cues, which did not specify the upcoming task, produced a target-locked differential switch positivity, followed by a differential switch negativity. This suggests that the initiation of processes associated with the differential switch negativity are dependent upon the completion of processes associated with the differential switch positivity. Similar differential switch negativity has been reported for both intentional and attentional switches of task set (Rushworth et al., 2002; 2005).

3.2.6 Summary of ERP studies of task-switching

The millisecond-resolution of ERPs means that they can show us the time course of preparatory and target-triggered processes leading up to a behavioural response, adding to our understanding of these processes from behavioural studies, and moving closer to developing a cohesive model of control processes required for efficient task-switching performance. A consistent finding in the literature is a differential positivity for switch relative to repeat trials in the interval leading up to an anticipated change in task (Karayanidis et al., 2003; Kieffaber & Hetrick, 2005; Nicholson et al., 2005; 2006a;

Swainson et al., 2006) which appears to be modulated by manipulations that affect reconfiguration. This component has been shown to reflect both stimulus-set and response-set updating (Rushworth et al., 2002; 2005), and can be broken down into a number of sub-components, including a preparation process that is specific to switch trials (Karayanidis et al., 2011). Integrating ERP and behavioural data has also shown that this preparatory component is a reliable marker of preparation efficiency (e.g. Lavric et al., 2008). Processing also differs for switch compared with repeat trials after target onset, with a target-locked differential switch negativity consistently reported. Together, these two components support multiple-component models of task-set reconfiguration (e.g. Rogers & Monsell, 1995; Rubinstein et al., 2001) that include both strategic preparation as well as target-driven adjustments.

3.3 fMRI evidence for neural networks associated with task-switching

While ERPs have allowed for a fine-grained analysis of the temporal course of processes involved in task-switching, one cannot deduce the underlying neural sources of these processes on the basis of scalp-recorded activity. Over the past decade, research has increasingly turned to fMRI as a technique for the identification of neural regions involved in task-switching, due to its high spatial resolution. Imaging studies have provided strong evidence for the existence of a fronto-parietal network involving the fronto-lateral cortex, the fronto-median cortex and posterior parietal cortex which is involved in the control of task-sets during task-switching (e.g. Dove, Pollmann, Schubert, Wiggins & von Cramon, 2000; Kimberg, Aguirre & D'Esposito, 2000; Sohn, Ursu, Anderson, Stenger & Carter, 2000). However, due to the slow BOLD response, activation within this network cannot be

reliably associated with a particular time window. Therefore, a significant challenge lies in determining which components of the fronto-parietal network are involved in preparatory control of task sets and which are involved in reactive changes in response to the target (see Ruge, Jamadar, Zimmermann & Karayanidis, 2013). The following sections comprise a focused review of studies that have attempted to isolate cue-related activation from target-related activation within the task-switching paradigm, in order to identify the networks underlying preparatory reconfiguration processes.

3.3.1 Dissociating cue-locked from target-locked processes in fMRI data

A number of strategies have been used in order to isolate cue-related processes from target-related processes in the task-switching paradigm. One approach uses a constant, long C-T interval (i.e., > 5 sec) to more effectively separate cue-related from target-related activity. This longer preparation interval allows more time for the cue-related BOLD response to strengthen, before the target-related response begins to take effect. However, studies which use these very long preparatory intervals typically do not show a reduction in switch cost when the cue is informative compared to when it is non-informative (e.g. Sohn et al., 2000; Luks, Simpson, Feiwell & Miller, 2002), suggesting that participants are not making use of the cue to prepare on switch trials. Another approach uses a variable C-T interval and incorporates a delay-related regressor in the general linear model in order to separate cue-related from target-related and delay-related activation (i.e., 'jittering'; e.g. Ruge et al., 2005; Brass et al., 2003). Importantly though, randomly varying the preparation interval has been found to interfere with preparatory processes (Rogers & Monsell, 1995), suggesting that studies which use these modified paradigms may be targeting processes that are different from those observed in behavioural and ERP studies.

Yet another strategy uses a 'partial' trials design, in which cue-only trials (i.e., cue presented, with no target following) are intermixed with standard cue-target trials (e.g. Brass & von Cramon, 2002; Ruge, Goschke & Braver, 2009). This allows for the use of a more standard C-T interval, comparable to those used in behavioural and ERP studies. However, it is possible that the absence of the target may elicit a response that interferes with the preparation-related activity associated with cue-only trials. Therefore, attempts to isolate cue from target-related processes carry with them some significant limitations that can affect interpretation of activation patterns, as well as comparisons with results from more standard task-switching paradigms. These limitations may be overcome by using cross-methodology approaches that more directly link cue-locked effects with activation.

3.3.2 Proactive vs reactive engagement of the fronto-parietal network

Of the studies that have attempted to separate cue from target processing, evidence has been found for fronto-parietal engagement both as part of preparation, as well as post-target adjustment. Brass and von Cramon (2002) used a task-switching design that included a fixed C-T interval and four different trial types: cue + target, no-cue + target, cue + no-target and null trials. By examining the temporal derivative of cue + no-target and no-cue + target trials, the authors examined whether there were differences between cue-only and target-only activations. Activation in the inferior frontal junction (IFJ; a region situated between the frontal sulcus and the inferior frontal sulcus), the pre-supplementary motor area (pre-SMA) and the ventrolateral prefrontal cortex (VLPFC) was delayed for target-only relative to cue-only trials. This suggests that these regions can be activated in a proactive manner when cues afford the opportunity to prepare, or in a reactive manner when there is no opportunity for preparation. However, it is important to note that this

activation did not differ for switch compared with repeat trials.

Ruge et al. (2005) compared prepared (C-T interval 2000 ms) and unprepared (C-T interval 100 ms) trials. Switch-related activation was found for unprepared trials in IFJ, inferior parietal sulcus (IPS) and SPL. In line with Brass and von Cramon's (2002) findings, these regions were also activated for both switch and repeat trials in the prepared condition. Thus, while these frontal and parietal regions were proactively engaged on all trials, they were also engaged reactively specifically on switch trials, to apply the already-activated task-set. In contrast, Badre and Wagner (2006) found that these regions were activated for both prepared and unprepared trials. These findings suggest that regions within the fronto-parietal network can be proactively or reactively engaged depending on the experimental context.

3.3.3 Can preparatory activity be attributed to cue encoding?

As discussed previously in Section 3.1.3, cue priming appears to play at least some part in the production of switch cost. Therefore, it is possible that activity reported in the previous two sections could be related to cue processing, rather than preparation. Brass and von Cramon (2004) used two successive cues per trial to isolate activation associated with cue encoding and switch preparation. On each trial, two cues were presented sequentially before the target (see Figure 3.6). Activity associated with cue encoding was examined by comparing cue-repetition with cue-switch conditions. This contrast produced activation in lateral premotor cortex, inferior temporal gyrus and fusiform gyrus. Preparation-related activation (controlling for a change in cue) was examined by comparing meaning-switch with cue-switch conditions. Activation was found in the left IFJ, right IFG and right intraparietal sulcus. Therefore, cue encoding and task preparation elicited activation in

distinct brain regions. While regions related to sensory processing were associated with cue processing, a network of inferior frontal as well as posterior parietal regions appeared to be more strongly related to preparation.

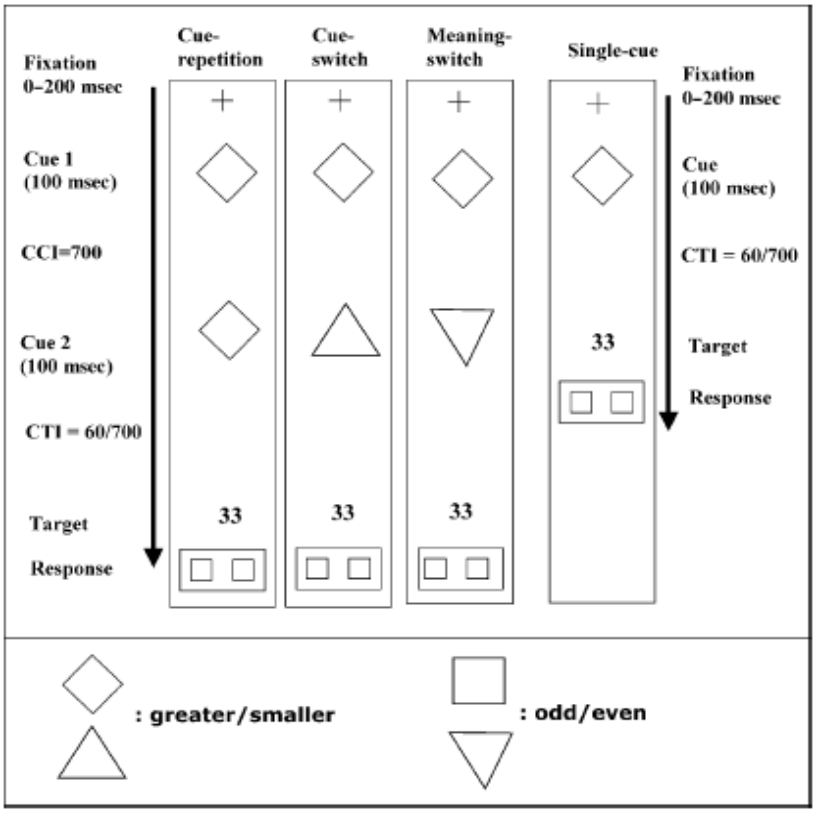


Figure 3.6: Brass and von Cramon's (2004) paradigm. The paradigm included three two-cue conditions, in which the second cue determined which task was required for the upcoming target. In the cue-repetition condition, the second cue was identical to the first. In the cue-switch condition, the second cue was different to the first, but was still mapped to the same task. In the meaning-switch condition, the second cue was different to the first, and also mapped to a different task. A single-cue condition was also included, which involved presentation of single cue followed by a target (Adapted from Brass & von Cramon, 2004).

3.3.4 Is there evidence for brain regions that are responsible for switch-specific preparation?

As described in Section 3.2, several ERP studies have suggested that a switch-specific preparation process can be disentangled from more general preparation processes required on switch and repeat trials (e.g. Karayanidis et al., 2011; Miniussi et al., 2005; Nicholson et al., 2006b). In fMRI data, switch-specific preparation processes would be indexed by significant activation in a particular brain region for switch, but *not* repeat trials. So far, fMRI studies have not been able to find evidence for such a switch-specific process. While many studies do report enhanced activation for switch relative to repeat trials, activation is increased for *both* switch and repeat trials compared to baseline (Barber & Carter, 2005; Braver, Reynolds & Donaldson, 2003; Crone, Wendelken, Donohue & Bunge, 2006). Further, a number of studies have reported no differential activation between switch and repeat trials (e.g. Brass & von Cramon, 2002; 2004; Luks et al., 2002; Ruge et al., 2005). Therefore, unlike ERP studies that show evidence for a dissociable switch-specific process (e.g. Karayanidis et al., 2011; Nicholson et al., 2006b), fMRI studies tend to support the existence of a general preparation process that is engaged more strongly on switch compared with repeat trials.

The studies that *do* show significantly increased activation for switch compared with repeat trials have produced largely heterogeneous findings in terms of the location of activation, as well as the circumstances under which these regions are activated, within the fronto-parietal network. One factor that appears to affect the location of activation is the type of switching required – that is, whether the paradigm involves attentional (stimulus-related) or intentional (response-related) switching (see Section 3.2.2). Crone et al. (2006) compared switching between bivalent targets associated with multiple response sets (i.e.,

intentional set switching) to switching between univalent response sets that were associated with only one response set. Increased switch-related activation was found in left DLPFC and ventrolateral prefrontal cortex (VLPFC), as well as bilateral posterior parietal cortex, including SPL for the bivalent targets compared to the univalent targets. Further, using a partial-trials design, Ruge, Müller and Braver (2010) also showed increased activation in DLPFC for switching between different intentional sets (i.e., different bivalent response mappings). In contrast, switching between attentional sets was associated with increased activation in posterior SPL. Therefore, it appears that DLPFC is associated with switching intentional set, while posterior parietal cortex plays a role in switching *both* intentional and attentional set.

Some studies have attempted to isolate switch-specific preparation by examining relationships between fMRI activation and behavioural measures, and between fMRI activation and ERP measures. Badre and Wagner (2006) showed that activation within the left VLPFC decreased with increasing C-T interval and was negatively correlated with a simulated reduction in switch cost computed based on a CAMS-TS model, suggesting that this region plays a specific role in switch-related preparation. Braver et al. (2003) showed increased activation for switch relative to repeat trials in left VLPFC, DLPFC and SPL. However, in contrast to Badre and Wagner's findings, the SPL showed increased switch-related activation for fast compared to slow trials, suggesting that proactive engagement of this region may modulate the size of the switch cost. Jamadar et al. (2010) further corroborated this finding, showing that switch-related activation in the posterior SPL correlated with the amplitude of the cue-locked differential switch positivity, but not the target-locked differential switch negativity. These studies again support a role for PPC in switch-related preparation, while also suggesting that VLPFC may additionally be involved

in such a process.

3.3.5 Summary of fMRI studies of task-switching

fMRI studies of task-switching have produced largely heterogeneous findings, possibly owing to the wide range of design modifications employed to circumvent the problem of slow and overlapping BOLD responses. However, a number of studies have consistently shown activation in a network comprising medial, dorsolateral and ventrolateral prefrontal areas, as well as posterior parietal areas. Studies that have isolated cue from target-related processing have shown activation within this network at both of these processing stages, however this activation is often similar for switch and repeat trials. Only a few studies have found evidence for switch-related preparatory activation, with these studies suggesting that DLPFC and PPC are involved in action-related and attention-related aspects of preparation, respectively.

3.4 Summary of behavioural, ERP and fMRI studies of task-switching

Behavioural studies of task-switching have produced evidence that multiple processes, including passive carry-over effects, preparatory task-set reconfiguration processes as well as target-driven reactive control processes contribute to switch cost. However, it is still unclear what type of active control process is carried out in anticipation of a switch in task – whether it is a process that is qualitatively distinct from those required to prepare for a repeat in task, or simply a stronger engagement of the processes engaged to prepare for a repeat in task.

ERP studies provide the millisecond resolution that is required to be able to

dissociate between these two interpretations. Consistent with multi-component models of task-switching (e.g. Rubinstein et al., 2001), these studies consistently show both cue-locked and target-locked effects of switching tasks. Further, more recently studies have provided evidence that cue-locked preparation processes can be broken down into multiple sub-components. A cue-locked differential switch positivity maps onto a switch-specific preparation process that can be dissociated from more general task preparation processes required for both switch and repeat trials. While lacking the temporal resolution required to unambiguously separate rapid cognitive processes, fMRI has yielded a wealth of information about the spatial dynamics of cognitive control processes in task-switching. These studies also support multiple-component models of task-switching, showing that regions activated at cue onset are also reactivated at target onset. However, these studies tend to support a theory of preparatory reconfiguration that entails greater activation of the same processes already recruited to prepare on repeat trials. Therefore, ERP and fMRI studies have led to divergent conclusions regarding the nature of the preparatory reconfiguration process.

3.5 Using a model-based neuroscience approach to decompose task-switching performance

While neuroimaging evidence has added valuable information to models of cognitive control processes in task-switching, further work is required to understand which specific cognitive control processes are indexed in these neuroimaging measures. Associations have been found between neuroimaging measures and behavioural performance (see Section 3.2.4), suggesting that these effects are behaviourally relevant. However, end-state behavioural measures represent the culmination of multiple cognitive

processes, and therefore lack the sensitivity required to tap specific cognitive processes underlying task-switching performance. Formal cognitive modeling addresses this problem by decomposing behavioural performance into latent cognitive processes that would otherwise not be directly measurable. Integrating these latent measures derived from formal cognitive modeling with neuroimaging measures allows for more specific inferences about the relationship between neuroimaging data and specific cognitive processes. As task-switching typically involves making a two-choice decision, the diffusion model (e.g. Ratcliff, 1978; see Section 2.1 in previous Chapter) appears particularly suited to investigating processes underlying task-switching performance. As discussed in Section 2.1 of the previous Chapter, this model produces estimates of nondecision time, drift rate and response threshold. The following sections discuss how each of these parameters may be modulated by control processes carried out within task-switching paradigms.

3.5.1 Nondecision time (Ter)

Nondecision time encompasses processes not related to the decision itself, such as target encoding and response activation and execution. In the context of task-switching, it would also make sense to assume that switch cost may also contribute to nondecision time. For example, Klauer, Voss, Schmitz and Teige-Mocigemba (2007) used an implicit association test in which participants switched from a flower-insect categorization task to a positive-negative word categorization task. Response mappings were either compatible (i.e., flower and positive mapped to one finger and insect and negative to another) or incompatible (i.e., flower and negative mapped to one finger and insect and positive to another). Nondecision time was greater when switching between incompatible mappings compared to compatible mappings, with the authors suggesting that this increase could be

at least partly attributed to the greater control processes required for switching between incompatible response sets (Klauer et al., 2007). Therefore, in addition to encoding and motor processes, nondecision time may also include reconfiguration processes that must be completed before the decision process can commence, such as loading of the correct task set and target-response mappings. In the context of cued task-switching, multiple component models would predict that nondecision time should be differentially modulated by the degree of preparation afforded by the cue, as this would affect the 'left-over' reconfiguration that would be required at target onset. As informative cues should result in highly-prepared states at target onset and therefore require less time for additional post-target reconfiguration relative to non-informative cues, we would expect cues affording greater preparation to be associated with lower nondecision time.

3.5.2 Drift rate (v)

Evidence accumulation is comprised of the systematic drive towards one response threshold, as well as noise in the system that produces random fluctuations between each response boundary. Drift rate captures the mean rate of this systematic component of evidence accumulation, and hence can be interpreted as a measure of both the efficiency of evidence accumulation, as well as the signal-to-noise ratio of the system. A higher drift rate corresponds to faster evidence accumulation and hence faster responses.

As drift rate is closely tied to the response selection process, multiple component models of task-switching would predict that this parameter is set by a culmination of processes leading up to the response itself. Therefore, drift rate may be at least partially affected by task-set activation processes such as task-set biasing and activation of the correct set of target-response mappings, which may be more strongly implemented on

repeat relative to switch trials. This parameter may additionally be modulated by more passive processes, such as carry-over of priming from the previous task and target-triggered interference. Drift rate may therefore be modulated by several processes that contribute to switch costs. Using a cued-trials task-switching paradigm, Madden et al. (2009) showed decreased drift rate for switch relative to repeat trials in both a younger and older sample, suggesting that the efficiency of evidence accumulation is indeed reduced when there is a requirement to switch tasks. This suggests that switch costs may be partially attributable to reduced quality of evidence accumulation for switch relative to repeat trials.

3.5.3 Response threshold (a)

In addition to the rate with which evidence is accumulated, the speed of response selection is determined by response threshold. A low response threshold (i.e., a small difference between response boundaries) means that the threshold is crossed more quickly, but at the increased risk of an error due to random oscillations in the evidence accumulation process. In contrast, a high response threshold allows more time for evidence to accumulate, resulting in slower responses that carry less risk of making an error. The setting of response threshold is therefore thought to reflect a participant's degree of response caution and to contribute to the speed-accuracy tradeoff. Participants have been shown to adjust response threshold according to performance incentives or perceived task difficulty. For example, Voss, Rothermund and Voss (2004) found that participants raised response threshold when offered reward for correct responses as well as under more difficult task conditions (i.e., incompatible response mapping).

In sum, response threshold adjustment appears to be driven by both extrinsic and intrinsic factors, and may be conceptualised as a controlled, strategic process that assists in

balancing the speed-accuracy tradeoff. This suggests that threshold adjustment may be a key regulatory process required to deal with the fluctuating demands of our environment, and so may be part of the strategic preparation processes required in anticipation of a switch or repeat in task within cued-trials task-switching.

3.5.4 Summary of evidence accumulation modeling in task-switching

The breakdown of overt measures of task-switching performance into latent constructs is one approach to more directly targeting the specific processes underlying cognitive control in this paradigm. For example, the extent of preparatory task-set reconfiguration completed prior to target onset can be indexed in the nondecision time parameter. Other parameters that contribute to the decision process itself can also inform about the type of processes that contribute to end-state measures. For example, the rate of evidence accumulation, or drift rate, has been shown to be higher for switch relative to repeat trials. In addition, while the response threshold parameter has not been directly examined within the task-switching paradigm, there is evidence to suggest that participants may strategically update their degree of response caution according to perceived task difficulty. Therefore, it would be expected that participants may set their response threshold higher when switching between tasks compared to repeating the same task. Using a model-based neuroscience approach that incorporates these parameters into the analysis of neuroimaging data can constrain interpretations of neuroimaging effects and therefore lead to the development of more detailed models of task-switching.

We used this approach to examine the specific cognitive control process or processes that are recruited to prepare for a switch in task, and combined this with a number of neuroimaging methodologies designed to target the temporal and spatial

properties of switch-specific preparation. Using this integrative approach, we add to current models of preparatory control in task-switching. In the following chapter, we first used ERPs to show that switch-specific preparation could be temporally distinguished from task preparation processes. We then used cognitive modeling to uncover the nature of this switch-specific preparation.

Chapter 4: Anticipatory reconfiguration elicited by fully and partially informative cues that validly predict a switch in task[1].

Task-switching paradigms require rapid alternation between two or more task-sets defined on the basis of distinct or partially overlapping target features. Typically, these paradigms produce *switch costs* - longer reaction times (RTs) and more errors when tasks are switched as compared with when tasks are repeated (e.g., Rogers & Monsell, 1995). In cued-trials paradigms, increasing the cue-target interval reduces RT switch cost, but a significant residual switch cost remains even with long preparation intervals (Meiran, Chorev & Sapir, 2000). Recent behavioral (e.g., Arrington, Logan & Schneider, 2007) and electrophysiological (e.g., Karayanidis, Coltheart, Michie & Murphy, 2003) studies support multi-component models of task-switching, with switch cost reflecting both active control processes (e.g., task-set reconfiguration; Rogers & Monsell) and passive target-driven processes (e.g., stimulus-response [S-R] priming; Wylie & Allport, 2000).

Although there is evidence of a role for inhibition in task-switching, it is unclear at what stage an inhibitory mechanism may be activated and whether it is a top-down process or a bottom-up process. Mayr and Keele (2000) argued that a longer RT on the third trial of an ABA sequence, as compared to a CBA sequence, supports an inhibitory control process, albeit a rather low level one, since inhibition was not overcome with increasing preparation. Koch and colleagues argued that this inhibition is a by-product of response activation, since studies have shown no backward inhibition (Schuch & Koch, 2003) or RT switch cost

[1] Published as Karayanidis., F., Mansfield, E. L., Galloway, K. L., Smith, J. L., Provost, A. & Heathcote, A. (2009). Anticipatory reconfiguration elicited by fully and partially informative cues that validly predict a switch in task. *Cognitive, Affective and Behavioral Neuroscience, 9,* 202-215.

(Koch & Philipp, 2005) following no-go trials that require task-set preparation but no response execution. Driesbach, Haider and Kluwe (2002) compared subjective expectancy for partially informative cues, which signal an impending switch trial without identifying which specific task to prepare, and fully informative cues, which indicate which task to switch to. Unlike fully informative cues, partially informative cues did not produce subjective expectancy effects Thus, knowledge that the task would change without specification of which task would be performed did not produce the differential response benefit that would be expected if inhibition of the previously active task set was required to switch tasks (see also Hubner, Dreisbach, Haider & Kluwe, 2003).

In contrast, Nicholson, Karayanidis, Davies and Michie (2006b) found event-related potential (ERP) evidence consistent with task-set inhibition during the cue-target interval. ERPs are systematic fluctuations in brain electrical activity that are extracted from the electroencephalogram (EEG), using signal averaging techniques (Andreassi, 2000), and have been shown to provide a high temporal resolution window into the processes underlying task-switching. In particular, ERP waveforms time-locked to cue onset consistently show a larger parietal positivity for switch, as compared with repeat, trials (e.g. Kieffaber & Hetrick, 2005; Miniussi, Marzi & Nobre, 2005; Nicholson, Karayanidis, Bumak, Poboka & Michie, 2006a; Nicholson, Karayanidis, Poboka, Heathcote & Michie, 2005; Rushworth, Passingham & Nobre, 2005). This *differential switch positivity* (D-Pos) emerges as early as 200ms post-cue and, with long preparation intervals, peaks prior to target onset. After target onset, ERPs for switch trials show a negative shift, relative to repeat trials, that emerges after 150 ms and extends more than 800 ms after target onset. D-Pos has been mapped to processes associated with task-set reconfiguration during the cue-target interval, whereas the switch negativity has been mapped to target-dependent

processes that cause residual switch cost (Karayanidis et al., 2003; Nicholson et al., 2006a; 2005).

Nicholson et al.'s (2006b) ERP evidence for task-set inhibition came from a cued trials task-switching paradigm in which participants randomly alternated between three tasks. As is usual in task-switching paradigms, different cues signaled task repetition (*repeat* cue) or a switch to a specified task (*switch-to* cue). A third, partially informative cue signaled only that the task would change (*switch-away* cue), with the actual task to be performed being specified only upon target onset (see Figure 4.1). An early cue-locked differential positivity (D-Pos1) was found for both *switch-away* and *switch-to* trials, relative to *repeat* trials (see Figure 3b in Nicholson et al.). *Switch-to* trials also showed a second differential positivity that occurred later within the cue-target interval (D-Pos2), whereas for *switch-away* trials, this component occurred after target onset. After target onset, both types of switch trials showed a differential negativity relative to *repeat* trials, but this was delayed until after D-Pos2 on *switch-away* trials.

Nicholson et al. (2006b) suggested that D-Pos2 reflects activation of the relevant task-set, which can occur prior to target onset for *switch-to* trials, but only after target onset for *switch-away* trials. Since both *switch-to* and *switch-away* trials indicate that the previously active task-set will not be repeated, the D-Pos1 component, which was common to both of these trial types, was interpreted as reflecting inhibition of the now irrelevant task-set. However, D-Pos1 might also be attributed to differences in cue processing between *repeat* and both types of switch trials. In particular, both *switch-to* and *switch-away* trials involved a physical cue change between trials, which may have resulted in greater cue processing being required than for the cue on a *repeat* trial, where cue processing may have been primed by cue repetition.

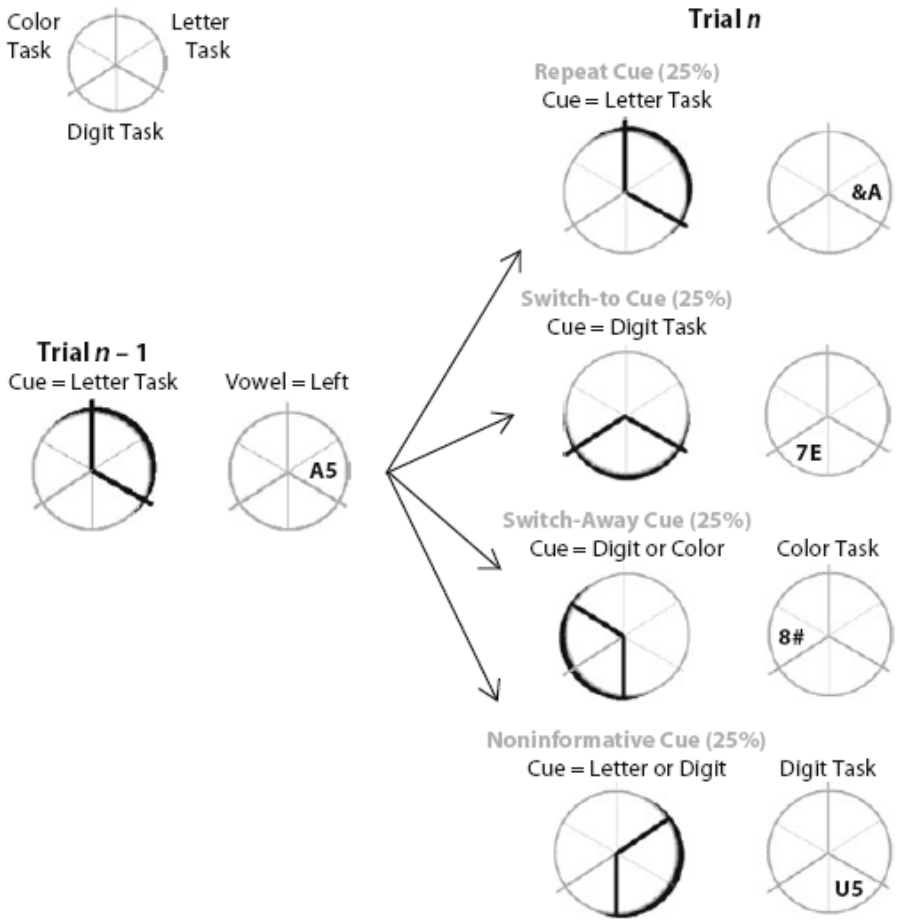
Nicholson et al. (2006b) found that switch cost was larger on *switch-away,* as compared to *switch-to,* trials,\ and that increasing the cue-target interval reduced RT switch cost for *switch-to,* but not *switch-away,* trials. The length of the cue-target interval may have had no effect on *switch-away* trials because task-set inhibition was complete before the target appeared, even at the short cue-stimulus interval (200 ms). However, it is also possible that there was no cue-target interval effect on *switch-away* trials simply because participants did not make any use of the *switch-away* cue. The equivalence of early ERP waveforms (D-Pos1) for *switch-to* and *switch-away* could then be attributed to participants undertaking the same cue-encoding processes in both conditions. If a *switch-away* cue does allow partial preparation, it should cause a reduction in switch cost, even though this reduction would be less than for *switch-to* cues. However, the behavioral benefits of the *switch-away* cue could not be established by Nicholson et al. since their design did not have a baseline condition.

4.1 Experiment 1

The present study addresses these issues, using an identical design to that of Nicholson et al. (2006b), with the exception that an extra, *non-informative* cue type was included. This cue signaled that the following trial might require a repeat *or* a switch in task (see Figure 4.1). Like *switch-to* and *switch-away* cues, *non-informative* cues involved a physical shift in cue position. However, unlike *switch-to* and *switch-away* cues, *non-informative* cues did not indicate that the previously active task-set would be irrelevant on the next trial. In fact, they indicated that there was a 50% chance that the task would be repeated. Although inhibition of the previously active task-set is an efficient strategy for

switch-to and *switch-away* cues, this is not the case for *non-informative* cues. Hence, if D-Pos1 represents processes associated with inhibition of the previously active but now irrelevant task-set, it should occur for *switch-to* and *switch-away* cues, but not for *non-informative* cues. Alternatively, if D-Pos1 represents processing of the change in cue position, it should occur for *switch-to*, *switch-away* and *non-informative* cues.

The *non-informative* cue condition also acted as a baseline that allowed us to investigate whether *switch-away* cues provide some behavioral benefit (i.e., reduce switch cost) by allowing partial preparation for a task switch. Note that *non-informative* and *switch-away* cues were equally informative about which task would occur next. That is, both of these cue types ruled out exactly one of the three possible tasks. Hence, a comparison of performance for these cue types controlled for task uncertainty, and specifically, tested for benefits related to knowing that the previous task would not be repeated.



Example of S–R Mapping	Left-Hand Response	Right-Hand Response
Letter Task	Vowel (A, E, I, U)	Consonant (G, K, M, R)
Digit Task	Even (2, 4, 6, 8)	Odd (3, 5, 7, 9)
Color Task	Cold (dark green, light green, dark blue, turquoise)	Hot (red, pink, orange, yellow)

Figure 4.1: Top left: Example of task-position mapping. Middle: The four types of cues used to indicate the requirements of the next trial (repeat, switch-to switch-away and non-informative). Each cue type was presented on 25% of trials. Bottom: Stimulus-response (S-R) mappings with the four possible stimuli associated with each response. These were counterbalanced across participants.

4.1.1 Method

4.1.1.1 Participants

Twenty-three undergraduate students (18 female, 5 male) with a mean age of 21.3 years (*SD* = 3.51) were recruited from an introductory psychology course and participated for course credit.

4.1.1.2 Stimuli and Tasks

The paradigm was identical to that used by Nicholson et al. (2006b) with the exception of the additional non-informative cue. Briefly, participants viewed a circle (5° of visual angle) divided into six wedges, with pairs of adjacent wedges grouped by thicker lines demarcating three task sections: digit, letter, and color (see Figure 4.1, top). Each target was a pair of characters consisting of combinations of a letter, a digit or a non-alphanumeric symbol and was presented either in grey or in color. Each target (e.g., A4) consisted of three dimensions (see Figure 4.1, bottom) – one relevant to the currently cued task (e.g., a letter mapped to left hand response), one selected randomly from one of the two alternative tasks and incongruently mapped with the relevant task (e.g., a digit mapped to right hand response) and one that was neutral (e.g., gray, not mapped to any response). The same target could not appear on two successive trials. Response-target interval was 1400 ms and included a 1000 ms cue-target interval.

Four cue types (i.e., *repeat, switch-to, switch-away* and *non-informative*) were defined by cue location and were presented with equal probability in a pseudo-random sequence so that the same cue was not repeated on more than three consecutive trials. Non-informative cues resulted equiprobably in a switch or a repeat trial which was defined by

the location of the target, thereby resulting in five trial types (i.e., *repeat, switch-to, switch-away, non-informative switch and non-informative repeat*). The target always appeared in one of the two segments highlighted by the cue.

4.1.1.3 Procedure

All the participants attended two sessions scheduled 7-14 days apart. The first session included task training and practice (732 trials on each task alone and switching between tasks). The second session included further practice (another 732 trials) followed by the behavioral and EEG testing session. The testing session consisted of nine runs of 96 trials each. The participants were encouraged to respond as quickly and accurately as possible. Auditory feedback was provided after an incorrect response, and behavioral feedback (mean RT and percentage correct) was displayed at the end of each run. EEG was continuously sampled at 2048 Hz/channel, reference free, from 64 scalp electrodes, the mastoids and nose using a Biosemi ActiView II system. Vertical electro-oculogram (EOG) was recorded from the supraorbital and infraorbital ridges of the left eye, and horizontal EOG from the outer canthi of each eye.

4.1.1.4 Data Analysis

The first five trials of every run, trials associated with an incorrect response, trials immediately following an incorrect response and trials on which RTs were shorter than 200ms (0.005%) or longer than 3 standard deviations above the participant's mean RT (1.7%) were excluded. A 3 (task: letter, digit, color) x 5 (trial: *repeat, switch-to, switch-away, non-informative repeat and non-informative switch*) repeated measures ANOVA was performed. Critical values were adjusted using the Greenhouse–Geisser correction to avoid

violating the assumption of sphericity (Vasey & Thayer, 1987), and simple comparisons for trial were corrected with family-wise error rate adjusted at α=.01(unless otherwise reported). For behavioral data, we compared *repeat* trials with each of *switch-to, switch-away* and *non-informative repeat* trials, and *switch-away* trials with each of *switch-to* and *non-informative switch* trials. Task did not interact with trial type for either RT (F=1.64) or error rate (F=2.43), so all behavioral and ERP analyses were averaged over task.

EEG data were analyzed using Brain Electrical Source Analysis (BESA v5.1). Scalp electrodes were re-referenced offline to linked mastoids, and EOG artifact correction was applied using a regression algorithm (Ille, Berg and Scherg, 2002). Cue and target-locked EEG epochs were extracted from 300 ms before to 1200 ms after each cue and target (200-ms pre-event baseline), and epochs with artifact exceeding a 100µV threshold were rejected. Averaged waveforms were created for each cue and target type, averaged over response hand and task. Both cue-locked and target-locked individual ERP waveforms included a mean of 130-140 trials, except for target-locked *non-informative switch* and *repeat* trials, which included half that number. Target-locked data from two participants were excluded because there were fewer than 40 epochs contributing to one of the non-informative trial types. Therefore, cue-locked data are reported from 23 participants, and target-locked data are from 21 participants.

Difference waveforms were calculated by subtracting the *repeat* waveform from each of the remaining waveforms and were visually inspected to determine time windows and scalp topography of maximal differentiation between cue types. For cue-locked waveforms, two mean amplitude windows were defined on the basis of the positivity for *switch-to* relative to *repeat* waveforms (250-400ms, 450-700ms) and were analyzed at the parieto-occipital midline site (POz) using a one-way ANOVA with 4 levels of cue type. We

compared *repeat* cues with each of the other three cues and *switch-away* with *switch-to* and *non-informative* cues. For target-locked waveforms, two mean amplitude windows were used to define an early positivity that emerged around the peak of the P2 and a second, later positivity around the latency of the N2 (180-250 and 300-370 ms, respectively) and were analyzed at F4 where the effects of trial were maximal. A third window (420-550ms) that targeted the negativity for *switch-to* relative to *repeat* trials was analyzed at Cz. Four contrasts were defined comparing *repeat* trials with each of the other three trial types. Where significant trial type differences emerged at these scalp sites, the scalp distribution of these differences was analyzed using paired-samples t-tests at each electrode and are displayed as head maps in Figures 4.2 and 4.3.

4.1.2 Results

Because Nicholson et al's (2006b) argument that task-set reconfiguration involves task-set inhibition as well as task-set activation was based on ERP data, we will discuss first the ERP findings in order to establish replication of the original finding and present the outcomes for the non-informative cue. Figures 4.2 and 4.3 show average cue-locked and target-locked waveforms, respectively. Figure 4.4 shows average behavioral and ERP estimates and the results of associated inferential tests.

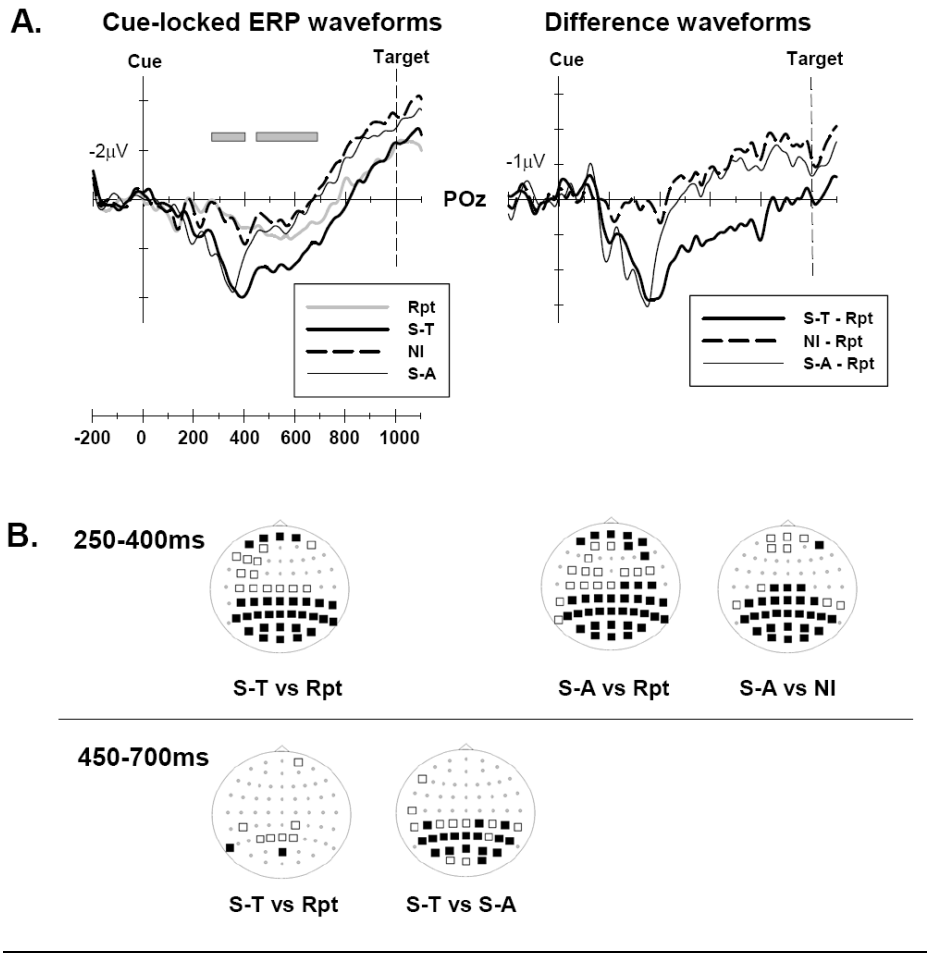


Figure 4.2: a) Cue-locked ERP and difference waveforms for each trial type at POz. Gray bars indicate the mean amplitude windows used in the analyses. b) Head maps showing sites of significant deviation between different trial types over 250-400ms and 450-700ms. Open squares: $\alpha = .05$; filled squares: $\alpha = .01$. Over 250-400 ms, the *switch-to* (S-T) vs. *repeat* (Rpt) contrast was most significant over parieto-occipital sites ($p=2.6^{-6}$ - 0.005). The *switch-away* (S-A) vs. Rpt contrast was most significant over frontal and parieto-occipital electrodes ($p=2.5^{-8}$ - 0.01). The *non-informative* (NI) vs. S-A contrast was most significant over parieto-occipital electrodes ($p=5.1^{-5}$ - 0.01). Over 450-700 ms, the *switch-to* vs. *repeat* contrast was most significant at POz ($p=0.009$). The S-T vs. S-A contrast was most significant at parieto-occipital sites ($p=.0009$ - 0.01).

4.1.2.1 Cue-locked waveforms

Cue-locked waveforms showed a sustained positivity over 100-800ms for all trial types (Figure 4.2a, left). The main effect of cue was significant at POz for both early and late positivities $F(3,66)=18.10$, $p<.001$; $F(3,66)=8.45$, $p<.001$, respectively. Difference waveforms were derived between each cue type and the *repeat* waveform (Figure 4.2a, right). A large broad positivity was evident over 150-800ms in the *switch-to* difference waveform. This was also evident in the *switch-away* difference waveform, but dissipated by 400ms. *Non-informative* cues did not show any positivity relative to *repeat* cues.

The early positivity was significantly larger for both *switch-to* and *switch-away* cues as compared to *repeat* cues, $F(1,22)=39.30$, $p<.001$; $F(1,22)=31.68$, $p<.001$, respectively (Figure 4.4b). This differential positivity for *switch-to* and *switch-away* relative to *repeat* cues emerged at central sites but was stronger at parietal and occipital sites and was also reflected at frontopolar locations (Figure 4.2b). Importantly, this early positivity was also larger for *switch-away* cues, as compared with *non-informative* cues, $F(1,22)=17.89$, $p<.001$, across most parietal-occipital sites (Figure 4.2b) and did not differ in amplitude between *repeat* and *non-informative* cues at any site. The later positivity was larger for *switch-to* than for both *repeat* cues and *switch-away* cues at POz, $F(1,22)=9.31$, $p=.006$, $F(1,22)=12.65$, $p=.002$, respectively (see Figure 4.4b), an effect that was distributed over the parietal-occipital scalp (Figure 4.2b). There was no difference between the other cue types in this latency range.

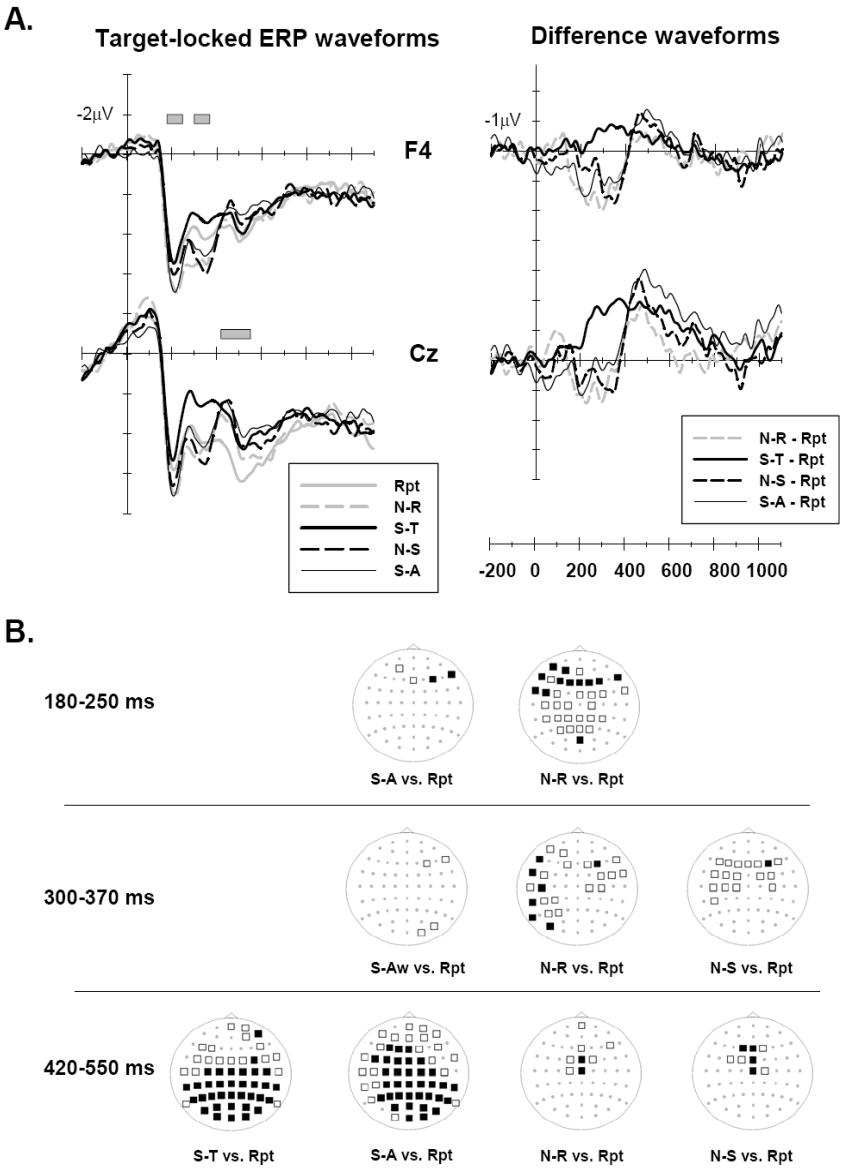


Figure 4.3: a) Target-locked ERP and difference waveforms at F4 and Cz. Gray bars indicate the respective mean amplitude windows used in analysis. b) Head maps showing sites of significant positive deviation relative to repeat (Rpt) trials over 180-250ms, 300-370ms and 420-550ms. Open squares: α=0.05; filled squares: α =0.01. Over 180-250ms, the *switch-away* (S-A) vs. Rpt contrast was most significant at F4 (*p*=0.009). The *non-informative repeat* (N-R) vs. Rpt contrast was most significant over frontal sites (*p*=0.002 - 0.01). Over 300-370ms, the S-A vs. Rpt contrast was most significant at F8 (*p*=0.02). The N-R vs. Rpt contrast was most significant over left centro-parietal sites (*p*=0.0009 - 0.01). The *non-informative switch* (N-S) vs. Rpt contrast was most significant at F4 (*p*=0.007). Over 420-550ms, the *switch-to* (S-T) vs. Rpt contrast and the S-A vs. Rpt contrast were most significant over centro-parieto-occipital electrodes (*p*=0.0001 -0.009; *p*=0.0003 - 0.009, respectively). The N-R vs. Rpt contrast was most significant at Cz (*p*=0.005) and the N-S vs. Rpt contrast was most significant over fronto-central sites (*p*=0.004 - 0.009).

4.1.2.2 Target-locked waveforms

Target-locked waveforms showed an early N1 and large fronto-central P2 followed by an N2 and LPC complex (Figure 4.3a, left). *Switch-to* minus *repeat* difference waveforms showed a broad negative shift spreading over 200-800ms after target onset that was largest at Cz (Figure 4.3a, right). All other difference waveforms show a right frontally maximal positivity over 200-400ms, followed by a broad centrally maximal negativity.

Target-locked difference waveforms for *switch-away*, *non-informative repeat* and *non-informative switch* targets showed two positive peaks: one within the latency range of the frontal P2 (180-250ms) and the other around 100ms later (300-370ms; Figure 4.3a, right). Both windows showed a significant main effect of trial type at F4, $F(4,80)=3.30$, $p=.043$, $\varepsilon=.538$; $F(4,80)=7.37$, $p<.001$. The early positivity (180-250 ms; Figure 4.4c) was larger for both *switch-away* and *non-informative repeat* targets as compared to *repeat* targets, $F(1,20)=8.45$, $p=.009$; $F(1,20)=11.85$, $p=.003$, respectively. This early target-locked differential positivity was more widespread over frontocentral sites for *non-informative repeat* cues but was fairly localized over the right frontal scalp for *switch-away* cues (Figure 4.3b). The later positivity (300-370ms) was larger for both *non-informative repeat* and *non-informative switch* targets as compared to *repeat* targets ($F(1,20)=10.77$, $p=.004$, $F(1,20)=9.03$, $p=.007$, respectively; Figure 4.4c), over both right frontocentral and left centroparietal sites (Figure 4.3b). This positivity was again evident for *switch-away* cues, but was only marginally significant over the right frontal scalp ($F(1,20)=4.77$, $p=.041$).

Mean amplitude over 420-550ms in the target-locked waveforms produced a significant main effect of trial at Cz ($F(4,80)=6.38$, $p=.002$; Figure 4.3a) reflecting a significant negative deflection for all trial types, relative to *repeat* targets (Figure 4.4c;

switch-to, $F(1,20)=16.65$, $p=.001$; *switch-away*, $F(1,20)=19.45$, $p<.001$; *non-informative switch*, $F(1,20)=8.37$, $p=.009$; *non-informative repeat*, $F(1,20)=10.03$, $p=.005$). This post-target switch negativity showed a broad scalp distribution for *switch-to* and *switch-away* targets, especially over centroparietal sites (Figure 4.3b), whereas the effect was restricted over the frontocentral midline for both *non-informative switch* and *non-informative repeat* targets.

4.1.2.3 Accuracy and Mean RT

Mean RT showed a significant effect of trial type, $F(4,88)=38.62$, $p<.001$, $\varepsilon=.320$ (Figure 4.4a). Responses for *repeat* trials were significantly faster than for *non-informative repeat*, $F(1,22)=61.49$, $p<.001$, *switch-to*, $F(1,22)=32.29$, $p<.001$, and *switch-away* trials, $F(1,22)=51.59$, $p<.001$. RT for *switch-away* trials was longer than for *switch-to* trials, $F(1,22)=37.36$, $p<.001$, but not significantlyshorter than for *non-informative switch* trials.

Although error rate was quite low (2.8-5.5%; Figure 4.4a), the main effect of trial type was significant, $F(4,88)=10.76$, $p<.001$, $\varepsilon=.673$. Repeat trials produced fewer errors than did all other trial types (*switch-to*, $F(1,22)=16.87$, $p<.001$; *switch away*, $F(1,22)=9.45$, $p=.006$; *non-informative repeat*, $F(1,22)=21.27$, $p<.001$). Error rates were also higher for *non-informative switch* than for *switch-away* trials, $F(1,22)=9.53$, $p=.005$.

We examined whether the amplitude of the early cue-locked positivity was associated with improved behavioral performance, using one-tailed Pearson correlations for *switch-to* and *switch-away* cues which showed clear and measurable D-Pos1. Larger positivity was associated with faster RT for *switch-to* trials ($r=-.691$, $p<.001$, n=23) and less strongly for *switch away* trials ($r=-.367$, $p<.05$, n=23) but showed no relationship with error rate.

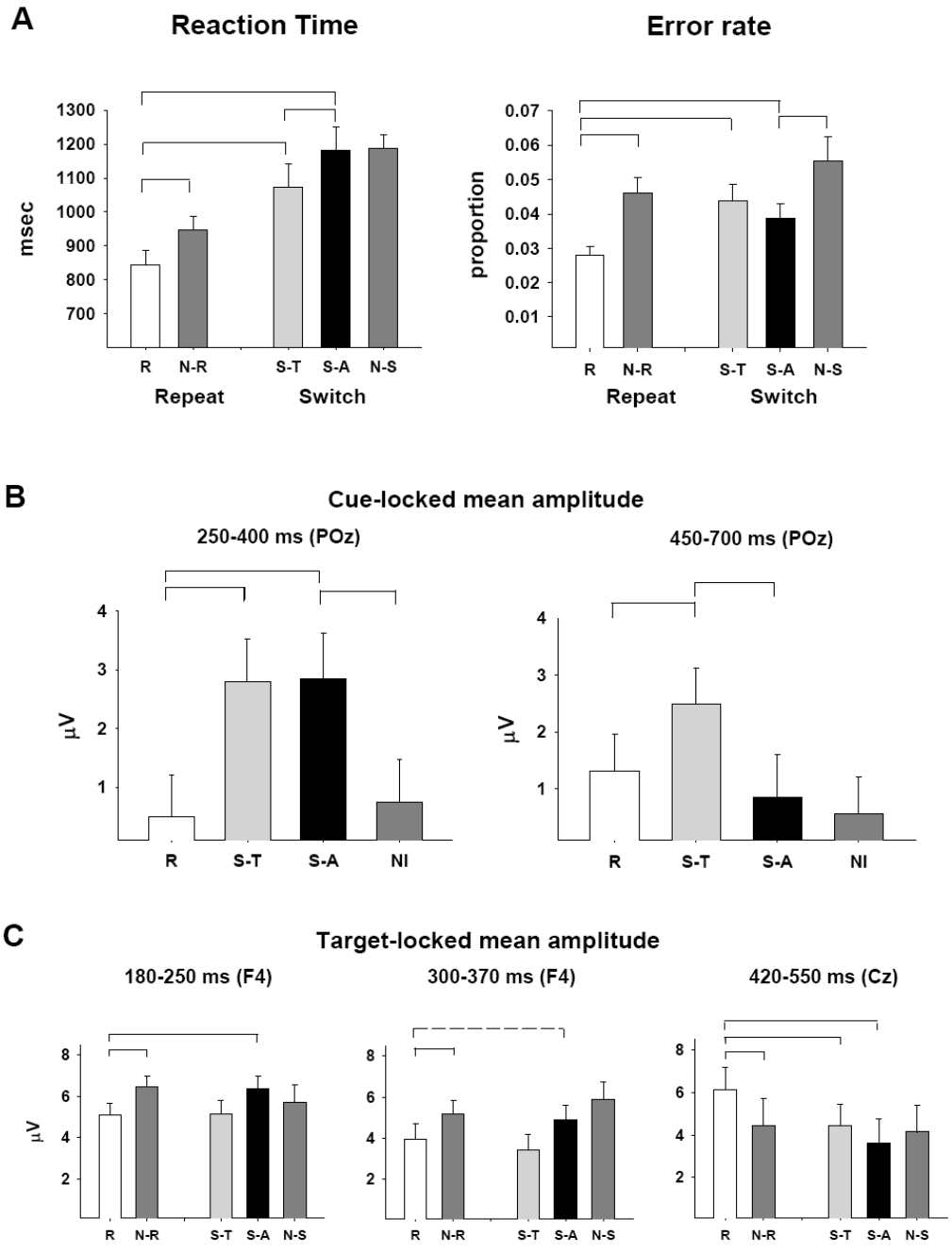


Figure 4.4: a) Mean RT and error proportion for each trial type. b) Cue-locked ERPs: mean amplitude over 250-400ms and 450-700ms post-cue at POz. c) Target-locked ERPs: mean amplitude over 180-250ms and 300-370ms post-target at F4 (left, middle) and over 420-550ms post-target at Cz (right). R = Repeat; N-R = Non-informative Repeat; S-T = Switch To; S-A = Switch Away; N-S = Non-informative Switch. Significant differences between conditions are shown by solid lines at $p<.01$ and broken lines at $p<.05$.

4.1.3 Discussion

The ERP data replicated Nicholson et al.'s (2006b) finding of a posterior cue-locked D-Pos1 for both *switch-to* and *switch-away* cues, followed by a D-Pos2 that was cue-locked for *switch-to* trials and target-locked for *switch-away* trials. Both *switch-to* and *switch-away* trials elicited a large post-target switch negativity, as compared to *repeat* trials, and the onset of this negativity was delayed until after resolution of the earlier positivity for *switch-away* trials, again suggesting that it reflects target-triggered processes such as completion of task-set reconfiguration or S-R priming.

Notably, within the cue-target interval, *non-informative* cues showed no evidence of any differential switch positivity relative to repeat cues. However, after the onset of the target that defined the currently active task-set, both *non-informative repeat* and *non-informative switch* trials showed a significant differential positivity relative to *repeat* trials. The finding that, unlike *switch-to* and *switch-away* cues, *non-informative* cues did not elicit the D-Pos1 within the cue-target interval indicates that this component does not reflect processing of a change in the physical position of the cue. It could be argued that although non-informative cues involved some spatial displacement, the degree of displacement differed between cue types (i.e., 60° for *non-informative*, 120° for *switch-to* and 180° for *switch-away* cues). However, if the cue-locked positivity is affected by degree of cue displacement, there should be correspondence between the angular displacement of the cue and D-Pos1 amplitude (i.e., *non-informative* < *switch-to* < *switch-away*). This was not the case in the present data.

Therefore, the D-Pos1 component appears to reflect a process that is activated by cues that validly signal that the previously active task-set will not be relevant to the next target and, consequently, that there will definitely be a switch in task on the next target (i.e.,

switch-to and *switch-away* cues), even when the cues do not specify which task will be relevant. Importantly, the process reflected by the D-Pos1 is not activated by cues that signal that the previously active task-set may (i.e., *non-informative* cues) or will (*repeat*) be relevant to the next target. This finding supports the contention that partially informative cues trigger some anticipatory reconfiguration process.

Replicating Nicholson et al.'s (2006b) finding, *switch-away* trials resulted in longer RT than did *switch-to* trials. This indicates that the additional information regarding the identity of the upcoming task afforded by *switch-to* cues led to greater anticipatory reconfiguration than on *switch-away* cues. However, mean RT did not differ between *switch-away* and *non-informative switch* trials. This result appears to contradict the idea that participants use *switch-away* cues to partially prepare for a switch trial. If preparation is a time-consuming process, then it should take longer to complete on *non-informative switch* trials than on the partially informative *switch-away* trials, and hence mean RT should be less in the latter condition.

This argument fails to take account of the fact that the *non-informative switch* trials had a reliably higher error rate than did *switch-away* trials. The error difference raises the possibility that participants used the information provided by *switch-away* cues to engage in a speed-accuracy tradeoff. That is, because *switch-away* cues provide certainty that the upcoming trial will require a switch in task, and hence will be more difficult and potentially error prone, participants may have required a higher standard of evidence before making a decision in order to reduce the possibility of making an error. If that were the case, the same higher standard of evidence would be expected to be applied on *switch-to* trials. Mean RT in the *switch-to* condition could still be less than in the *non-informative switch* condition if the extra time required to make a decision using a higher standard of evidence

on *switch-to* trials was less than the time saved by being able to complete reconfiguration in the cue-target interval. In the *switch-away* condition, in contrast, the lesser amount of time saved by partial reconfiguration could be canceled out by the extra time taken to make a decision, so that overall mean RT in the *switch-away* and *non-informative switch* conditions would be equal.

Fortunately, as we describe next, it is possible to directly test our speculation about speed-accuracy tradeoff differences between cue conditions. Speed-accuracy tradeoff is a pervasive phenomenon in choice tasks ranging from simple stimulus categorization to recognition memory (for a summary, see Luce, 1986, pp. 237–245). It has been intensively studied and it is now almost universally agreed that it can be explained in detail by evidence accumulation models. Evidence accumulation models of the decision process provide a detailed account of the mechanism by which speed-accuracy tradeoffs is accomplished. They also predict that a speed-accuracy tradeoff will have a quite specific effect on aspects of the RT distribution, such as RT variance, which are neglected by an analysis of mean RT alone. Hence, by fitting an evidence accumulation model to our data we are able to provide a rigorous test of whether the lack of a mean RT difference between *non-informative* and *switch-away* trials is a by-product of speed-accuracy tradeoff.

4.2 Evidence Accumulation Model Analysis

Evidence accumulation models fractionate mean RT within two-choice response tasks into two independent components: decision time and nondecision time. Decision time includes processes directly involved in choosing a response to the current stimulus - that is, stimulus categorization and response selection. Nondecision time includes the time to

complete processes that do not directly contribute to the decision, typically including processes such as stimulus encoding and response activation/execution. Evidence accumulation models assume that a decision is reached by accumulating (i.e., repeatedly sampling and combining) stimulus information about a choice until the evidence favoring one choice exceeds the evidence favoring other choices by a criterion amount. Decision time, therefore, is determined by the conservativeness of the evidence criterion and the rate of evidence accumulation. A speed-accuracy tradeoff occurs when participants differ between conditions in conservativeness (i.e., maintain a different evidence criterion).

Wagenmakers, van der Maas and Grasman (2007) advocated the use of parameter estimates from a particular type of evidence accumulation model, a diffusion model, to account for speed-accuracy tradeoff. Their *EZ* diffusion method estimates three parameters. The evidence accumulation or *drift* rate (*v*) and the evidence criterion (*a*) parameters together determine decision time (*dt*). The remaining portion of the RT that is due to nondecision processes is determined by the *Ter* parameter. We applied a more recent development of this approach, the EZ2 method (Grasman, Wagenmakers & van der Maas, in press), which also estimates a decision bias parameter, although this parameter is not of substantive interest in the present application.

Within task-switching paradigms, when reconfiguration is completed before target onset (i.e., anticipatory reconfiguration with predictable switch cues and long cue-target interval), there is no effect of reconfiguration on RT and any residual RT switch cost is assumed to reflect post-target processes related to S-R priming. However, if reconfiguration is not completed before target onset (i.e., very short cue-target interval and/or unpredictable switch trials), RT would increase by the amount of time required to complete reconfiguration, as the initiation of decision processing will be delayed. Such delays would

increase estimates of the nondecision time (*Ter*) parameter. In our paradigm, *switch-to* trials allow complete reconfiguration before target onset and so there should be little or no contribution by reconfiguration to nondecision time. In contrast, on *non-informative switch* trials, reconfiguration should make a large contribution to nondecision time. If *switch-away* trials involve partial reconfiguration, nondecision time should be less in *switch-away* than in *non-informative switch* trials.

In summary, we predict that nondecision time should be shortest for *switch-to* trials, intermediate for *switch-away* trials, and longest for unprepared *non-informative switch* trials, since the amount of reconfiguration that can be completed in the cue-target interval decreases across these conditions. Predictions related to nondecision time for the *repeat* cue trials are less constrained, because the reconfiguration process itself may be primed in this condition. Generally, we would expect *repeat* trials to have a shorter nondecision time than all other trial types, because they require no reconfiguration or, at least, minimal reconfiguration. *Switch-to* trials may be an exception, since the relatively long cue-target interval may have been sufficient to complete preparation to the same level as that on *repeat* trials.

Decision time is determined by criterion and drift rate; a longer decision time may result from a high response criterion, a lower drift rate, or a combination of both. Hence, if, as we suggested, participants use a more cautious (larger) evidence criterion in the *switch-away* than the *non-informative switch* condition, a longer decision time would be predicted in the former condition. We argue that it is the fact that these two conditions have opposite effects on nondecision and decision time that can account for our finding of no difference between them in mean RT. As both *switch-to* and *switch-away* cues certainly indicate the next trial will be a switch, no difference in criterion or decision time is predicted between

these conditions. However, we predict that *switch-to* trials will have a shorter mean RT because of their shorter nondecision time.

4.2.1 Method

Wagenmakers et al.'s (2007) EZ diffusion method estimates three separate parameters for each response to a task, the evidence accumulation or drift rate (*v*), the evidence criterion (*a*), which together determine mean decision time (*dt*), and a parameter for the remaining portion of mean RT, nondecision time (*Ter*). These three parameters are estimated analytically on the basis of three aspects of the data for each response: accuracy and the mean and variance of RT for correct decisions. The EZ method assumes that decisions are unbiased, whereas the more recently developed EZ2 method (Grasman et al., in press) does not need to make this assumption, since parameter estimates are obtained for the entire task, rather than for each response separately. These parameters are: two drift rate and two nondecision time parameters (one for each response), the criterion for one of the responses (*a*; the criterion for the other response is assumed to be zero without loss of generality) and the starting point for evidence accumulation (*z*). These size parameters are estimated on the basis of six data points, accuracy and the mean and variance of correct RT for each response.

Hence, as is the case for EZ, the number of parameters estimated equals the number of data points, but for EZ2, the equation relating the two cannot be solved analytically. However, the EZ2 equation implicitly defines a unique solution that can be easily and reliably found by numerical methods using programs provided by Grasman et al. (2009). Our use of EZ2 was not so much motivated by its affording an estimate of response bias

(which we do not report, since there was no evidence of bias or differences in bias across conditions) as by the fact that it requires fewer assumptions and is in our experience more robust and efficient than EZ estimation, and because it corresponds more directly to the diffusion model's assumption that one evidence accumulation process is responsible for both choices.

In our experiment, mean RT showed a reliable difference between tasks and a reliable interaction between task and response hand. Since EZ2 analysis depends on variance estimates, and these can be distorted by pooling over conditions that differ in their mean, we applied the diffusion analysis to data broken down by task and response as well as by trial type. This resulted in small sample sizes for correct responses (less than 20) for some conditions in some participants.

In order to make mean and variance estimates robust, we based them on fits of the Ex-Gaussian distribution to correct RT deciles (Heathcote, Brown & Mewhort, 2002; see Wagenmakers, van der Maas, Dolan & Grasman, 2008, for a related approach to EZ estimation). We also based EZ2 estimates on the robust accuracy measure recommended by Snodgrass and Corwin (1988). In a few cases (<1%), estimates of *Ter* were too small to be plausible (<100ms). In such cases, we obtained parameter estimates by solving the EZ2 equations under the constraint that *Ter*>100ms. Note that without constraint EZ2 parameters produce a perfectly accurate account of accuracy and correct RT mean and variance. Although this is not necessarily the case when a constraint is imposed, the effect of the constraint used on our data was negligible, so that the account of these measures remained essentially perfect.

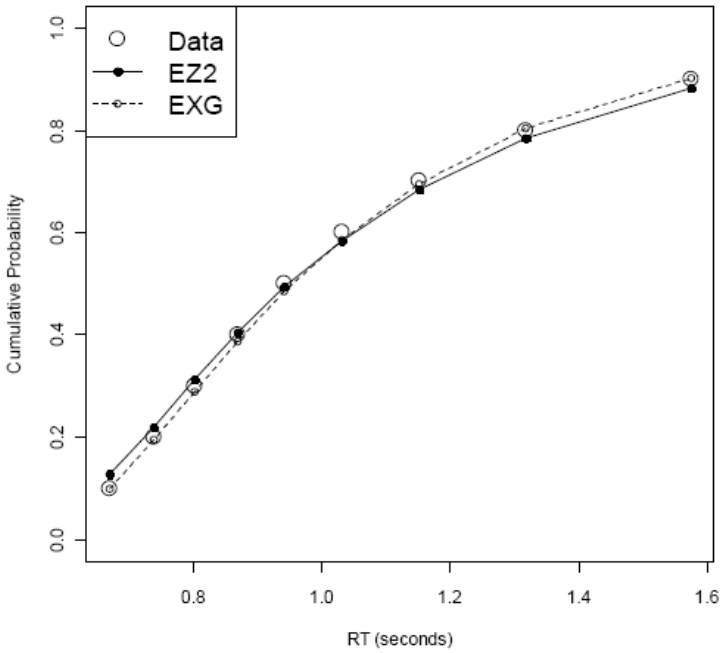


Figure 4.5: Cumulative distribution functions created by averaging data deciles over participants and conditions, and similarly averaged deciles produced by Ex-Gaussian and EZ2 fits.

Since the Ex-Gaussian usually provides an excellent descriptive account of RT distribution, our methods also provided a gold standard against which to compare the diffusion model's account of the data, thus addressing concerns raised by Ratcliff (2008) about EZ estimation. A qualitative check provided by inspecting Figure 4.5 shows that for our data, EZ2 estimation produced an accurate account of the full distribution of correct RT, which was only slightly inferior to that of the Ex-Gaussian. A small disadvantage is to be expected given the diffusion model accounts for accuracy as well as RT using the same number of parameters as the Ex-Gaussian, which only accounts for RT.

4.2.2 Results

EZ2 parameter estimates were derived for each of the 23 participants from Experiment 1. Mean RT, RT variance and error rate were used to estimate the nondecision time, evidence criterion and drift rate parameters at each level of task and trial type. These parameter estimates were analyzed using 3 (task: letter, digit, color) x 5 (trial type: *repeat, switch-to, switch-away, non-informative repeat* and *non-informative switch*) repeated measures ANOVA, followed by five simple comparisons for trial with family-wise error rate adjusted at α=.01. As well as the drift rate, criterion and nondecision time parameters, we analyzed decision time. We present result for all four measures for clarity, but it is important to keep in mind that these measures are related, since decision time is a function of the drift rate and criterion, and decision time and nondecision time sum to mean RT. Task did not interact with trial type in any of these analyses so we report results averaged over task (Figure 4.6). As in earlier analyses, five planned contrasts compared *repeat* trials with *switch-to, switch-away* and *non-informative repeat* trials, and *switch-away* trials with *switch-to* and *non-informative switch* trials. We also will report correlations between EZ2 parameters and the early cue-locked switch positivity.

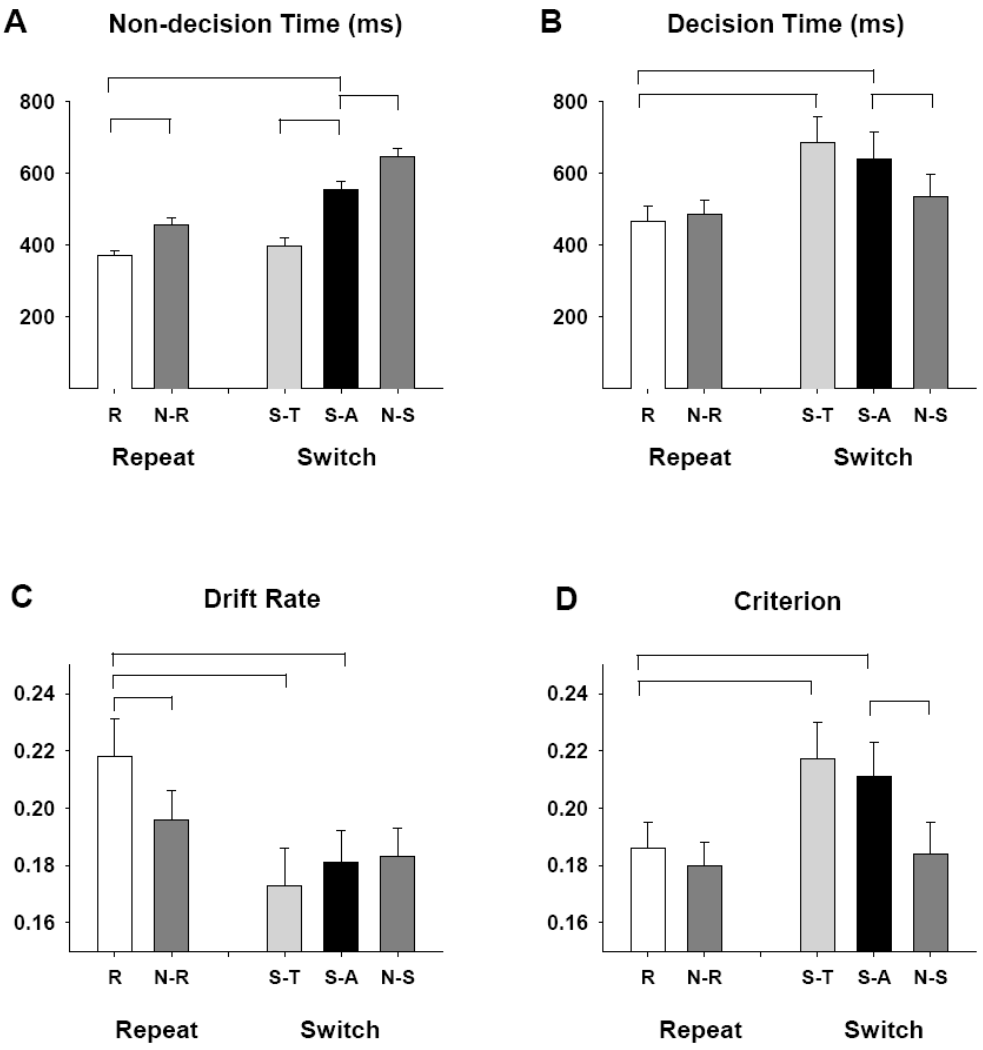


Figure 4.6: Diffusion model parameters. R = Repeat; N-R = Non-informative Repeat; S-T = Switch To; S-A = Switch Away; N-S = Non-informative Switch. Significant differences between conditions are shown by solid lines at $p<.01$.

Figure 4.6a shows that nondecision time varied from 370ms for *repeat* trials to 650ms for *non-informative switch* trials (trial $F(4,88)=71.06$, $p<.001$, $\varepsilon=.673$). Nondecision time was significantly shorter for *repeat* trials than for *switch-away* and *non-informative repeat* trials, $F(1,22)=71.41$, $p<.001$, $F(1,22)=59.69$, $p<.001$, respectively (although not part of the planned set, note that the *repeat* and *non-informative switch* trials comparison was also highly significant, $F(1,22)=213.78$, $p<.001$). Nondecision time did not differ

between *repeat* trials and *switch-to* trials (F<1.5), but *switch-away* trials had a significantly shorter nondecision time, as compared with *non-informative switch* trials, $F(1,22)=28.49$, $p<.001$, and a longer nondecision time as compared with *switch-to* trials, $F(1,22)=112.8$, $p<.001$. Larger cue-locked positivity was associated with shorter nondecision time for *switch-to* cues ($r=-.397$, $p<.05$) and marginally for *switch-away* cues ($r=-.349$, $p=.051$).

As shown in Figure 4.6d, response criteria were low on *repeat* and both types of *non-informative* cue trials. However, criteria were significantly higher for both *switch-to* and *switch-away* trials (trial, $F(4,88)=14.74$, $p<.001$, $\varepsilon=.465$; *repeat* vs. *switch-to*, $F(1,22)=14.07$, $p=.001$; *repeat* vs. *switch-away*, $F(1,22)=9.73$, $p=.005$). Decision time was also significantly affected by trial type, $F(4,88)=11.71$, $p=.001$, $\varepsilon=.341$ (see Figure 4.6b). Both *switch-to* and *switch-away* trials had significantly longer decision time than did *repeat* trials, $F(1,22)=18.32$, $p<.001$, $F(1,22)=9.14$, $p=.006$, respectively. Decision time was also lower for *non-informative switch* than for *switch-away* trials, $F(1,22)=16.76$, $p<.001$. This can be accounted for by differences in response criterion, $F(1,22)=44.06$, $p<.001$, but not drift rate, F<1 (Figure 4.6c). Drift rate for *repeat* trials was significantly higher than for all other trial types (*switch-to*: $F(1,22)=62.05$, $p<.001$; *switch-away*: $F(1,22)=27.67$, $p<.001$; *non-informative repeat*: $F(1,22)=13.36$, $p=.001$). Larger cue-locked positivity on *switch-to* trials was associated with a shorter decision time ($r=-.414$, $p<.05$), lower criterion ($r=-.425$, $p<.05$) and a faster drift rate ($r=.366$, $p<.05$). *Switch-away* cues showed no significant correlations between cue-locked positivity and these diffusion measures.

4.2.3 Discussion

The nondecision time findings are consistent with predictions based on our assumption that the cues preceding *non-informative switch, switch-away and switch-to* trials results in differential degree of activation of an anticipatory reconfiguration process. Partially informative *switch-away* cues, which provided certainty about an upcoming task switch without indicating which task will be active, offered a reliable behavioral advantage over *non-informative* cues that were equally likely to be followed by a switch or repeat trial. In particular, this advantage was evident in nondecision time[2], a latent measure that, in the context of cued task-switching, is affected by the degree of anticipatory reconfiguration afforded by the cue. In the present paradigm, the only common information provided by *switch-to* and *switch-away* cues and not afforded by *non-informative* cues is that the task that was relevant on the previous trial *will not* be repeated. The finding that this information resulted in a reduction in nondecision time suggests that both *switch-away* and *switch-to* cues elicit some degree of anticipatory reconfiguration and that this partial preparation results in a behavioral advantage over *non-informative* cues that are equally likely to result in a switch or repeat trial.

[2] For readers concerned that this behavioural effect is entirely dependent on the diffusion model being correct, it is important to note that differences in *Ter* between conditions equal differences in the fastest RTs for those conditions. Hence, an interpretation of these results purely in terms of observed behaviour is that *switch-away* cues reliably speed up the fastest responses relative to *non-informative* cues.

Just as predicted by our speed-accuracy tradeoff account, response criterion adjustment occurred only for cues validly predicting a change in task (*switch-to, switch-away*), but not for cues signaling that the task may repeat (*non-informative*)[3]. This criterion adjustment caused decision time to be greater in the *switch-to* and *switch-away* conditions than the *non-informative switch* condition. The decision time difference between *switch-away* and *non-informative* cues masked the nondecision time advantage that partial preparation afforded to *switch-away* cues over *non-informative switch* cues, resulting in no observable difference in mean RT.

This pattern of reduced nondecision time and increased response criterion in the *switch-away* and *switch-to* conditions may appear counterintuitive. It suggests that anticipatory reconfiguration (reflected in reduced nondecision time) resulted in longer rather than shorter decision times – a disadvantage, rather than an advantage, of preparation. However, seeing this effect as only a disadvantage fails to appreciate the full range of behavior displayed by participants, and the task demands which they must satisfy in terms of accuracy, as well as speed. The increase in response criterion had the advantage of decreasing the probability of an error, which explains why accuracy was higher in the *switch-away* and *switch-to* conditions than the *non-informative switch* condition, even though the quality of the evidence (drift rate) was the same in all three conditions. By setting the criterion as they did, participants were able to achieve greater accuracy in the *switch-to* condition without sacrificing speed relative to the *non-informative* conditions,

[3] As with nondecision time effects, criterion differences correspond to an observable behavioural difference. In the case of criterion effects this is RT variance. When drift rate (which also affects RT variance) is the same between two conditions (e.g., *switch-to* and *non-informative* in our data) but one condition has a larger criterion (e.g., *switch-to* has a greater criterion than *non-informative* in our data) it will also have a larger variance.

since the increased decision time cost was canceled by the nondecision time advantage afforded by partial preparation.

4.3 General Discussion

Nicholson et al. (2006b) reported an early cue-locked differential switch positivity for both fully informative (*switch-to*) and partially informative (*switch-away*) cues, suggesting a common anticipatory reconfiguration process. They argued that, since the only common information provided by these cues was that the previously active task would not be repeated, this switch positivity could reflect suppression or disengagement of the now irrelevant task-set. However, the absence of a demonstrated behavioral benefit afforded by *switch-away* cues, and the fact that both *switch-to* and *switch-away*, but not *repeat*, cues involved a change in spatial position suggested another interpretation – that the early switch positivity reflects processing of the change in the spatial position of the cue or repetition priming for the *repeat* cue. In the present study, we tested this alternative explanation by including *non-informative* cues that, like *switch-to* and *switch-away* cues, involve a change in spatial position (and therefore do not involve cue identity repetition) but, unlike *switch-to* and *switch-away* cues, are not associated with any strategic benefit in suppressing the previously active task-set. The ERP data showed that the early posterior cue-locked D-Pos1 was elicited for both *switch-to* and *switch-away* cues but not for *non-informative* cues. Therefore, D-Pos1 does not simply reflect processing of a change in cue position.

These results indicate that partially informative cues trigger a subcomponent of an anticipatory reconfiguration process represented by the D-Pos1 to both *switch-to* and *switch-away* cues. Surprisingly, *switch-away* cues signaling that the upcoming trial requires

a change in task-set, without specific information about which task-set to prepare, did not appear to provide any advantage in speed, relative to non-informative cues signaling that a change may or may not be necessary. However, error scores provided evidence that the failure to find a *switch-to* advantage in mean RT was due to a speed-accuracy tradeoff.

We examined the issue of speed-accuracy tradeoff by using the EZ2 analysis method (Grasman et al., 2009), which combines measurements of response accuracy with measurements of response speed and variability in order to fit an evidence accumulation model of the task decision process. Critically for our purposes, this model produces estimates of the criterion amount of evidence required to make a decision and of the mean time to complete nondecision and decision processes. Diffusion model analyses provided evidence of a behavioral effect on RT of the partial information provided by *switch-away* cues. Specifically, nondecision time, a latent measure that includes the time to complete reconfiguration after target onset, did not differ between *repeat* and *switch-to* cues, but increased progressively across *switch-to*, *switch-away* and *non-informative* cues. Hence, cues that allowed full reconfiguration showed no effect of reconfiguration on nondecision time, whereas cued that allowed partial reconfiguration provided a nondecision time advantage over cues providing no information about the likelihood of a switch trial.

These results are consistent with the idea that the partial preparation afforded by the information that the previously active task-set will not be repeated is a time consuming part of the reconfiguration process. Nondecision time was negatively correlated with the amplitude of the early cue positivity, suggesting that activation of the processes reflected in this early switch positivity resulted in greater anticipatory reconfiguration. Importantly, the diffusion analysis demonstrates that behavioral results are consistent with the interpretation of D-Pos1 as being representative of preparation for an upcoming change in task-set. These

data provide a crucial link between behavioral and ERP data that does not exist when only mean RT is considered.

Although these findings strongly support the contention that partially informative cues trigger some anticipatory reconfiguration process, there are at least two possible interpretations about the precise nature of this process. One possibility is inhibition of the previously relevant task-set, which both *switch-to* and *switch-away* cues indicate will not be relevant on the current trial (Nicholson et al., 2006b). Another is activation of one or more task-sets that the cues indicate are likely to be relevant for the following target[4]. In the latter case, *switch-away* cues could either activate both possible task-sets or randomly activate one of the two possible task-sets. If both possible task-sets are activated, it seems likely that cue-locked waveforms would reflect greater processing for *switch-away* trials than *switch-to* trials. Hence, cue-locked differentiation between *repeat* and switch trials (i.e., D-Pos1) should be larger or more prolonged for *switch-away* cues than for *switch-to* cues (i.e., *switch-to* trials = one task-set activation, *switch-away* trials = two task-set activations). Furthermore, *non-informative* cues are also likely to activate the non-repeat task-set. Therefore, the cue-locked positivity should show amplitude changes so that *repeat*<*switch-to*=*non-informative*< *switch-away*. This order is not compatible with the pattern of differences observed in cue-locked waveforms.

If *switch-away* cues activate only one of the two cued task-sets in a random or semi-random fashion, the behavioral advantages that we found for *switch-away* over *non-informative* cues are difficult to understand. Since both types of cues afford the same level of uncertainty reduction about the nature of the upcoming task, it seems likely that both will be used to activate the corresponding task-sets in the same way. If this were the case then

[4] We thank an anonymous reviewer for this suggestion.

there should be no behavioural advantage for *switch-away* trials over *non-informative* trials, which is not what was observed. It remains possible, however, that the task-set activation account is correct if participants only, or more efficiently, use *switch-away* cues for task-set activation, although it is unclear why this might be the case.

The alternative interpretation (Nicholson et al., 2006b) is that anticipatory task-set reconfiguration is a multi-component process that encompasses both inhibition of the previously active task-set, reflected in the early D-Pos1, and activation of the now relevant task-set, reflected in the later D-Pos2. Variation across *switch-to*, *switch-away* and *non-informative* cues in both D-Pos1 and nondecision time is compatible with a process of suppression or inhibition of the previously active task-set, which may be conceptualized as being similar to the idea of disengagement of attention to spatial location invoked in cued spatial attention tasks (e.g., Posner, 1980; but see Cohen, Romero, Servan-Schreiber, & Farah, 1994). This interpretation is strengthened by the finding that the amplitude of the early cue-locked positivity for both *switch-to* and *switch-away* cues was inversely related to mean RT and nondecision time, suggesting that greater anticipatory reconfiguration, which we argue involves inhibition of the irrelevant task-set, leads to faster RT by reducing nondecision time.

The evidence accumulation (diffusion) model analysis provided not only evidence for a behavioral benefit arising as a result of task-set inhibition but also a plausible explanation of why this behavioral benefit is not evident in mean RT measures. Specifically, model parameters indicated that the nondecision time advantage offered by this partial preparation was not evident in mean RT because it was counteracted by another process that was also activated by cues that provided certainty of an upcoming switch in task, which resulted in an increase in the decision time component of RT. Estimates of the

criterion amount of evidence required to make a decision indicated that participants responded to cues that provided certainty of an upcoming switch in task (i.e., *switch-away* and *switch-to* cues) by requiring a higher standard of evidence, resulting in slower but more accurate decision for *switch-away* than for *non-informative switch* trials.

This more fine-grained analysis of the behavioral data produced results that, in contrast to traditional approaches, are able to provide a unified explanation of both accuracy and speed. The fact that *switch-to* and *switch-away* cues were associated with both a reduction in nondecision time and an increase in evidence criterion suggests third interpretation of the anticipatory preparation process reflected in the early cue-locked positivity. Specifically, it is possible that D-Pos1 reflects the process of increasing the evidence criterion and that this is a time-consuming process that contributes to nondecision time. When this process can be completed before target onset, D-Pos1 is elicited in the cue-stimulus interval, and nondecision time is reduced. When it is completed after target onset, D-Pos1 is elicited after target onset and nondecision time is higher. Although this explanation is compatible with most of our results, it predicts that evidence criterion should be higher for all switch trials, but this was not the case for *non-informative switch* trials. This account is also not easily reconciled with the fact the target-locked positivity was elicited for both *non-informative switch* and *non-informative repeat* trials, even though neither showed an increase in evidence criterion. Furthermore, it predicts that the amplitude of the early cue positivity will be associated with a higher evidence criterion for both *switch-to* and *switch-away* cues. However, a larger early cue positivity was associated with faster nondecision time and *lower* evidence criterion, the latter being significant only for *switch-to* cues.

In conclusion, we have replicated evidence for an early cue-locked positivity which is elicited by cues that provide certainty of an upcoming switch in task. We provided strong evidence that this positivity is associated with an anticipatory component of the task-set reconfiguration process and with a behavioral benefit in the nondecision component of RT. We have identified a number of alternative interpretations of this process and have shown that most fail to explain the full set of behavioral and ERP data. It seems to us arguable, therefore, that although the data do not provide *direct* evidence for task-set inhibition as a component of anticipatory task-set reconfiguration, this interpretation provides the most plausible and comprehensive account of the data.

More broadly, the finding that simple behavioral measures and ERP measures may lead to theoretically opposed interpretations of the underlying cognitive processes suggests that such simple behavioral measures alone may be limited. We argue instead, that more sophisticated model-based analyses of behavior, combined with ERP and other neuroimaging measures, are likely to be more successful in providing a full account of all relevant processes (see also Forstmann et al., 2008a).

Chapter 5: Switch-related and general preparation processes in task-switching: Evidence from multivariate pattern classification of EEG data[5]

The ability to deal with constantly changing demands within our environment is aided by external cues that allow preparation in anticipation of change. In cued task-switching paradigms, changing tasks involves a switch cost, i.e., poorer performance on task switch relative to task repeat trials (e.g. Meiran, 1996). This switch cost reduces with increased opportunity for preparation, indicating that switch trials require additional or more time-consuming preparation compared to repeat trials. However, it is unclear whether switch preparation involves stronger engagement of the same preparation process needed for task repetition or a distinct process.

Within the cue-to-target interval, event-related potentials (ERPs) show an early *centro-parietal positivity* that is greater for switch than repeat trials (e.g. Kieffaber & Hetrick, 2005; Nicholson et al., 2005) and a *frontocentral pre-target negativity* that is similar for both trial types (e.g. Nicholson et al., Jamadar et al., 2010). Consistent with a switch-related preparation process, the early cue-locked positivity is elicited only by cues that predict a definite change in task, regardless of whether they identify the upcoming task (Karayanidis et al., 2009). Moreover, consistent with a general task-readiness preparation process, the pre-target negativity is similar for cues that identify the upcoming task, regardless of whether the task repeats or changes. Similarly, Karayanidis et al. (2011) showed that cue-locked positivity amplitude varies as a function of RT only for switch

[5] Published as Mansfield, E. L., Karayanidis, F. & Cohen, M. X. (2012). Switch-related and general preparation processes in task-switching: Evidence from multivariate pattern classification of EEG data. *The Journal of Neuroscience, 32,* 18253-18258.

trials, while pre-target negativity amplitude varies as a function of RT for *both* switch and repeat trials. However, this evidence for a switch-related preparation process relies on null findings, e.g. the absence of a significant cue-locked positivity for cues that do not predict a definite switch trial (Karayanidis et al., 2009).

We provide new evidence for a switch-related preparation process that is temporally and spatially distinct from a general preparation process. A novel multivariate pattern *mis*classification approach was developed, to identify core preparation processes based on common frequency band-specific topographical patterns in EEG activity. Four cue types provided varying degrees of specificity about the task relevant to the upcoming target. *Repeat* cues indicated a definite task repeat. *Switch-to* cues indicated a definite task switch and identified the relevant task. *Switch-away* cues also indicated a definite task switch but not task identity. *Non-informative* cues indicated that a task repeat and task switch were equally likely. Thus, some cues specified an upcoming switch trial with certainty (*switch-to*, *switch-away*), whereas other cues specified the upcoming task with certainty (*repeat*, *switch-to*). We hypothesized that (1) a switch-related preparation process would be evidenced by *switch-away* trials being misclassified as *switch-to* trials in the latency range of the cue-locked positivity and (2) a task readiness process would be evidenced by *repeat* trials being misclassified as *switch-to* trials in the latency range of the pre-target negativity. These effects were expected to be represented in the alpha band (e.g. Serrien et al., 2004; Sauseng et al., 2006) and at frontal and parietal areas, respectively (Ruge et al., 2013).

5.1 Methods

5.1.1 Participants

Twenty-three participants (18 female, 21.3 +/- 3.5 years) were included in this analysis. The study was approved by the University of Newcastle Human Research Ethics Committee.

5.1.2 Stimuli and Tasks

Detailed information about stimuli used can be found in the article by Karayanidis et al. (2009). A circle (5º diameter) was divided into six segments, with two adjoining segments corresponding to letter (vowel/consonant), digit (odd/even), and color (hot/cold) classification tasks (see Figure 5.1a). On each trial, a target was presented in one segment. Targets consisted of a pair of characters (letter, number, non-alphanumeric symbol) presented either in gray or in color. Each target consisted of one dimension that was relevant to the current task (e.g., digit mapped to left hand response), one that was incongruently mapped to the currently relevant task (e.g., letter mapped to right hand response), and one neutral dimension (e.g., target presented in gray). Targets for each task (see Figure 5.1b) were selected pseudorandomly, so as to avoid immediate repetition. The target remained for 5s or until a response was emitted (response-cue interval 400 ms). Data were pooled across tasks.

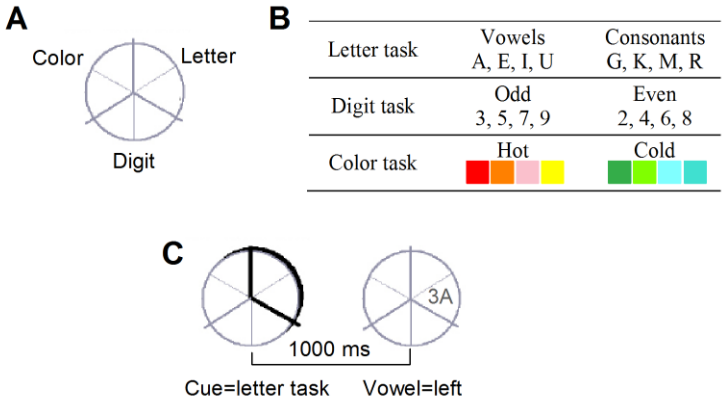


Figure 5.1: Paradigm. (A) Mapping of the three tasks to each of the main segments of the circle. (B) Target sets associated with each task. (C) Example cue-target sequence, showing the cue highlighting two adjacent segments, followed by the target appearing within one of the cued segments. Words are shown here to illustrate the task and were not seen by the participant.

Four cue types were defined by the position of a highlight that surrounded two adjoining segments of the circle and preceded target onset by 1000ms (Figure 5.1c). On *repeat* trials, the cue highlighted segments corresponding to the same task as the preceding trial, predicting a definite task repeat. On s*witch-to* trials, the cue highlighted segments corresponding to one of the other tasks, predicting a definite switch to that task. On s*witch-away* trials, the cue highlighted two adjoining segments corresponding to the two tasks that were not completed on the previous trial, predicting a definite task switch but not the task to be switched to. On *non-informative* trials, the cue again highlighted two adjoining segments, one corresponding to the task just completed and one to another task, indicating that a repeat of the previous task or a switch to this other task was equally likely. For both *switch-away* and *non-informative* cues, the location of the target defined which task would be performed. The same cue could not appear on more than three successive trials.

5.1.3 Procedure and EEG Recording

Training included 1400 trials over two sessions on both single-task and mixed-task blocks. The EEG testing session included nine blocks of 96 trials, separated by rest. Immediate auditory error feedback was delivered. Mean RT and error rate were presented after each block. EEG was continuously sampled at 2048 Hz/channel from 64 scalp electrodes, left and right mastoids, nose and left supraorbital and infraorbital ridge and outer canthi of the eyes using a Biosemi ActiveTwo system relative to common mode sense (CMS) and driven right leg (DRL) electrodes.

5.1.4 Data analysis

The first five trials of each block, error trials, and trials following an error were excluded from analysis. Fast (<200 ms) and slow (>3SD above participant's mean RT) trials were also excluded. Greenhouse-Geisser correction was applied when appropriate (Vasey & Thayer, 1987).

5.1.4.1 EEG pre-processing.

EEG data were high-pass filtered at 0.5 Hz and epoched from 1.0 s before to 3.5 s after each cue. All trials were visually inspected and those containing facial EMG or other artifacts not related to blinks were manually removed. Independent components analysis was computed using EEGLAB software (Delorme & Makeig, 2004) and components containing blink/oculomotor artifacts or other artifacts that could be clearly distinguished from brain-driven EEG signals were subtracted from the data. All data were current-source-density (CSD) transformed prior to analyses (Kayser & Tenke, 2006). CSD is a high-pass spatial filter that minimizes volume conduction by removing large spatially broad (and

therefore likely volume conducted) activities (Srinivasan et al., 1996; 2007, also called scalp Laplacian). This sharpening filter limits spatial autocorrelation as well as the spread of any residual oculomotor artifacts, making the data more amenable to spatial multivariate pattern analysis based on local topographical features. This approach enhances spatial resolution but does not offer precise anatomical localization.

5.1.4.2 Power analysis.

Analyses were performed in Matlab. Single-trial data were first decomposed into their time-frequency representation by multiplying the power spectrum of the EEG (obtained from the fast-Fourier-transform) by the power spectrum of complex Morlet wavelets ($e^{i2\pi f} e^{-t^2/(2*\sigma^2)}$, where *t* is time, *f* is frequency, which increased from 2 to 50 Hz in 20 logarithmically spaced steps, and *s* defines the width of each frequency band, set according to n/(2πf) where n increases logarithmically from 3 to 14 as a function of frequency), and then taking the inverse fast-Fourier-transform. From the resulting complex signal, an estimate of frequency-band-specific power at each time point was defined as the squared magnitude of the result of the convolution *Z* (real[z(t)]^2 + imag[z(t)]^2). Power was normalized using a decibel (dB) transform (dB power = 10*log10[power/baseline]), where baseline activity was taken as the average power at each frequency band, averaged across conditions, from -300 to -100 ms pre-cue. Power was calculated for each electrode, separately for *repeat*, *switch-to* and *switch-away* trials, relative to *non-informative* trials.

Statistics on time-frequency changes in power were performed by map-wise t-tests, along with a combination of pixel- and cluster-level thresholding. Individual pixels in time-frequency space were considered significant at $p<0.01$. Clusters of pixels were considered

significant if there were more pixels per cluster than expected under the null hypothesis at $p<0.05$. Cluster size was obtained via permutation testing (Nichols & Holmes, 2002). T-values were computed based on a randomly shuffled subject-condition mapping, and the statistical map was thresholded again. This time, the number of pixels in the largest supra-threshold cluster was stored. This was repeated 500 times, generating a distribution of maximum cluster sizes under the null hypothesis. The cluster threshold was defined as the standardized distance from the mean of the maximum cluster distribution corresponding to $p<0.05$.

5.1.5 Multivariate pattern analysis

This analysis entailed constructing a set of local electrode weights based on local topographical differences between activity elicited during *switch-to* vs. *non-informative* conditions, and then testing whether those weights could be used to distinguish topographical patterns associated with *repeat* and *switch-away* conditions. The following procedure was done separately for each subject. The classifier was first trained to distinguish patterns associated with *switch-to* and *non-informative* trials. *Switch-to* cues allow preparation for both a switch in task and the upcoming task itself, whereas *non-informative* cues do not elicit either of these preparation processes. Thus, these cues demand the greatest and the least amounts of preparation, respectively. The first step created a set of topographical weights based on differences in local spatial patterns between *switch-to* and *non-informative* trials. Weights were calculated based on a cluster including the central electrode and the seven immediately surrounding electrodes (fewer electrodes were used near the edges of the EEG cap; no analysis entailed fewer than 4 electrodes). At each eight-electrode cluster, the mean activity across electrodes for each condition was

subtracted to ensure that effects could not be attributed to overall amplitude differences between conditions. However, even with such amplitude normalization, topographical patterns may still not be representative of the precise configurations of source location and polarity (Urbach & Kutas, 2002). After the multivariate analysis was applied to this cluster (see below), another electrode was taken as the central electrode, and the process was repeated.

Trials were grouped into 20 bins of randomly selected trials and then averaged within each bin. This binning procedure increased signal-to-noise and ensured an equal number of 'trials' for analyses within each subject (this procedure is often used in functional MRI multivariate analyses, e.g., Kahnt et al., 2011). Z-normalized data at each time-frequency point were entered into a general linear model (using Matlab's glmfit function with 'probit' logistic regression) in which the set of weights was obtained that best distinguished *switch-to* and *non-informative* conditions. In other words, we constructed, for each time-frequency-electrode cluster point, a regression model of the form: $y = \sum w_e x_e$, where *w* is a vector of weights (regression coefficients) for electrodes *e*, and *x* is the normalized power estimate at each electrode (the intercept is zero because of normalization). Y is a Boolean operator coded as 0 for *switch-to* trials and 1 for *non-informative* trials. This is similar to a 'searchlight' procedure (Kriegeskorte et al., 2006) except that we searched across space, time, and frequency.

These weights were then taken to the next stage of analysis. Here, the model (via Matlab's glmval function) used these weights to classify *repeat* and *switch-away* trials as being more similar to *switch-to* or *non-informative* trials. Because the model was never trained on any of the test conditions (*repeat* and *switch-away*), its answers were necessarily

"wrong." Thus, if the model labels, for example, a *repeat* trial as *switch-to* at a specific time-frequency-electrode cluster point, this indicates that the model considers the local spatial pattern during *repeat* trials to be similar to that during *switch-to* trials (and that the pattern for *switch-away* trials is necessarily more similar to that during *non-informative* trials). This approach eliminates any potential "double-dipping," because the model was tested on data it did not have access to during training. The misclassification value hence reflects the bias in misclassifying *repeat* as *switch-to* compared with misclassifying *switch-away* as *switch-to* at each time/frequency/electrode point. Fifty percent performance indicates that there is no bias in how *repeat* vs. *switch away* trials were misclassified (i.e., the model misclassifies *repeat* and *switch-away* equally likely as *switch-to* vs. *non-informative*). This is therefore considered chance-level performance, and at the group level, misclassification results across subjects were evaluated against 0.5. Pixel and cluster level thresholding of time-frequency changes in misclassification values was carried out according to the procedure described above for time-frequency changes in power. Average misclassification values at each timepoint within the alpha band (8-12 Hz) were submitted to one-sample t-tests at $p<0.05$, with a minimum of 100 ms of contiguously significant points (see Figure 5.4, bottom row).

To ensure that effects were not due to differences between cue types in small horizontal eye movements around the circle, we examined ERPs at the horizontal electro-oculogram channels and found no systematic effects of cue type on eye movements that could have contributed to our results.

5.2 Results

5.2.1 Behavioral results

The effect of trial type on mean RT was significant, $F(4,88)=38.62$, $p<.001$, $\varepsilon=.320$. Responses on *repeat* trials were faster than on *switch-to*, $F(1,22)=32.29$, $p<.001$, *switch-away*, $F(1,22)=51.59$, $p<.001$, and *non-informative repeat* trials, $F(1,22)=61.49$, $p<.001$, that is trials where a non-informative cue led to a *repeat* trial (Figure 5.2, left). *Switch-to* trials were significantly faster than *switch-away* trials, $F(1,22)=37.36$, $p<.001$, which, in turn were faster than *non-informative switch* trials, albeit not significantly so.

Repeat trials produced fewer errors than *non-informative repeat*, $F(1,22)=21.27$, $p<.001$, *switch-to*, $F(1,22)=16.87$, $p<.001$, and *switch-away* trials, $F(1,22)=9.45$, $p=.006$ (Figure 5.2, right). *Non-informative switch* trials produced more errors than *switch-away* trials, $F(1,22)=9.53$, $p=.005$.

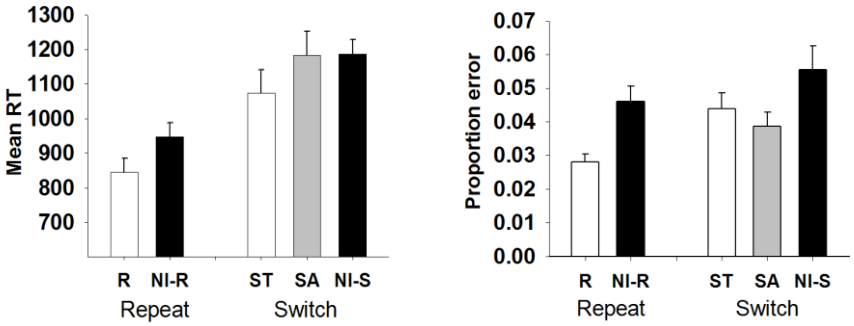


Figure 5.2: Mean reaction time (left) and error proportion (right) for each trial type, with standard error bars. R = *repeat*, NI-R = *non-informative repeat*, ST = *switch-to*, SA = *switch-away*, NI-S = *non-informative switch.*

5.2.2 Power analyses

Because this rapid task design lacked a pure "baseline" period, we show time-frequency results relative to *non-informative* trials (Figure 5.3a). Figure 5.3b shows time-frequency plots at FC4, PO7 and PO8, where effects were strongest. At approximately 400 ms post-cue, significant alpha/theta suppression was observed for *repeat* cues, especially over right fronto-central sites (Figure 5.3). This effect was not evident for *switch-to* or *switch-away* cues. Instead, during this time window, there was greater alpha power over bilateral parieto-occipital electrodes for both switch cues (Figure 5.3a), although this effect only reached significance for *switch-away* cues at left parieto-occipital sites (Figure 5.3b). Beginning around 600 ms for *repeat* cues and 800 ms for *switch-to* cues, there was an increase in alpha and beta power over bilateral parieto-occipital sites (Figure 5.3a). This effect was only significant for *repeat* cues (Figure 5.3b). There was no power increase over these electrodes for *switch-away* cues.

This pattern suggests that an early preparation process common to both *switch-to* and *switch-away* cues could be distinguished from a later preparation process common to both *repeat* and *switch-to* cues in the alpha band. Both processes were evident parieto-occipitally and were not topographically distinct.

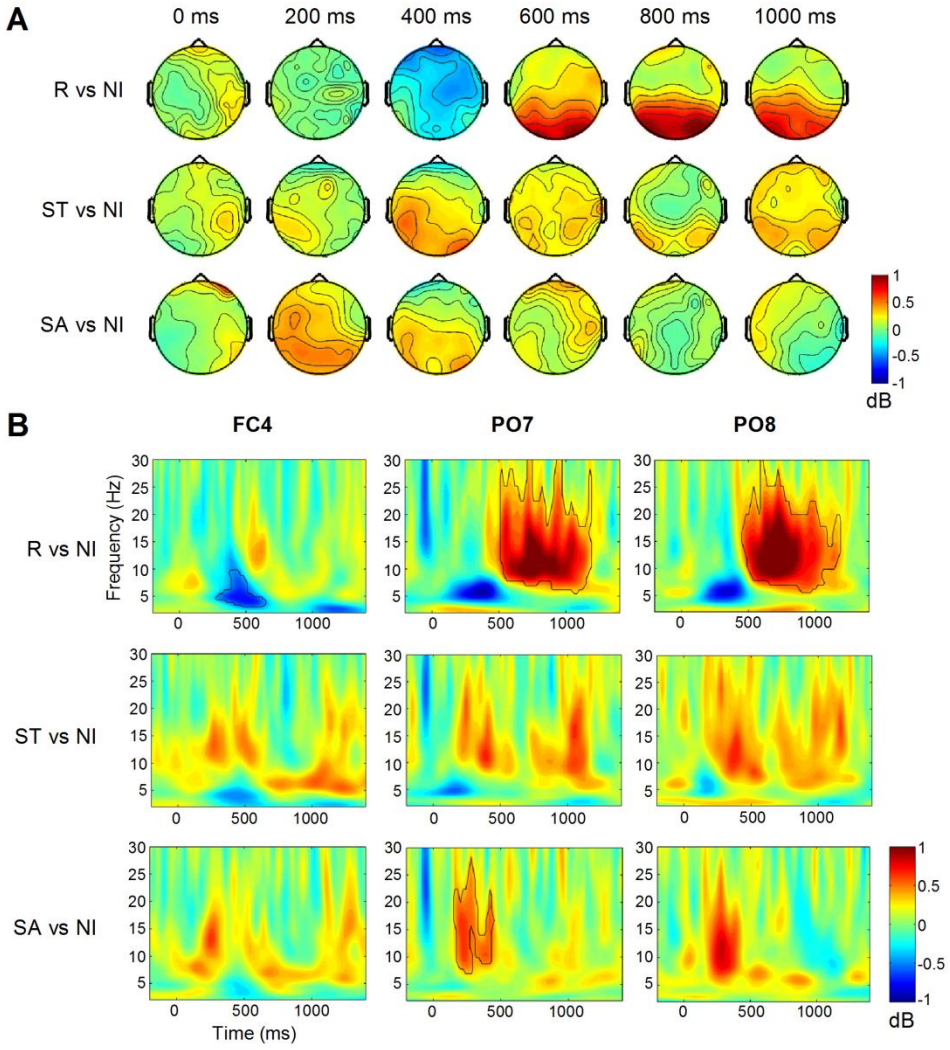


Figure 5.3: Power analysis. (A) Topographical plots showing alpha power (8-12 Hz) for *repeat*, *switch-to* and *switch-away* cues relative to *non-informative* cues, within the cue to target interval. (B) Time-frequency plots for each cue type relative to *non-informative* cues, at electrodes FC4, PO7 and PO8. Significant clusters of pixels are outlined.

5.2.3 Multivariate pattern analysis

The multivariate pattern classification in the alpha band (8-12 Hz) is presented in Figure 5.4. The greatest misclassification effects occurred over two electrode clusters (Figure 5.4 top): one over right lateral frontal sites (F6, F8, FC6) and another over right parietal sites (CP2, P2, P4). Figure 5.4 (middle) shows the full time-frequency misclassification plots for each cluster, with significant points outlined. Misclassification effects were largest in the alpha band. Misclassification values within this band at the frontal cluster (Figure 5.4, bottom) show that, over 300-500 ms, activity on *switch-away* trials was classified as *switch-to* more than activity on *repeat* trials was classified as *switch-to*. In contrast, at the parietal cluster, from around 850 ms until target onset, activity on *repeat* trials was classified as *switch-to* more than activity on *switch-away* trials was classified as *switch-to*. Thus, *switch-away* cues were misclassified as *switch-to* cues most strongly at right lateral frontal sites around the time of the early cue-locked positivity in ERP waveforms, whereas *repeat* cues were misclassified as *switch-to* cues at right parietal sites during the ERP pre-target negativity.

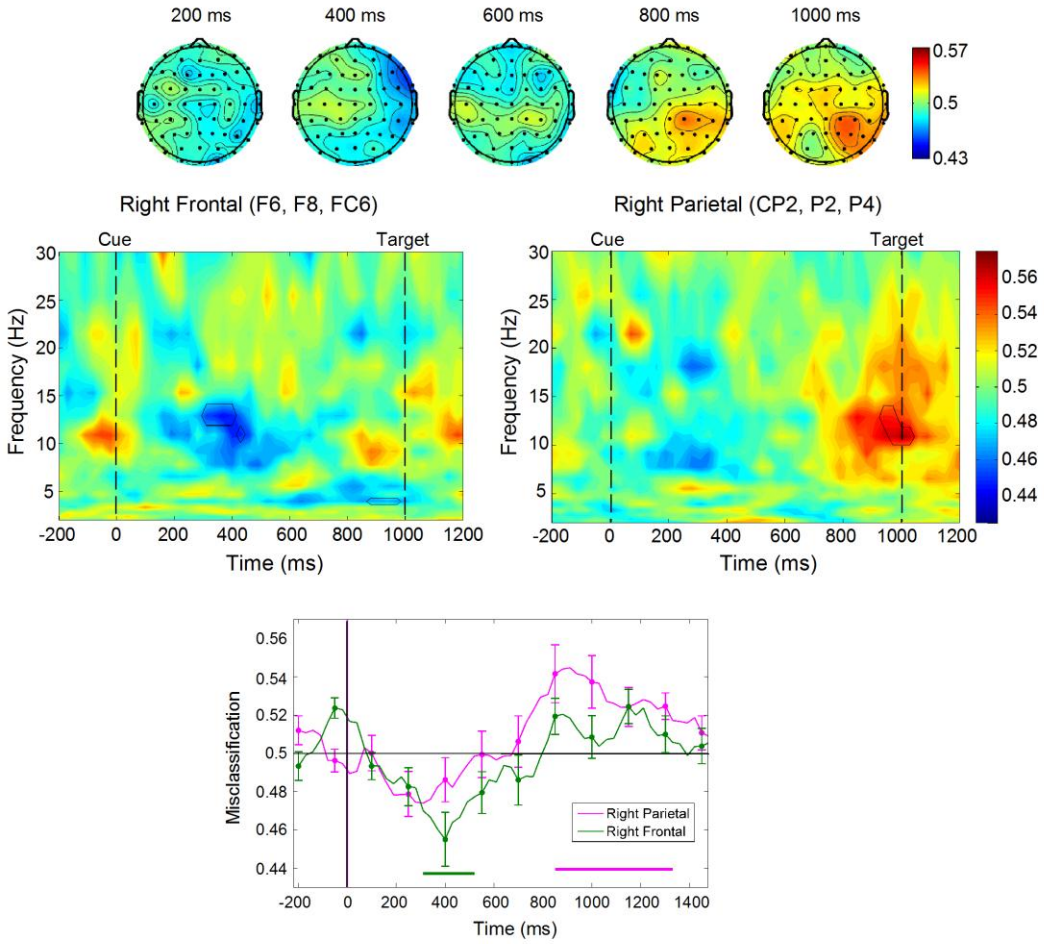


Figure 5.4: Multivariate pattern analysis. Top row: Topographical plots showing misclassification of *repeat* and *switch-away* activity as *switch-to* activity within the alpha band. Red = *repeat* misclassified as *switch-to*, blue = *switch-away* misclassified as *switch-to*. Middle row: Time-frequency plots for right frontal and right parietal clusters, with significant clusters of pixels outlined. Bottom row: Misclassification values within the alpha band at right frontal and right parietal clusters plotted against time. Values > 0.50 show greater misclassification of *repeat* as *switch-to*, values < 0.50 show greater misclassification of *switch-away* as *switch-to*. Coloured bars represent time windows in which misclassification values were significantly different from 0.50.

5.3 Discussion

The decline in behavioural performance when switching tasks compared to repeating the same task has been explained as arising from the need to recruit an additional process in order to prepare to switch task. However, while ERP studies consistently report differential activation for switch relative to repeat trials (see Karayanidis et al., 2010) many fMRI studies do not find *any* differential switch activation (see Ruge et al., 2013), leaving unanswered the question of whether a switch-related preparation process can be dissociated from more general preparation processes. We used a paradigm that differentiated between these processes by including some cues that specified with certainty that the task would change (*switch-to, switch-away*) and some cues that specified with certainty what the upcoming task would be (*repeat, switch-to*). Using a novel pattern classification approach, we corroborate previous evidence for temporally distinct switch-related and general task preparation processes (Karayanidis et al., 2009; 2011) and show new evidence that these processes may be linked to distinct neural generators.

An initial time-frequency analysis produced evidence for an early process in response to cues that predicted a definite task switch and a later process to cues that specified the upcoming task. These effects were evident in alpha power changes relative to *non-informative* cues over bilateral parieto-occipital electrodes and at latencies consistent with the cue-locked positive component for *switch-to* and *switch-away* cues and the pre-target negativity for *switch-to* and *repeat* cues reported in Karayanidis et al. (2009). However, still, these analyses do not provide evidence that these component processes are associated with different neural generators, as both processes showed increases in power over very similar posterior scalp regions.

Multivariate pattern analysis provided this critical evidence by reliably *mis*classifying *repeat* and *switch-away* trials as *switch-to* trials at different latencies and locations. Patterns of activation associated with *switch-away* cues were more strongly misclassified as *switch-to* patterns over right frontal sites from 300-500 ms post-cue. Thus, cues that specified with certainty that the task would change produced common patterns of activation. In contrast, from 850-1000 ms, activation patterns for *repeat* cues were more strongly misclassified as *switch-to* patterns over right parietal sites. So, fully informative cues (i.e., cues that identified the task to be completed) produced similar activation over this parietal region, compared to cues that did not identify the upcoming task. In summary, distinct patterns of activation were found when the cue predicted a definite change in task, compared to when the cue predicted the upcoming task with certainty.

5.3.1 Switch-related preparation

Consistent with evidence of a cue-locked ERP component that is only elicited in response to switch cues (Karayanidis et al., 2009), the current data support a preparation process that is engaged specifically on switch trials. The fact that this switch-related process is associated with frontal patterns of activation is suggestive of a higher-order process that responds to an increased demand for cognitive control. Karayanidis et al. (2009) argued that the early switch-related process may reflect an inhibitory function, as both *switch-to and switch-away* cues specify that the previous task set will no longer be required. In fact, for *switch-away* cues, this is the *only* information that is conveyed by the cue. For both of these cue types, suppression of the previous task-set is a beneficial strategy, potentially reducing interference from the previous task-set. Although anatomical localization on the basis of EEG topographical patterns remains speculative, the finding

that the location of this common activation corresponded to right inferior frontal cortex, a region strongly linked to inhibitory control (Aron et al., 2004; Jamadar et al., 2010), is consistent with this interpretation.

Alternatively, it could be argued that shifts in spatial attention associated with *switch-to* and *switch-away* cues could explain this early effect. This explanation appears unlikely, as we have previously shown that amplitude differences in the early cue-locked ERP component elicited in this paradigm are not consistent with simple spatial reallocation of attention (Karayanidis et al., 2009). While this component was elicited for both switch cues, it was not elicited for *non-informative* cues, which also require a shift in spatial attention. Thus, the early similarity between *switch-to* and *switch-away* activity is more consistent with a strategic, switch-related preparation process.

5.3.2 General task readiness

The later general task preparation process was associated with activation over a right parietal region that approximately corresponded to the superior parietal lobule (SPL). There is evidence that activation in the SPL varies as a function of task certainty. For example, SPL activation was greater when participants had to select between multiple tasks than when the task was fixed (Forstmann et al., 2006) and when a bivalent target was presented before the task cue resulting in activation of more than one task-set (Ruge et al., 2009). In the current context, this suggests that the differential activation over the SPL for *repeat* and *switch-to* cues relative to *switch-away* and *non-informative* cues is consistent with task-set activation when the cue defines the upcoming task with certainty. This preparatory component may reflect a response readiness process, conceptualised as either

reinforcing (*repeat* cues) or re-loading (*switch-to* cues) the correct set of stimulus-response mappings prior to target onset.

5.3.3 Conclusion

Our novel technique has provided additional evidence for multiple transient preparation processes that involve rapidly changing networks in the lead up to target onset. We find evidence for sequential switch-specific and general task preparation processes that are associated with distinct neural generators, in line with models of preparation that include both context-updating and task-specific components (Jennings & van der Molen, 2005). These findings also highlight the value of using pattern classification approaches to identify core components of cognitive flexibility based on similarities in activation patterns across experimental conditions.

Chapter 6: Strategic adjustment of response caution in task-switching

6.1 Trial-by-trial response threshold adjustments

The speed-accuracy tradeoff can be controlled by adjusting one's degree of response caution according to current task demands. As discussed in Chapter 2, response caution is indexed in evidence accumulation models of two-choice decision making by a response threshold parameter (a)[6], which estimates the criterion amount of evidence that needs to be accumulated for a response to be selected (Figure 2.1). Setting a lower response threshold increases the risk of crossing the response threshold prematurely, resulting in more risky responding. In contrast, setting a higher response threshold allows more time for evidence to accumulate, resulting in more cautious responding.

In Chapter 4, we found evidence for trial-by-trial adjustment of response threshold within the cued-trials task-switching paradigm, with a higher threshold set in response to cues that indicated a definite task switch, and a lower threshold set in response to cues that indicated a definite task repeat. This suggests that when participants anticipate an easy repeat in task, they lower their threshold, as there is little risk of making an error. In contrast, when a more difficult switch trial is expected, participants increase their response threshold to deal with the higher level of interference on these trials. In addition, response threshold was negatively correlated with the amplitude of the cue-locked switch positivity for *switch-to* cues, providing further evidence that this adjustment is part of the preparation processes carried out within the cue to target interval. While these are certainly intriguing

[6] Note that this parameter is referred to as 'criterion' or 'response threshold'. In the following chapters we use the latter terminology for consistency with previous literature on the neural basis of the speed-accuracy tradeoff.

findings, it is unclear whether these adjustments are similar to those carried out within two-choice decision making tasks, upon which models of the speed-accuracy tradeoff are based.

One way in which these two processes may be compared is by examining whether they are implemented in common neural networks. Recently, there has been increasing interest in the neural basis of the speed-accuracy tradeoff in two-choice decision making (Bogacz et al., 2010). Strategic changes in response caution are induced by instructing participants to respond either quickly or accurately (e.g. Forstmann et al., 2008a; van Veen et al., 2008). These studies have shown that adjustment of response caution between accuracy and speed instructions is associated with activation in cortico-basal ganglia networks shown to be responsible for action selection (DeLong & Wichmann, 2007; see Figure 6.1). However, the exact location and configuration of networks across these studies has been inconsistent, giving rise to different theories regarding the neural level at which control of the speed-accuracy tradeoff occurs (see Figure 6.1).

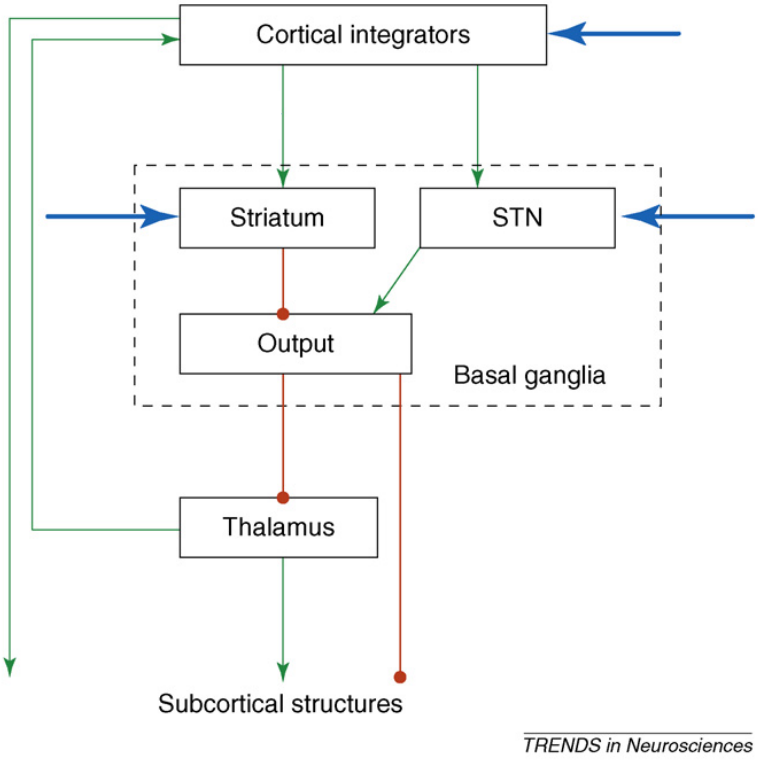


Figure 6.1: Illustration of the cotrico-basal ganglia-thalamic network. Output corresponds to the globus pallidus and substantia nigra pars reticulata. Green lines represent excitatory pathways, while red lines represent inhibitory pathways. Blue arrows indicate points at which input could be provided to the system in order to modulate response threshold (Figure: Adapted from Bogacz et al., 2010).

In some studies, higher-order frontal regions were found to be co-activated with cortical regions that have previously been associated with the accumulation or integration of sensory inputs towards a response (cortical integrators; see Schall, 2001; Gold & Shadlen, 2007). This has given rise to the *cortical* theory which suggests that, in response to instructions emphasising speed over accuracy, cortical integrators receive additional top-down input that increases their baseline activity (e.g. Furman & Wang, 2008; Ivanoff, Branning & Marois, 2008; van Veen, Krug & Carter, 2008). For example, using a Simon task, van Veen et al. (2008) examined both sustained baseline activity and transient response-related activity in blocks of trials that emphasised either response speed or

response accuracy. The DLPFC and inferior parietal lobule (IPL) showed increased *sustained* activity in blocks that emphasised speed. In addition, the IPL showed reduced *transient* response-related activity in response to trials on which speed was emphasised. It has been shown that lateral parietal regions, such as the area LIP in the monkey, are responsible for the accumulation of evidence towards a sensorimotor decision (e.g. Gold & Shadlen, 2002; Roitman & Shadlen, 2002). Thus, can Veen et al. argued that, under speed instructions, input from the DLPFC increases baseline activity in the IPL, resulting in less transient activation being required to reach the response threshold.

In contrast, other theories propose that the speed-accuracy tradeoff is controlled at the level of the basal ganglia. The *striatal* theory (Forstmann et al., 2008a) suggests that response threshold shifting is modulated by a network incorporating both cortical regions and the striatum, which controls the output of the basal ganglia. In their default state, output nuclei of the basal ganglia (globus pallidus and substantia nigra pars reticulata) tonically inhibit the thalamus and other subcortical regions in order to prevent movement execution (DeLong & Wichmann, 2007). Under instructions emphasising response speed, it is argued that top-down biasing from cortical regions results in increased activation in the striatum, which in turn lessens the inhibitory control that basal ganglia output nuclei exert on the brain. Forstmann et al. (2008a) found support for this theory using a model-based neuroscience approach that involved relating response threshold estimates to brain activation. Instructions emphasising speed over accuracy produced increased activation in both the pre-SMA and the striatum. Furthermore, the degree of activation in these regions was higher for individuals who had set their response threshold lower for speed as compared to accuracy instructions. Forstmann et al. suggested that, under low-risk conditions in which minimal conflict is encountered, the pre-SMA sends top-down input to

the striatum. This is consistent with evidence that pre-SMA plays a role in the preparation of internally-generated action plans (Nachev, Kennard & Husain, 2008). Moreover, Forstmann et al. (2010a) found support for the involvement of this network in threshold shifting, showing that white matter tract strength between pre-SMA and striatum was associated with increased flexibility in threshold setting.

Finally, the subthalamic nucleus (*STN*) theory suggests that under instructions emphasising accuracy, the STN receives input from medial and lateral prefrontal cortex (Frank, Scheres & Sherman, 2007). The STN sends excitatory input to the output nuclei of the basal ganglia, such that increased activity in this structure would have the effect of slowing or blocking motor output. Thus, the STN may control the speed-accuracy tradeoff by allowing more information to accumulate before making a decision. This theory is supported by evidence showing that conflict-induced slowing of motor responses is accompanied by increased activation in a right-lateralized network incorporating the STN, pre-SMA and IFC (Aron, Behrens, Smith, Frank & Poldrack, 2007, Aron & Poldrack, 2006). In addition, Aron et al showed that increased coherence in organization of white matter tracts linking these regions was associated with greater efficiency of response inhibition. Further, computational modeling work suggests that when conflict is detected, activation in the STN may promote slower and more accurate decision-making (Bogacz & Gurney, 2007; Frank, 2006).

In Chapter 7, we examine whether the regions shown to modulate response threshold in response to speed vs. accuracy instructions in two-choice decision making paradigms are also involved in threshold adjustment in response to repeat and switch cues in the cued-trials task-switching paradigm. Repeat cues may be seen as analogous to instructions emphasising speed, as repeating the same task is associated with minimal task-

related conflict and a low response threshold. In contrast, switch cues are similar to cues emphasising accuracy, in that they signal that task-related conflict is likely on the upcoming trial and are associated with a high response threshold. We examine whether the striatal theory can explain the low response threshold setting in response to repeat cues, and whether the STN theory can account for the high response threshold setting in response to switch cues.

6.2 Intrinsic setting of response threshold

The previous section focused on strategic trial-by-trial threshold adjustment in response to external cueing. However, response threshold may also be influenced by intrinsic preferences to be more cautious or more risky. This would affect overall setting of response threshold, rather than trial-by-trial response threshold adjustment. We may ask the question whether those networks shown to adjust response threshold on a trial-by-trial basis also underlie the preference to adopt an overall higher or overall lower threshold setting within the cued-trials task-switching paradigm.

Individual differences in global preferences for risky vs. cautious responding may be conceptualized as being similar to individual differences in personality-based impulsivity. There is evidence that fronto-striatal networks mediate impulsivity in normative samples. For example, using a go/no-go task, Brown, Manuck, Flory and Hariri (2006) showed that scores on the Barratt Impulsiveness Scale (BIS; Patton, Stanford & Barratt, 1995) were positively correlated with differential activation for no-go relative to go trials in bilateral ACC and caudate. They suggested that the greater activation in these regions for higher impulsivity individuals indicates a greater need for regulatory processes

under conditions of increased conflict (i.e., no-go trials). Other studies have found that striatal activation correlates with greater risk preference. For example, Rao, Korczykowski, Pluta, Hoang and Detre (2008) compared voluntary with involuntary risk taking using the Balloon Analog Risk Task (BART; Lejuez et al., 2002). Under voluntary task risk, participants decide whether to continue inflating a balloon for reward but at a risk of losing the reward if the balloon bursts. In the involuntary risk-taking condition, participants are required to continue inflating the balloon regardless of its size. In the voluntary condition only, an increase in balloon size was associated with an increase in activity in bilateral frontal regions (DLPFC and ACC) and striatum, suggesting that this fronto-striatal network is only activated under risk conditions involving agency.

These studies suggest that fronto-striatal networks may be associated with not only trial-by-trial adjustment of response caution, but also with individual variability in trait impulsivity. Chapter 8 takes a multi-modal approach to examine the question of whether the networks involved in trial-by-trial updating of response threshold within a cued-trials switching paradigm are also responsible for participants' preference to adopt an overall more cautious or overall more risky response regime. More specifically, we examine whether structural differences within these networks are related to individual differences in overall levels of response caution.

We also return to a question left unanswered in Chapter 7. In that Chapter, we showed evidence for the involvement of distinct cortico-basal ganglia networks in trial-by-trial adjustment of response caution. However, due to the slow nature of the BOLD response, we could only speculate that these networks were activated within the C-T interval, as part of an anticipatory threshold control process. Therefore, in this Chapter, we

combine structural measures with cue-locked ERPs to examine the association between these networks and trial-by-trial, anticipatory threshold setting.

Chapter 7: Adjustments of response threshold during task switching: A model-based fMRI study[7]

Contextual cues often provide guidance as to the degree of cautiousness required in decision making. For example, when there is little traffic on the road, the driver's decision to change lanes can be made quickly, with little sampling of information. However, in heavy traffic, a more cautious decision is required as more information must be sampled. In evidence accumulation models (e.g. Ratcliff, 1978; Grasman et al., 2009), response cautiousness is indexed using the *response threshold* parameter which represents the amount of information that needs to be accumulated before a decision can be made.

Adjustments in response threshold have been shown to be supported by cortico-basal ganglia networks (Bogacz et al., 2010). In two-choice response tasks, trial-by-trial threshold adjustment in response to instructions emphasising response speed over accuracy was associated with higher activation and increased structural connectivity in a network including the pre-supplementary motor area (pre-SMA) and striatum (Forstmann et al., 2008a; 2010a). Forstmann et al. (2008a) argued that, under conditions that emphasise speeded responding, the striatum is activated in order to lower the response threshold, releasing the motor system from a baseline state of global inhibition and thereby enabling rapid execution of a planned action. In contrast, the sub-thalamic nucleus (STN) was shown to respond to the need for greater response cautiousness (Frank, 2006; Fleming et al., 2010). Under high levels of response conflict, excitatory input from cortical regions

[7] Published as Mansfield, E. L., Karayanidis, F., Jamadar, S., Heathcote, A., & Forstmann, B. U. (2011). Adjustments of response threshold during task switching: A model-based functional magnetic resonance imaging study. *The Journal of Neuroscience, 31*, 14688-14692.

(including anterior cingulate cortex, ACC and inferior frontal cortex, IFC) to the STN slows the output of the basal ganglia thereby allowing more information to accumulate before a decision is made (Aron et al., 2007; Frank et al., 2007). In summary, distinct cortico-basal ganglia networks support adjustments in response caution as a function of speed compared with accuracy instructions, consistent with basal ganglia models of speed-accuracy tradeoff (see Bogacz et al., 2010).

Using a task-switching paradigm, we have shown previously that fully and partially informative switch cues produce higher response threshold estimates than repeat cues, indicating that participants set a more conservative threshold in response to cues that indicate upcoming conflict between action sets (Karayanidis et al., 2009). In this study, we test whether the cortico-basal ganglia networks that support adjustment of response caution in speed-accuracy manipulations are also involved in adjustment of response threshold as a function of trial-by-trial variation in cue informativeness in task-switching. We use an anatomical region of interest (ROI) approach that focuses on regions previously shown to form specialized networks for the adjustment of response threshold and examine the relationship between inter-individual variation in threshold setting and activation within these regions. We hypothesise that (a) repeat cues will show greater activation in the pre-SMA and striatum than switch cues; (b) switch cues will show greater activation in the STN than repeat cues; (c) response threshold on repeat cues will be inversely related with pre-SMA and striatal activation; and (d) response threshold on switch cues will be positively related to STN activation.

7.1 Methods

7.1.1 Participants

Twenty participants (8 males and 12 females; 25.35 ± 4.8 years, all right-handed, $20 reimbursement for travel costs) with no prior exposure to the paradigm underwent an initial training session, an ERP test session, and an fMRI/diffusion tensor imaging (DTI) test session (ERP and DTI data are not reported here).

7.1.2 Stimuli and Tasks

Three tasks were defined, each requiring a binary decision: a letter task (vowel/consonant), digit task (odd/even), and color task (hot/cold). A circle divided into six segments was continuously displayed, with groups of two adjacent segments demarcating three task regions (see Figure 7.1a). On each trial, a target appeared in one segment and consisted of a pair of characters (letter, number or symbols) presented in color or gray. Each target included three dimensions – one was relevant to the current task, one was incongruently mapped to the response on the current task, and one was neutral (i.e., non-alphanumeric character or target presented in grey). The same target could not appear on two successive trials. Responses were made with both hands, with response-hand mappings counterbalanced across participants.

Each trial began with a cue that highlighted two of the six segments (see Figure 7.1a). Four cue types were presented with equal probability (see Figure 4.1 in Karayanidis et al., 2009). The same cue could not appear on more than three consecutive trials. Cue to target interval (CTI=1000ms) and response to target interval (RTI=1400ms) were fixed. *Repeat* cues indicated that the same task would be repeated. *Switch-to* cues indicated that

the task would change and defined the new task. *Switch-away* cues indicated that the task would not repeat, but did not specify which of the other two tasks would be relevant (i.e., the cue overlapped two segments mapped to tasks that were not relevant on the previous trial). In this case, the location of the target defined which task would be performed. *Non-informative* cues indicated that a switch or a repeat trial was equally likely and were included to differentiate between preparatory and cue encoding processes in ERP waveforms. They are not included in the present analyses as, by definition, they provide no information that could contribute to threshold adjustment in preparation for the upcoming target.

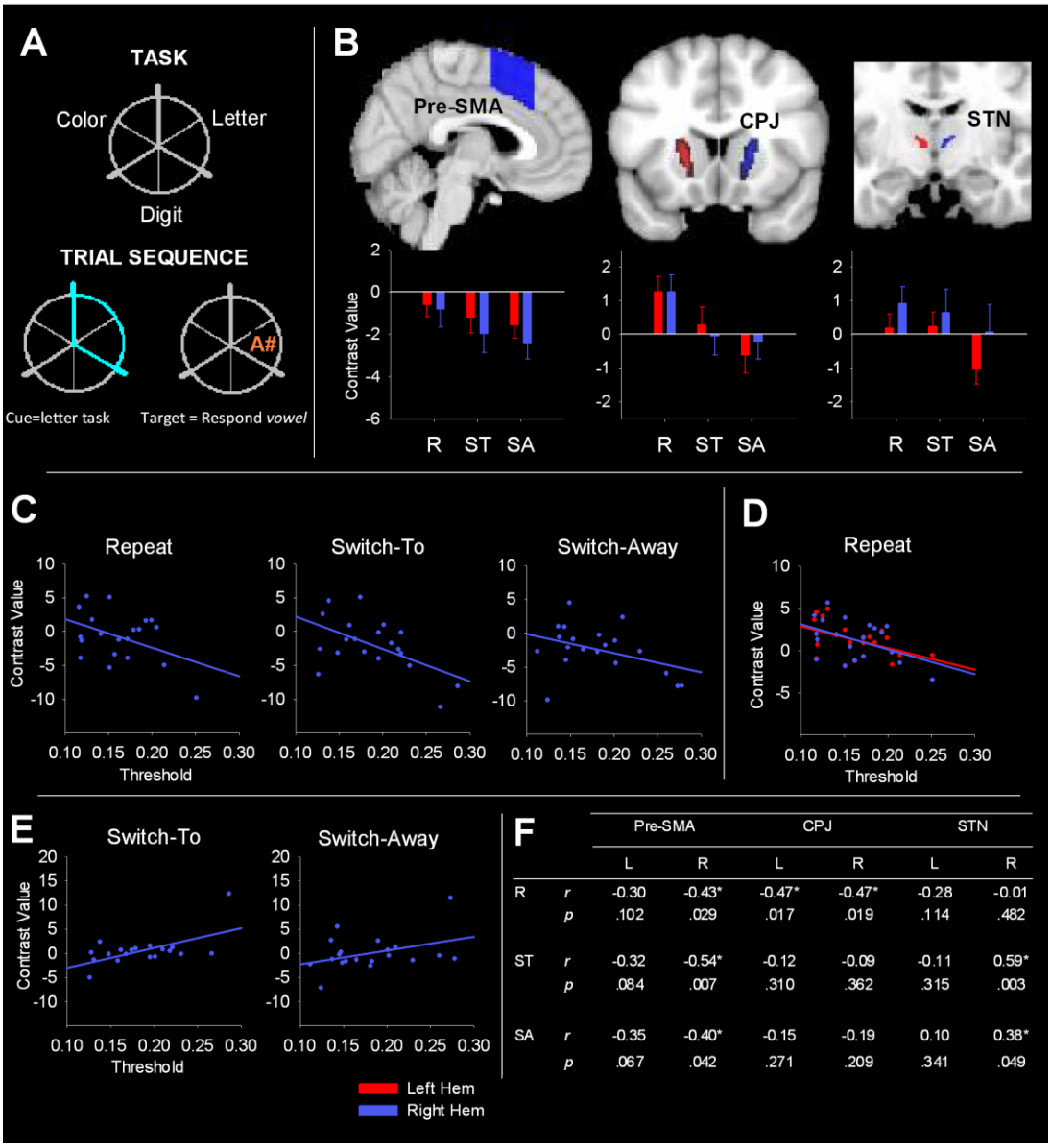


Figure 7.1: (A) Top: Task-location mapping. Bottom: Example trial sequence (B) Top: ROI masks. Bottom: mean contrast value for each cue type. (C, D, E) Significant correlations between threshold estimates and pre-SMA, CPJ and STN contrast values, respectively. (F) Coefficients and p-values for all correlations (see Methods). Significant correlations are marked with an asterisk. R = *repeat*, ST = *switch-to*, SA = *switch-away*.

7.1.3 Procedure

Participants attended three sessions. Session 1 involved task training (768 trials of single-task and mixed-task blocks). Training was repeated at onset of session 2. Sessions 2

and 3 included fMRI testing (five blocks of 101 trials) or ERP testing (ten blocks of 101 trials). All but five participants completed the fMRI session first.

For the fMRI session, participants lay supine in the scanner bore. Stimuli were presented against a white background and back-projected onto a mirror that was mounted on the head coil (visual angle 5°). Responses and scanner pulses were relayed through a custom built response box. Participants were instructed to perform the task as quickly and as accurately as possible. Auditory error feedback was provided after each incorrect response using MRI-compatible piezoelectric headphones. Mean RT and error feedback was given after each block.

7.1.4 Behavioral and EZ2 parameter analysis

The first five trials of each block, trials associated with or immediately following an error, and trials with RT<200ms or RT>3sd from participant's mean RT were excluded from analysis. Response threshold was derived using the EZ2 diffusion model of Grasman et al. (2009; cf. Karayanidis et al., 2009). Mean RT, error rate and all model parameters essentially replicated our earlier findings (see Table 7.1 for a summary of model parameters). Our hypotheses are specific to adjustments in response threshold, and hence we only report results relevant to this measure. There was no main effect or interaction of session (ERP vs. fMRI) or session order (i.e., ERP/fMRI vs. fMRI/ERP) on threshold. We report data from the ERP session because it had twice the number of trials and produced stronger effects than the fMRI session.

Response threshold was analysed using a 3 task (letter, digit, color) x 3 cue type (*repeat, switch-to, switch-away*) repeated measures ANOVA. There was a main effect of task (p=.033), with the letter task producing a higher threshold than both the digit and the

color task. However, because there was no interaction between task and cue type, all analyses were averaged over task. We examined differences between cue types using simple comparisons between repeat and each of the switch cues with Bonferroni correction.

7.1.5 Functional magnetic resonance image acquisition and data analysis

MRI data were acquired using a Siemens Avanto 1.5 T whole-body MR scanner equipped with a Siemens quadrature head coil. Anatomical images were collected using a T1-weighted MPRAGE protocol (TR = 1980 ms, TE = 4.3ms, flip angle = 15º, 256x256 matrix, FOV = 256mm, voxel size = 1x1x1mm, 176 slices). Functional images were acquired using a T2*-weighted echo planar imaging (EPI) sequence (4 mm slice thickness, 32 slices, TR = 3700 ms, TE = 70ms, flip angle = 90 º, FOV = 256mm, 64x64 matrix, voxel size = 4x4x4 mm, 92 scans per run). EPIs were obtained as ascending slices (with no gap) relative to the anterior-posterior commissural line.

Image pre-processing and statistical analyses were performed using SPM8 (Wellcome Department of Neurology, London). To allow for T1 saturation effects, the first 5 images from each run were removed. All images were checked for excessive motion or artefact using ArtRepair (http://spnl.stanford.edu/tools/ArtRepair/Docs/ArtRepairHBM2009.html); none of the images showed evidence of either excessive motion or artefact. Differences in EPI slice acquisition timing were corrected using the central slice as reference. Imaging time series were then realigned to the first EPI image and a mean realigned EPI image created. Motion was corrected using a rigid-body rotation and translation correction (Andersson et al., 2001). Each participant's T1 image was co-registered to the mean image and normalized to the SPM8 T1 template. The parameters from this transformation were then applied to all

EPI images. Accuracy of registration between functional and structural data was assessed by visual inspection of the overlay of each individual subject's mean EPI and normalised structural image. Normalized EPIs were then smoothed with a 8mm FWHM Gaussian kernel.

fMRI time series were analysed by fitting a convolved canonical haemodynamic response function and its temporal derivative (Josephs et al., 1997) to the onset of the cue for each cue type separately. Trials associated with errors were modeled as a separate factor, resulting in four experimental regressors (*repeat, switch-to, switch-away, errors*). Realignment parameters were modeled as regressors of no interest to account for motion artefact in the data. For each subject, each run was modeled separately.

7.1.6 ROI analysis

ROIs were selected based on the networks identified by Forstmann et al. (2008a) and Frank et al. (2007). Anatomically-defined ROIs were drawn onto the standard-space MNI152 template (voxel size 2 x 2 x 2mm) provided with FSLView (Functional MRI of the Brain Analysis Group, Oxford University, Oxford, UK; see Figure 7.1b). A pre-SMA mask was defined with rostro-caudal boundaries ranging from y = 0 to y = 30, based on the mask used by Johansen-Berg et al. (2004). A mask was also drawn over the region joining the caudate and putamen (caudate/putamen junction, or CPJ mask). The selection of this striatal region was motivated by a previous finding (Forstmann et al., unpublished data) that individual peak activations for threshold shifts under speed instructions lie between the caudate and putamen. Finally, an STN mask was derived from the structural 7T MRI scans identified by Forstmann et al. (2010a). Each mask was drawn bilaterally, resulting in a total of six ROIs. These masks were applied to contrast maps comparing each cue type to

baseline (*repeat > baseline, switch-to > baseline, switch-away > baseline,* herein referred to as *repeat, switch-to* and *switch-away* contrasts, respectively). The mean contrast value within each ROI for each participant was extracted using MarsBar version 0.42 (Brett et al., 2002).

Mean contrast values for each ROI were analysed with a 2 hemisphere (left, right) x 3 cue type (*repeat, switch-to, switch-away*) repeated measures ANOVA. Critical values were adjusted using Greenhouse-Geisser correction (Vasey and Thayer, 1987). Significant effects of cue were examined using polynomial contrasts and simple comparisons with Bonferroni correction. At each ROI, we examined correlations between mean ROI contrast value and response threshold value using Pearson's coefficients with one-tailed values given the directional nature of hypotheses and $\alpha=0.05$ (uncorrected).

7.2 Results

Response threshold showed a significant main effect of cue, $F(2,38)=10.76$, $p=.001$, with a strong quadratic trend ($p=.001$; see Table 7.1). This resulted from the large increase in response threshold from *repeat* to *switch-to* cues, $F(1,19)=19.16$, $p<.001$, and a smaller marginally significant difference between *repeat* and *switch-away* cues, $F(1,19)=5.78$, $p=.027$.

Table 7.1: Means and standard errors for each of the diffusion parameters for each cue type.

	Response Threshold		Drift Rate		Non-decision Time	
	Mean	SE	Mean	SE	Mean	SE
Repeat	0.163	0.011	0.244	0.013	383	12
Switch-To	0.189	0.007	0.194	0.012	384	21
Switch-Away	0.180	0.011	0.202	0.011	550	21

7.2.1 ROI analyses

Figure 1b shows ROI masks and activation values in pre-SMA, CPJ and STN. Pre-SMA activation showed a significant main effect of cue type, $F(2,38)=3.87$, $p=.039$, and a significant cue type x hemisphere interaction, $F(2,38)=4.77$, $p=.025$. All cue types showed deactivation relative to baseline, with greater deactivation in the right than the left hemisphere, especially for switch cues. The right pre-SMA showed a significant linear trend across *repeat*, *switch-to* and *switch-away* cues, $F(1,19)=7.27$, $p=.014$, with a significant difference between *repeat* and *switch-away* cues, $F(1,19)=7.27$, $p=.014$, and a marginally significant difference between *repeat* and *switch-to* cues, $F(1,19)=4.73$, $p=.042$. Weaker effects in the same direction were evident in the left pre-SMA.

Activation in the CPJ showed a significant main effect of cue type, $F(2,38)=12.32$, $p<.001$. A strong linear decline in activation was found across cue type, $F(1,19)=28.24$, $p<.001$ (see Figure 7.1b), and simple comparisons showed higher activation for *repeat* relative to *switch-to* cues, $F(1,19)=8.58$, $p=.009$, and *switch-away* cues, $F(1,19)=28.24$, $p<.001$. These differences were more pronounced in the left CPJ.

Although there was no significant effect of hemisphere or interaction with cue type ($p>0.10$), the effect of cue type was significant when analysing activation in the left STN

alone, $F(2,38)=4.85$, $p=.016$. Activation was smaller for *switch-away* cues than either *repeat* or *switch-to* cues ($F(1,19)=6.45$, $p=.02$, $F(1,19)=10.38$, $p=.004$, respectively). While the right STN showed a similar pattern of findings, the effects were not significant.

7.2.2 Individual differences

We examined whether individual variation in cortico-basal ganglia activation was associated with variability in response threshold. Figure 7.1, c and f, shows significant negative correlations between right pre-SMA activity and response threshold estimates for *repeat*, *switch-to* and *switch-away* cues. A significant negative correlation between CPJ activation bilaterally and response threshold was found for *repeat* cues only (Figure 7.1d, f). In contrast, the right STN (Figure 7.1e, f) showed positive correlations between contrast values and response threshold for both switch cue types. The correlation for *switch-to* cues was weakened with the removal of one participant whose right STN contrast value was an outlier, $r=0.33$, $p=.082$. There was no significant correlation between contrast values in the STN and response threshold for *repeat* cues. It is important to note that these correlations must be interpreted with caution, because they were obtained with one-tailed, uncorrected $\alpha=0.05$.

7.3 Discussion

This study aimed to determine whether cortico-basal ganglia networks shown to be responsible for threshold shifts in two-choice decision-making paradigms (e.g. Forstmann et al., 2008a) are also involved in threshold shifts in response to cues of different information value within a task-switching paradigm. The findings support a role

of these networks in the adjustment of response threshold. In addition, they show that these models may be extended to higher-order threshold adjustment processes involved in setting an appropriate degree of conservativeness for an upcoming task repetition or task switch trial. Moreover, individual differences analyses delineate the distinct role of these cortical and basal ganglia regions in dynamically adjusting response threshold.

As predicted, *repeat* cues showed the greatest activation in pre-SMA. In addition, the pattern of cue type effects in the pre-SMA showed that this region was particularly sensitive to the degree of information provided by the cue, such that higher activation was elicited by *repeat* cues, followed by *switch-to* and *switch-away* cues. The parametric pattern of activation in pre-SMA in response to cue information is consistent with a prominent role in the preparation of action plans (Cunnington et al., 2005). *Repeat* cues that signal that the previous action set is to be maintained, result in very high readiness for action. *Switch-to* cues that signal that an abandoned action set needs to be reloaded, result in less readiness for action and hence less pre-SMA activation than repeat cues. *Switch-away* cues do not signal which action set will need to be loaded and hence show the least preparation for action and the least pre-SMA activation.

In line with the pre-SMA findings, activation in the striatum was also larger for repeat cues relative to switch cues. Thus, the fronto-striatal network that is engaged to adjust response threshold in response to speed instructions on a two-choice decision-making task (Forstmann et al., 2008a) was activated here in response to *repeat* cues, which specify with certainty which task will be required and that the demand for cognitive control will be low. In addition, a linear pattern of activation was seen across cue types in CPJ, similar to that found for pre-SMA. It is interesting to note that this pattern of effects is inconsistent with the quadratic pattern of threshold differences between cue types, which

showed threshold increasing from *repeat* to *switch-away* to *switch-to* cues. Based on these effects, we would have expected less activation in these regions for *switch-to* relative to *switch-away* cues, but this was not the case. This inconsistency between threshold setting for switch cues and activation in these regions again supports the notion that this network is activated to adjust threshold in response to repeat cues only.

To further examine whether this was the case, we tested whether pre-SMA and striatal activation was associated with threshold estimates for each participant. Striatal activation was negatively correlated with threshold estimates for *repeat c*ues only, consistent with Forstmann et al.'s (2008a) finding that increased striatal activation is associated with more liberal response thresholds. However, we found negative correlations between right pre-SMA activation and threshold estimates for *all* cue types. Thus, although striatal activation was specifically associated with threshold setting in response to repeat cues, i.e, when participants were informed that a more liberal response regime could be implemented on the upcoming trial, right pre-SMA activation was associated with threshold setting in response to any type of cue information.

This unexpected finding that pre-SMA is related to threshold setting regardless of cue type may be explained by previous anatomical tracing studies in monkeys showing projections between pre-SMA and dorsolateral prefrontal cortex (DLPFC; Lu et al., 1994; Wang et al, 2005), a region coding for goal directed behavior, including the maintenance and manipulation of action-sets (e.g. Fassbender et al., 2006; Hester et al., 2007; Jamadar et al., 2010). The DLPFC is believed to increase baseline activity in motor-related and decision-related networks to control the speed-accuracy tradeoff (van Veen et al., 2008). Applied to our findings, this would predict that the DLPFC biases activation in pre-SMA according to the degree of cautiousness required for the upcoming task. Thus, pre-SMA

may be involved in threshold setting whenever the need for some form of goal-directed behavior is required, whether this involves maintenance of a particular task (*repeat* cues) or disengagement from the currently active task (*switch-to* and *switch-away* cues).

Together, our findings suggest that pre-SMA biases the striatum to set an appropriate response threshold specifically in situations in which cues call for more liberal response regimes. This provides further evidence that these two regions represent a 'go' pathway that releases the motor system from global inhibition, thereby facilitating execution of rapid responses when minimal response conflict is encountered (Mink, 1996).

Also in line with our hypotheses, we found that activation in right STN was positively correlated with threshold estimates for both types of switch cues, but not repeat cues. This provides strong evidence that the right STN plays a significant role in setting response threshold more conservatively so that more information can be accumulated before making a decision (Frank, 2006). These findings are inconsistent with the cue-related differences in left STN, which showed decreased activation for *switch-away* cues relative to *repeat* and *switch-to* cues. The present hemispheric differences offer the intriguing possibility of a dissociation in function between the left and right STN in terms of responsiveness to conflict. The decrease in activation for *switch-away* cues in the left STN is in line with Frank's suggestion that excessive uncertainty may result in the STN being switched off altogether. In contrast, the right STN appears to be involved in increasing response conservativeness when conflict is detected, despite not showing any overall change in activation depending on cue information. This discrepancy between hemispheres may be explained by the argument of Aron et al. (2007) for a right-lateralized network in which the STN is responsible for conflict-induced slowing. Thus, the right STN may be specifically involved in setting response criteria to produce slowing of output.

Our finding of right STN involvement in adjusting response caution is novel. Although Forstmann et al. (2008a) found that response threshold adjustment was related to activation in a fronto-striatal network including pre-SMA and striatum, they found no relationship with STN activation. This may have been due to the use of a whole brain approach, which is less sensitive to activation in small regions such as the STN. In this study, we defined a very precise STN mask using 7T structural scans from Forstmann et al. (2010a), which allowed for a more sensitive analysis of STN involvement.

Finally, it should be noted that, although we have discussed differences between cue types within these ROIs as relative differences in activation, in some cases we actually recorded *deactivation* relative to an implicit baseline. This effect was especially present in the pre-SMA, in which all cue types showed deactivation from baseline. Although, to our knowledge, no other study has shown this effect in pre-SMA, other studies have shown that nearby medial prefrontal regions, such as ACC, are deactivated in response to external cues demanding complex cognitive control (Lawrence et al., 2003; Hester et al., 2004). This suggests that the pre-SMA, along with regions in medial prefrontal cortex, may be globally inhibited in response to demanding cognitive tasks involving high levels of uncertainty and released from inhibition according to the ease with which action sets are retrieved.

Our findings reveal that prefrontal and basal ganglia regions play distinct roles in threshold adjustments depending on cue information. Although pre-SMA is involved in more general threshold adjustments in response to any type of information, the striatum and STN appear to control threshold adjustment under different circumstances. Bilateral striatum is involved specifically in threshold adjustments in situations where the upcoming task is well defined in advance of the target, whereas the right STN is involved in shifting criteria when conflict between task-sets is anticipated. These findings highlight the

importance of considering basal ganglia networks in neural models of executive control processes in task-switching (Karayanidis et al., 2010).

Chapter 8: Individual differences in strategic adjustments of response caution: Combined evidence from diffusion MRI and electrophysiology

Contextual cues provide guidance as to the degree of caution required when taking action within a particular situation. For example, when we see that the footpath is wet, we may take smaller, more cautious steps, compared to when the footpath is dry. Adjustments in response caution have been examined in evidence accumulation models using a response threshold parameter, which estimates the amount of evidence that needs to be accumulated before one response option is selected over another (Ratcliff, 1978; Wagenmakers et al., 2008; Grasman et al., 2009). When a low response threshold is set little evidence is required to make a decision, resulting in fast and more error-prone responses. In contrast, setting a high response threshold allows more evidence to accumulate, resulting in slower and more accurate responses.

Previous research suggests that cortico-basal ganglia networks are responsible for adjustments in response threshold (e.g., Forstmann et al., 2008a; 2010a; van Maanen et al., 2011; van Veen et al., 2008; see Bogacz et al., 2010 for a review). Forstmann et al. (2008a) showed that, on a two-choice decision-making task, instructions emphasizing speed over accuracy were associated with increased activation in the pre-supplementary motor area (pre-SMA) and striatum. In addition, individuals who set lower, more risky response thresholds showed greater activation within these regions than individuals who set more cautious thresholds. They argued that under a more liberal response regime the pre-SMA sends biasing signals to the striatum, which releases its inhibitory influence over output regions of the basal ganglia, resulting in fast responses. Mansfield et al. (2011) supported this conclusion by showing that, in a cued-trials task-switching paradigm, activity in these

regions was associated with threshold setting in response to cues of different information value. Pre-SMA activation was higher for individuals who set a lower response threshold, regardless of whether the cue predicted a difficult (task switch) or easy (task repeat) trial. The same negative relationship was found between response threshold and striatal activation, but only in response to cues predicting a repeat trial. In contrast, the subthalamic nucleus (STN) was found to play a role in setting a more cautious response threshold. STN activation was higher for individuals who set higher response thresholds in response to switch cues only. This finding is consistent with the argument that when increased conflict is encountered, frontal regions such as the anterior cingulate and inferior frontal gyrus (IFG) provide input to the STN, which in turn slows down motor output (e.g. Frank et al., 2007). Thus, fMRI data suggest that different networks are involved in threshold adjustment depending on whether a task cue calls for a more conservative (switch) or liberal (repeat) response regime.

Diffusion weighted imaging (DWI) – a technique that enables examination of white matter microstructure – has provided direct evidence for the existence of distinct pathways that enable communication between cortical and basal ganglia regions. For example, Forstmann et al. (2010a) showed that greater white matter connectivity between the pre-SMA and striatum was associated with lower response threshold setting, supporting the suggestion that, under speed stress conditions, the pre-SMA sends a biasing signal to the striatum (see also Forstmann et al., 2011a). In contrast, the STN has been shown to connect to the IFG (Aron et al., 2007), an area that has been strongly associated with conflict-induced slowing (Aron et al., 2003; 2004; Aron & Poldrack, 2006; Forstmann et al., 2008b), supporting the notion that these regions form a network that is responsible for increasing response caution.

8.1 Cortico-basal ganglia network integrity and overall response threshold setting

In sum, converging evidence from functional and structural imaging studies suggests that trial-by-trial adjustments of response threshold associated with more risky and more cautious decisions are supported in distinct cortico-basal ganglia networks. Individual differences in response threshold adjustment are not restricted to transient trial-by-trial adjustment - they can also emerge at the level of setting a sustained baseline for a particular task. That is, individual trait differences may determine whether participants have a general preference for setting a high or low response threshold, independent of trial-by-trial task demands. We investigate the physical basis of this trait difference by asking whether individuals classified as cautious or risky show differences in cortico-basal ganglia network connectivity.

Individual differences in impulsivity have been shown to be associated with variability in striatal activation. For example, Brown et al. (2006) showed that scores on the Barratt Impulsiveness Scale (BIS; Barratt, 1994) were positively correlated with caudate activation in response to a modified Go/No-Go task. This evidence suggests that the cortico-basal ganglia networks which have previously been shown to drive trial-by-trial setting of response threshold may also be responsible for individual differences in general preference for more cautious or more risky decision-making.

In the current study, we examine whether the cortico-basal ganglia regions which were differentially associated with cue-related changes in response threshold setting in a task-switching paradigm (Mansfield et al., 2011), also show structural differences between participants who adopt an overall more risky or more cautious response regime. In line with previous studies showing evidence for distinct networks associated with the direction of

response threshold adjustments, we expect that individuals who tend to set a lower, more risky, response threshold will show increased connectivity in a network incorporating striatum and pre-SMA, whereas individuals who prefer to set a higher, more cautious, response threshold will show increased connectivity in STN and IFG.

8.2 Cortico-basal ganglia network involvement in anticipatory threshold adjustment

High spatial resolution neuroimaging methods do not allow us to reliably tease apart the temporal dynamics of cognitive processes. However, behavioral evidence for trial-by-trial adjustments in response thresholds in a cued-trials task-switching paradigm has been found as a function of both the difficulty of the upcoming trial (Karayanidis et al., 2009) and the amount of time available to prepare for the upcoming target (Schmitz & Voss, 2012). Karayanidis et al. provided electrophysiological evidence that the amplitude of an early cue-locked event-related potential (ERP) component was negatively correlated with response threshold on task switch trials. So, it appears that, given sufficient time to prepare, participants can adjust their response threshold in advance of an upcoming trial, depending on how difficult or error-prone they expect this trial to be.

We take advantage of high temporal resolution of electrophysiological measurement to investigate the role of cortico-basal ganglia networks in the anticipatory control of thresholds. In particular, we examine whether individual differences in these structures are related to the cue-locked ERP correlates of threshold setting (Karayanidis et al., 2009). It has been suggested that DWI measures may be able to explain variability in ERP measures, as scalp-recorded electrophysiological activity represents the synchronous activity of large cell assemblies, which is influenced by the extent of axonal myelination

(Bartzokis, 2003). If these cortico-basal ganglia networks do support preparatory shifts in threshold, structural integrity within these regions should be able to account for at least some of the relationship between the cue-locked ERP component and response threshold setting (Karayanidis et al., 2009).

8.3 Methods

8.3.1 Participants

Twenty right-handed participants (12 females, 8 males) with mean age 25.35 years (SD = 4.8) had no prior exposure to the paradigm and gave written informed consent. Model parameters and fMRI data from these participants have previously been reported in Mansfield et al. (2011). For the current study, three participants were excluded due to large amounts of noise in the EEG or problems with the DWI acquisition resulting in a final sample of seventeen participants who had both ERP and DWI data.

8.3.2 Stimuli and Tasks

The paradigm was identical to that used by Karayanidis et al. (2009). A circle divided into six segments that were grouped into three major task segments (letter, digit, color) was presented continuously in the centre of the screen (see Figure 8.1a). Targets consisted of a pair of characters made up of combinations of letters, digits and non-alphanumeric symbols (Figure 8.1b). The targets consisted of three dimensions – one relevant to the currently active task, one selected from one of the other tasks and incongruently mapped with the currently active task, and one dimension that was neutral

(i.e., not mapped to any response). So, for example, a letter mapped to a left hand response would be paired with a digit mapped to a right hand response and would be presented in grey. The same target could not appear on two successive trials.

Each trial began with a cue, which was a highlight surrounding two adjacent segments of the circle (visual angle 5º). Four cue types (i.e., *repeat, switch-to, switch-away* and *non-informative*) were defined by cue location and were presented with equal probability in a pseudo-random sequence so that the same cue could not be repeated on more than three consecutive trials. *Repeat* cues highlighted the two task segments corresponding to the task performed on the previous trial, thus reliably predicting a repeat in task (Figure 8.1c). *Switch-to* cues highlighted two task segments associated with a task that had not been completed on the previous trial, reliably predicting a task switch, and defining the new task. *Switch-away* cues highlighted two task segments overlapping the two tasks not completed on the previous trial, reliably predicting a task switch, but not the task to be switched to. Hence, the task to be performed was defined when the target appeared. *Non-informative* cues highlighted two task segments overlapping the task performed on the previous trial, and a task that was not relevant on the previous trial. Thus, these cues specified that a switch or a repeat trial was equally likely. This cue type was designed to control for cue encoding processes in ERP waveforms and is excluded from the current analyses as, by definition, these cues do not provide any information that could contribute to preparatory threshold adjustment processes. Responses were made using the right and left shift keys. The cue-target interval was 1000 ms and the response-target interval was 1400 ms.

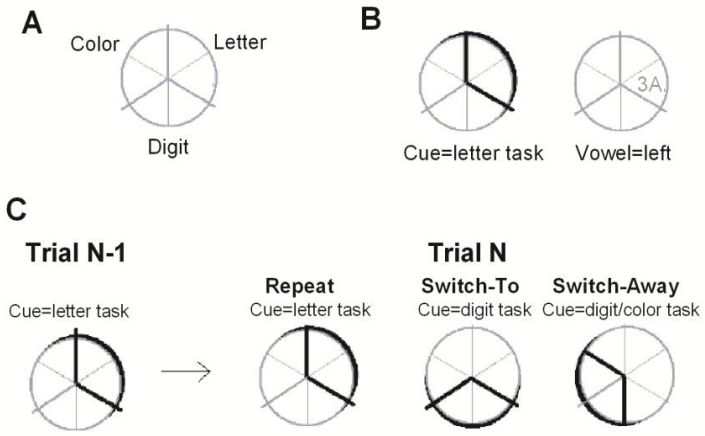


Figure 8.1: (A) The circular grid, including task-location mapping. (B) Trial sequence showing the cue followed by the target. (C) Sequence of two trials demonstrating the three cue types.

8.3.4 Procedure

Participants attended three sessions, with a maximum of 18 days between the first and last session. Task training included 768 trials in both session 1 and session 2. In session 2, training was followed by fMRI testing (which included the DWI scan) and session 3 consisted of ERP testing (10 blocks of 101 trials). Four participants completed ERP and fMRI/DWI sessions in reverse order. Participants were instructed to perform the task as quickly and as accurately as possible, and speed (mean RT) and accuracy (% error) feedback was given at the end of each block of trials. Errors were followed by auditory feedback.

8.3.5 Modeling of behavioral data

The first five trials of each block, trials associated with an error or immediately following an error were excluded from the analysis, as were trials on which RT was faster than 200 ms or slower than 3 standard deviations above each participant's mean RT. Model

parameters were estimated using the EZ2 diffusion model method (Grasman et al., 2009) separately for each participant and ERP and fMRI session. RT, error rates, and all model parameters replicated Karayanidis et al.'s (2009) substantive findings. Here, we report only response thresholds, as our hypotheses are specific to this parameter. The session type (ERP vs. fMRI) and session order did not produce any significant main effect or interaction in threshold estimates. We report threshold estimates from the ERP session for compatibility with ERP effects.

Response threshold was analysed using a 3 (task: letter, digit, color) x 3 (cue type: *repeat, switch-to, switch-away*) repeated measures ANOVA. Although there was a significant main effect of task, there was no interaction between task and cue type, so all analyses were averaged over task. We examined differences between cue types using Bonferroni corrected planned comparisons between repeat and each of the switch cues.

After confirming that threshold estimates were significantly correlated across cue type, participants were classified into a risky and a cautious group using a median split based on response threshold scores averaged across all cue types (one participant had the median score and was excluded). A 2 group (risky, cautious) x 3 cue type (*repeat, switch-to, switch-away*) mixed factors ANOVA was run to confirm that cue type did not interact with the group factor. We also ran simple effects analyses to examine whether these groups displayed similar patterns of trial-by-trial shifts in response threshold.

8.3.6 DWI acquisition and data analysis

8.3.6.1 DWI acquisition parameters

DWI data were acquired using a Siemens Avanto 1.5 T whole-body MR scanner. DWI was performed using an optimized version of the Siemens diffusion tensor sequence (TR 8400 ms, TE 88 ms, FOV 250x250 mm^2, acquisition matrix 104x104, 65 slices of 2.4mm thickness without gap). The 65 images acquired at each location consisted of one low-diffusion-weighted (b=0) and 64 high diffusion-weighted images (b=1000s/mm^2). The acquisition phase lasted 9.5 minutes.

8.3.6.2 Whole brain analysis using TBSS

DWI preprocessing and analysis were performed in FSL v4.1 (FMRIB's Software Library, www.fmrib.ox.ac.uk/fsl). Measures of fractional anisotropy (FA) were first derived before the data was submitted to Tract-Based Spatial Statistics (TBSS; Smith et al., 2006), a voxel-wise statistical analysis tool. FA indexes the relative directionality of diffusion of water molecules across tissue, with higher values indicating greater directionality of diffusion (known as anisotropic diffusion). Thus, in white matter, measurements of FA may be affected by properties such as axonal density, myelination, or compactness of tracts.

Affine registration to a reference volume was first performed to correct for eddy currents and head movement. To create FA images, a tensor model was fit to the raw images using FMRIB's Diffusion Toolbox (FDT). FA values close to 1 indicate the presence of anisotropic diffusion of water molecules, signifying the increased coherence of white matter tracts. Values approaching 0 indicate greater isotropic diffusion, which corresponds to a decrease in strength or coherence of white matter tracts. The resulting FA images were brain-extracted using FSL's Brain Extraction Tool (BET; Smith, 2002), before each participant's FA image was aligned to a common 1mm-space template using FMRIB's

Non-linear Image Registration Tool (FNIRT; Andersson, 2007). The mean of all FA images was then computed and thinned to create the mean FA skeleton, which was composed of the centers of tracts common to the group.

Each subject's FA data were projected onto the skeleton and the resulting images were submitted to TBSS. Separate general linear models were set up using demeaned response threshold for each cue type as covariates. To further confirm the results of these correlations, we examined differences in FA between the risky and cautious groups using t-tests. Correlations and group differences were tested at $p<0.01$, with a cluster-size threshold of 30 contiguous voxels (see Jänke et al., 2009).

8.3.6.3 Tractography

A post-hoc tractography analysis was performed to examine pathways associated with two striatal regions of interest (ROIs) that showed significant correlations with response threshold in the TBSS analysis. This technique allowed us to examine whether these regions form broader cortico-striatal networks responsible for threshold adjustment. More specifically, we examined qualitative differences between the networks associated with each of these striatal regions, as well as differences between the risky and cautious groups within these pathways. Fiber-tract estimation was performed using probabilistic tractography, based on a crossing-fiber model as implemented in bedpostX (FSL v4.1).

The two striatal ROIs were used to create MNI-space masks, which were then registered into each participants' native space. Tractography was performed using these masks as seed regions in probtrackX, with 5000 tract-following samples from each voxel, and a curvature threshold of 0.2. This analysis was carried out in each participant's native space, with resulting tract-maps registered to standard space to enable cross-participant

comparisons. Individual participants' tract maps were thresholded so that only tracts with at least 50 samples were kept. Thresholded maps were then binarized and added together within each group to produce separate group tract maps for risky and cautious groups. Hence, the value of a specific voxel within these maps indicates the number of participants who showed at least 50 tract samples passing through that voxel. The resulting group maps were further thresholded to only keep tracts that were present for at least two out of the eight participants in each group. As the results did not differ depending on whether the striatal ROIs were taken from the *switch-to* or the *switch-away* correlations, we display data from the *switch-to* correlations for compatibility with the following DWI/ERP/behavior analysis.

8.3.7 EEG acquisition and data analysis

8.3.7.1 EEG acquisition parameters

EEG was continuously sampled at 2048 Hz/channel from two mastoid and 64 scalp electrodes relative to a common mode sense (CMS) electrode and a driven right leg (DRL) electrode using a Biosemi ActiveTwo system. Vertical electro-oculogram was recorded from the supra-orbital and infra-orbital ridges of each eye and horizontal electro-oculogram was recorded from the outer canthi of each eye.

8.3.7.2 EEG data analysis

EEG data were analysed using Brain Electrical Source Analysis (BESA v5.3) software. Scalp electrodes were re-referenced offline to linked mastoids. EOG artifact correction was applied using a regression algorithm (Ille et al., 2002). Cue-locked EEG

epochs were extracted from 300ms before cue onset to 200 ms after target onset, with a 100ms baseline calculated from 50 ms pre- to 50 ms post-cue onset. Epochs with artifact exceeding a 100 μV threshold were rejected. Cue-locked waveforms were created for each cue type, averaged over response hand and task.

Waveforms were visually inspected to determine the time window of maximal differentiation in cue-locked positivity amplitude across cue types. Mean amplitude over 220-300 ms at a cluster of parieto-occipital electrodes (PO3, POz and PO4) was analyzed using a repeated measures ANOVA with three levels of cue type. Bonferroni corrected planned comparisons were carried out between each of the three cue types.

8.3.8 DWI, ERP and behavior analysis

Karayanidis et al. (2009) showed that the amplitude of the cue-locked positivity for *switch-to* trials was negatively correlated with threshold. We investigated whether this temporal information could be linked to spatial information about threshold adjustment, as indexed by our FA measures. More specifically, we examined whether the relationship between cue-locked positivity amplitude and demeaned response threshold was mediated by any of the white matter regions shown to significantly correlate with threshold. Such a mediating relationship would allow us to determine whether the preparatory strategy associated with threshold shifting (as indexed by the cue-locked positivity) was being driven by specific neural structures.

Using our TBSS results, we focused on frontal and striatal regions that were significantly correlated with threshold, and that have previously been shown to form networks responsible for threshold shifting (e.g. Forstmann et al., 2008a; Mansfield et al., 2011). Hence, we selected a region within the right external capsule in which FA showed a

negative correlation with threshold, and regions in the right IFG and right anterior limb of the internal capsule, in which FA was positively correlated with threshold. We also examined a pre-SMA region, which was negatively correlated with threshold for *repeat* trials, but did not reach the cluster threshold for *switch-to* trials. We first correlated FA from each of these regions with the cue-locked positivity for *switch-to* trials. Then, we examined whether the strength of the correlation between the cue-locked positivity amplitude and threshold was affected when partialling out FA within each of these regions. All correlations were two-tailed and type I error was controlled using Bonferroni correction.

8.4 Results

8.4.1 Response Threshold

Response threshold differed significantly between cue types, $F(2,32)=8.87$, $p=.003$. Response threshold for *repeat* cues ($M=0.161$, $SE=0.009$) was significantly lower than for *switch-to* cues ($M=0.189$, $SE=0.011$), $F(1,16)=15.73$, $p=.001$, and marginally lower than for *switch-away* cues ($M=0.179$, $SE=0.012$), $F(1,16)=4.95$, $p=.041$.

8.4.1.1 Median split analysis

Response threshold estimates correlated strongly between all three cue types (*repeat* and *switch-to*, $r=.79$, $p<.001$; *repeat* and *switch-away*, $r=.75$, $p=.001$; *switch-to* and *switch-away*, $r=.94$, $p<.001$). Thus we used a median split based on average response threshold to assign participants to a risky or a cautious group. The groups differed significantly in

response threshold, $F(1,14)=25.23$, $p<.001$: 0.142 and 0.21 for risky and cautious groups, respectively (Figure 8.2). However, importantly, there was no interaction between cue type and group, $F(2,28)=1.92$, $p=.17$. For both risky and cautious groups, response threshold for *repeat* cues was significantly lower than for *switch-to* cues, (risky: $F(1,7)=16.57$, $p=.005$; cautious: $F(1,7)=11.65$, $p=.011$), but not *switch-away* cues, (risky: $p=.23$; cautious: $p=.14$). Hence, despite being overall more risky or more cautious, participants showed similar trial-by-trial threshold adjustment between cue types.

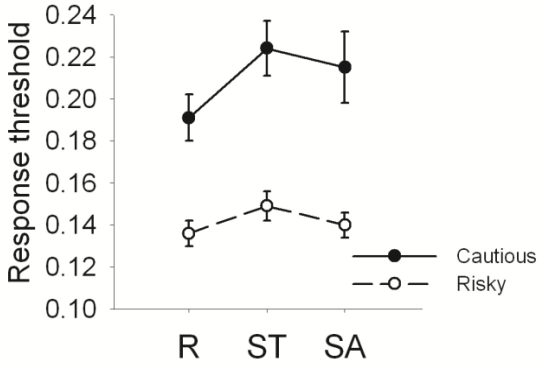


Figure 8.2: Response threshold means (and standard errors) for cue type and group (risky vs. cautious). R = Repeat, ST = Switch To, SA = Switch Away.

8.4.2 DWI analysis

8.4.2.1 Whole brain analysis

Using a whole brain analysis approach, white matter FA showed significant correlations with response threshold for each cue type (Table 8.1 and Figure 8.3a: negative correlations; Table 8.2 and Figure 8.3b: positive correlations). Regions in right pre-SMA

and right superior parietal lobule were negatively correlated with threshold for *repeat* trials. A region in right pre-SMA also correlated with response threshold for *switch-to* cues, however it did not reach the cluster-level threshold. The only region that negatively correlated with threshold for switch cues was in the external capsule, a region lateral to the putamen. A non-significant cluster in this region also correlated with threshold for repeat cues. Hence, white matter regions within pre-SMA and lateral to the putamen both showed increased integrity in individuals who set lower response thresholds (see Figure 8.3a).

In contrast, a distributed network of white matter in frontal, striatal and posterior parietal regions correlated positively with threshold (see Table 8.2). Across all cue types, FA in right IFG correlated with threshold, whereas FA in left IFG correlated with threshold for switch cues only. Interestingly, a region between right caudate and putamen and within the anterior limb of the internal capsule positively correlated with threshold only for the switch cues (Figure 8.3b).

Table 8.1: MNI co-ordinates and r-values for white matter (WM) regions that showed significant negative correlations with response threshold. All contrasts were thresholded at $p<.01$, and at least 30 contiguous voxels.

Region (BA)	Left Hemisphere		Right Hemisphere	
	MNI	r	MNI	r
Repeat				
WM region in dorsal pre-SMA	-	-	7, 15, 62	.69
WM region in ventral superior parietal lobule	-	-	28, -50, 49	.78
Switch-To				
External capsule	-	-	30, 12, 4	.73
Switch-Away				
External capsule	-	-	29, 13, 4	.77

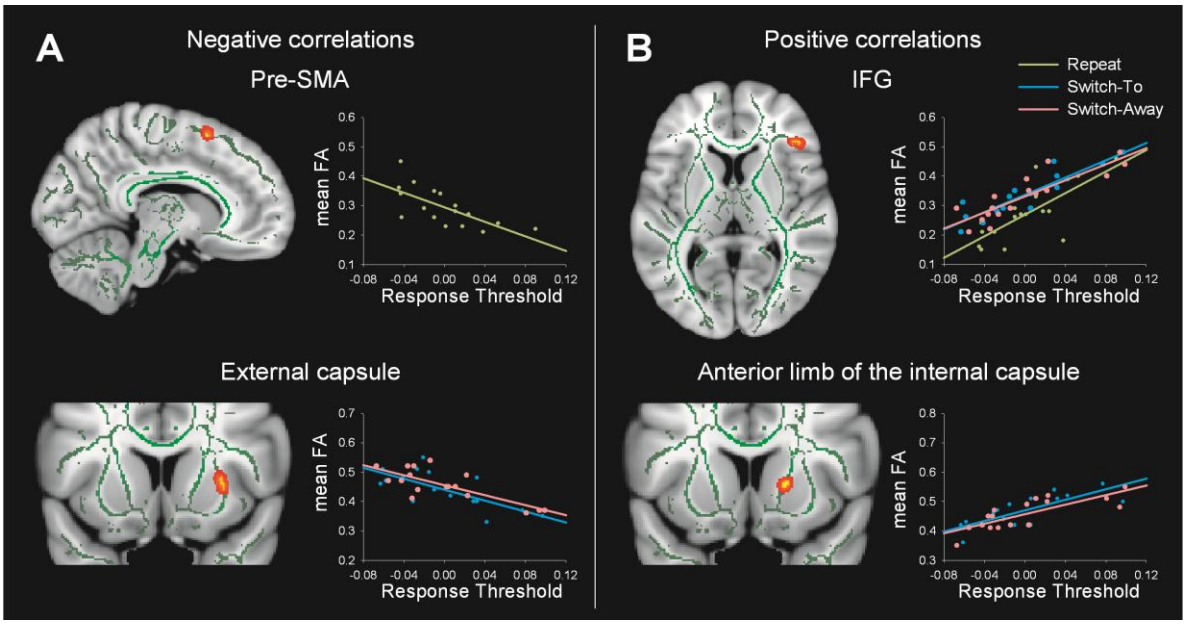


Figure 8.3: FA regions showing significant negative (A) and positive (B) correlations with demeaned response threshold. Regions (red-yellow) are thickened to aid visualization and overlaid on the mean FA skeleton (green-light green). As these regions showed a high degree of overlap across cue types, the displayed regions are taken from the *switch-to* correlations, for compatibility with subsequent DWI/ERP/behavior analyses.

Hence, the TBSS analysis produced two striatal regions that appear to show dissociable functions – a region in right external capsule in which increased FA was associated with more risky responding, and a region in the right anterior limb of the internal capsule in which increased FA was associated with more cautious responding. These regions significantly correlated with response threshold only for switch cues. However, both regions showed similar clusters for repeat cues that did not reach threshold. This pattern of effects suggests that white matter organization within distinct regions of the striatum may be responsible for lower threshold setting in more risky participants and higher threshold setting in more cautious participants, respectively.

To examine the robustness of these effects within the striatum, we compared FA within these regions for risky and cautious groups. The external capsule showed significantly higher FA for the risky as compared to the cautious group (*switch-to:* $t(14)=-4.5$, $p<.001$; *switch-away:* $t(14)=-3.82$, $p=.002$). However, FA in the anterior limb of the internal capsule did not differ significantly between cautious and risky groups (both $p>.01$).

Table 8.2: MNI co-ordinates and r-values for white matter (WM) regions that showed significant positive correlations with response threshold. All contrasts were thresholded at $p<.01$, and at least 30 contiguous voxels.

Region (BA)	Left Hemisphere		Right Hemisphere	
	MNI	r	MNI	r
Repeat				
Frontal				
WM region in posterior frontal orbital gyrus	-	-	18, 15, -18	.77
WM region in ventral inferior frontal gyrus (pars triangularis)	-	-	48, 25, -2	.73
WM region ventro-medial to middle frontal gyrus	-	-	28, 28, 21	.81
Parietal				
WM region lateral to posterior cingulate	-18, -54, 27	.83	14, -42, 21	.79
WM region ventral to posterior cingulate	-	-	6, -31, 23	.72
WM region lateral to precuneus	-13, -61, 46	.80	24, -56, 28	.71
Occipital				
WM region medial to lateral occipital gyrus (inferior division)	-	-	26, -90, 2	.80
WM region ventro-medial to lateral occipital gyrus (superior division)	-	-	27, -65, 24	.78
Cerebellar				
WM region adjacent to cerebellar tonsil	-	-	27, -47, -36	.75
WM region adjacent to cerebellar pyramis	-12, -70, -32	.88	17, -70, -30	.75
Switch-To				
Frontal				
WM in dorsal frontal orbital cortex	-	-	17, 16, -17	.82
WM in ventral inferior frontal gyrus (pars triangularis)	-	-	45, 27, 0	.90
WM region medial to inferior frontal gyrus (pars opercularis)	-33, 13, 23	.80	-	-
WM region posterior to insula	-33, -26, 3	.75	-	-
WM region lateral to paracingulate gyrus	-	-	17, 8, 41	.67
WM region in ventral superior frontal gyrus	-10, 32, 45	.73	-	-
Parietal				
WM region anterior to precuneus	-16, -52, 24	.86	19, -46, 20	.87
WM region lateral to precuneus	-	-	27, -64, 24	.90
WM region medial to parietal operculum	-35, -36, 26	.70	-	-
WM region in ventral postcentral gyrus	-38, -25, 42	.76	-	-
Subcortical				
Anterior limb of the internal capsule	-	-	17, 12, 2	.77
Occipital				
WM region anterior to occipital fusiform gyrus	-24, -79, 5	.69	-	-
WM region lateral to intracalcarine cortex	-	-	24, -79, 8	.72

WM region medial to lateral occipital gyrus (superior division)	-22, -79, 17	.76	-	-
WM region in posterior cuneus	-12, -85, 30	.75	-	-
Cerebellar				
WM region adjacent to cerebellar tonsil	-	-	31, -45, -38	.83
Switch-Away				
Frontal				
WM region in anterior frontal orbital cortex	-	-	39, 36, -11	.74
WM region in ventral inferior frontal gyrus (pars triangularis)	-	-	47, 25, 0	.86
WM region medial to inferior frontal gyrus (pars opercularis)	-33, 14, 22	.78	-	-
WM region lateral to anterior cingulate	-	-	17, 8, 41	.69
WM region ventral to precentral gyrus	-	-	15, -17, 55	.74
Parietal				
WM region anterior to precuneus	-17, -53, 23	.91	-	-
WM region lateral to precuneus	-	-	28, -64, 18	.87
WM region medial to parietal operculum	-35, -37, 26	.73	-	-
WM ventral to postcentral gyrus	-36, -25, 42	.69	-	-
Subcortical				
Anterior limb of the internal capsule	-	-	17, 11, 2	.79
Occipital				
WM region ventral to lateral occipital gyrus (superior division)	-	-	24, -81, 7	.80
WM region ventral to lateral cuneus	-12, -85, 30	.75	-	-
Cerebellar				
WM region adjacent to cerebellar tonsil	-	-	32, -45, -38	.78

8.4.2.2 Tractography

To examine whether the above two striatal regions form separable networks responsible for threshold adjustment, we conducted probabilistic tractography using these regions as seed masks and compared results for the risky and cautious group (Figure 8.4a and b). Projections from right external capsule overlapped with anterior portions of the cortico-spinal tract, as well as posterior portions of the superior longitudinal fasciculus (Figure 8.4a). These projections innervated the right pre-SMA, right posterior parietal and

superior temporal regions, and were more extensive for the risky group (blue) than the cautious group (orange).

In contrast, the anterior limb of the internal capsule was part of a pathway that largely overlapped with the anterior thalamic radiation, incorporating both right anterior prefrontal cortex (PFC) and IFG (Figure 8.4b). Although connections to anterior PFC were equally strong for risky and cautious groups, the cautious group showed increased connectivity within the right IFG.

In summary, tractography analyses showed that the two striatal regions were part of distinct neural networks that varied in strength across risky and cautious groups.

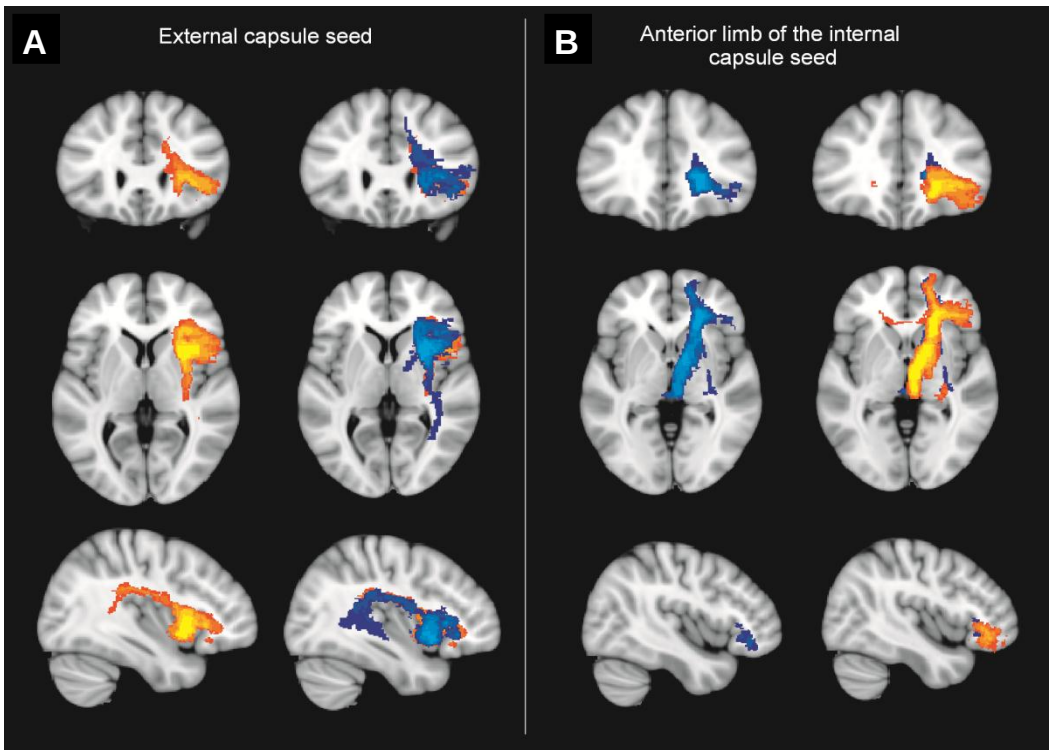


Figure 8.4: Probabilistic tractography analysis for (A) tracts originating from right external capsule seed. Left column shows significant tracts for the cautious (orange) group and right column shows significant tracts for the risky (blue) group, overlaid on the cautious group. (B) tracts originating from right anterior limb of the internal capsule seed. Left column shows significant tracts for the risky group and right column shows significant tracts for the cautious group, overlaid on the risky group.

8.4.3 ERP analysis

Figure 8.5a shows cue locked waveforms at a parieto-occipital cluster of electrodes (PO3, POz, PO4), which showed the largest cue-locked positivity. Cue-locked waveforms showed an N2-like component which was followed by a prolonged positivity over approximately 200 to 650 ms and a later pre-target negativity. The timeframe and amplitude of these effects differed as a function of cue type. We examined the early portion of the cue-locked positivity (mean amplitude over 220-300 ms), which has been previously shown to correlate with threshold adjustment (Karayanidis et al., 2009). There was a significant main effect of cue type, $F(2,32)=36.66$, $p<.001$. *Switch-to* cues ($M=4.86$, $SD=2.92$) and *switch-away* cues ($M=4.72$, $SD=3.38$) showed a larger early cue positivity than *repeat* cues ($M=0.49$, $SD=3.38$; $F(1,16)=66.2$, $p<.001$; $F(1,16)=35.79$, $p<.001$, respectively), but did not differ from each other.

8.4.4 DWI, ERP and behavior analysis

Consistent with Karayanidis et al. (2009), a larger cue-locked positivity for *switch-to* cues was associated with lower response threshold, $r=-.47$ (see Figure 8.5b), although the relationship was only marginally significant ($p=.056$). A larger cue-locked positivity was also associated with lower response threshold for *repeat* and *switch-away* cues, but these correlations did not reach significance.

Figure 8.5c shows correlations between the cue-locked positivity amplitude and FA. After correction, there was a marginally significant positive correlation between the cue-locked positivity and FA in the external capsule, $r=.58$, $p=.02$, while the pre-SMA showed a non-significant trend in the same direction ($p=.1$). In contrast, a marginally significant negative correlation was found between the cue-locked positivity and FA in the anterior

limb of the internal capsule, r=-.56, p=.02, but there was no relationship between positivity and FA in IFG (p>.3). Thus, a large cue-locked positivity was associated with *higher* FA in the external capsule, and *lower* FA in the anterior limb of the internal capsule.

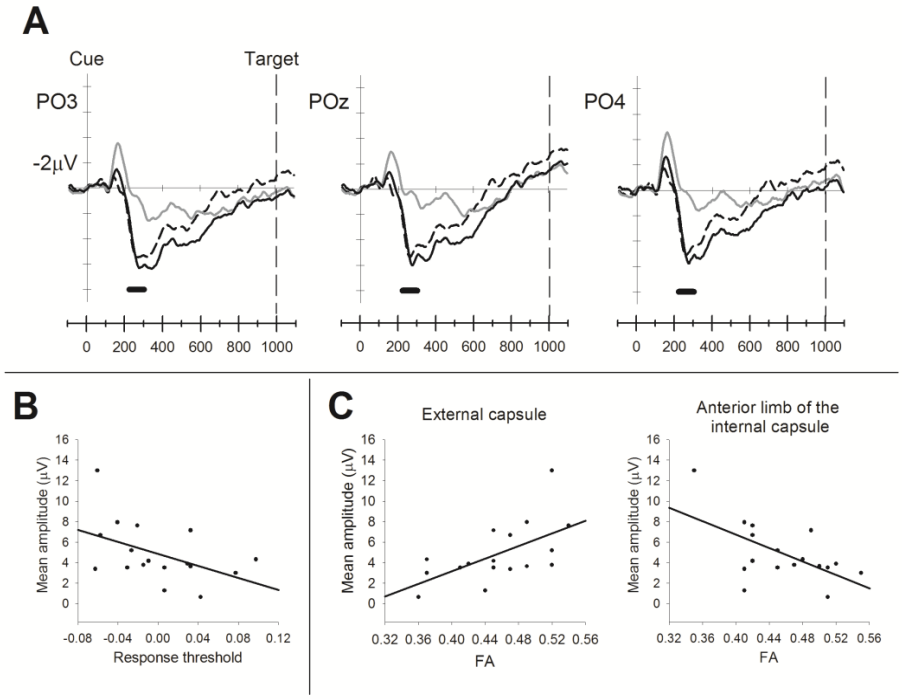


Figure 8.5: (A) Cue-locked ERP waveforms for *repeat* (grey), *switch-to* (black solid), and *switch-away* (black dashed) trial types. Bold black bars show the 220-300 ms mean amplitude window. (B) Correlation between demeaned response threshold and mean amplitude of the cue-locked positivity for *switch-to* cues. (C) Correlation between mean amplitude of the cue-locked positivity for *switch-to* cues and FA in the right external capsule (left) and right anterior limb of the internal capsule (right).

We ran partial correlations to determine whether FA in any of these regions mediated the relationship between ERP amplitude and response threshold. When FA values from the frontal regions were entered as covariates, the relationship between cue-locked positivity amplitude and threshold was inconsistently either weakened (in the case of pre-

SMA, r=-.29, p=.28) or strengthened (in the case of IFG, r=-0.59, p=.02). However, the relationship between cue-locked positivity amplitude and threshold was completely eliminated when variability associated with FA in either the external capsule *or* the anterior limb of the internal capsule was partialled out (r=-0.09, p=.74; r=-0.08, p=.77, respectively). Hence, FA in striatal, but not frontal regions mediated the relationship between the preparatory ERP component and response threshold.

8.5 Discussion

Previous studies suggest that response threshold can be adjusted on a trial-by-trial basis depending on external cue information within a cued-trials task-switching paradigm (Karayanidis et al., 2009; Schmitz & Voss, 2012). However, the setting of response threshold may also depend on traits intrinsic to individual participants. That is, people may have an overall preference for more cautious or more risky decision-making, while at the same time making transient adjustments of response caution in response to incoming information from the environment. We examined whether trait differences can be explained by structural organization in the same cortico-basal ganglia networks that subserve trial-by-trial response threshold adjustment. Additionally, we sought to determine whether these networks could explain individual differences in anticipatory control of response thresholds. The results revealed that white matter organisation in distinct fronto-striatal networks could account for individual differences in preference for high or low response threshold setting. In addition, white matter structure in striatal, but not frontal, regions accounted for individual differences in anticipatory threshold adjustment.

A median split analysis was used to produce risky and cautious participant groups that differed in overall response threshold but not in their ability to make trial-by-trial threshold adjustments in response to informative task cues. We used both correlational and group-based analyses to identify structural differences in white matter organisation of fronto-striatal networks associated with setting a more cautious or more risky response threshold.

8.5.1 FA-response threshold relationships

Whole-brain analysis using TBSS (Smith et al., 2006) produced multiple regions in which FA significantly correlated with response threshold for each cue type (Tables 8.1 and 8.2). Response threshold was negatively correlated with FA in a white matter region in the pre-SMA for repeat cues and in the right external capsule of the striatum for both switch cue types. Thus, we found evidence that the fronto-striatal network that plays a role in decreasing response threshold in response to task instructions (e.g., Forstmann et al., 2008a) also underlies the tendency to take an overall more risky approach to responding.

In contrast to the very focused network shown to be associated with the tendency to set a low 'risky' response threshold, the tendency to set a high 'cautious' threshold was associated with increased FA in a more diffuse network incorporating orbital frontal, inferior frontal and medial parietal cortex. In addition, the medial part of the right striatum (anterior limb of the internal capsule) was associated with increased threshold setting for switch cues. The fact that setting a higher response threshold was associated with increased FA in this wider network of frontal, parietal and striatal regions suggests that this intrinsic tendency may be attributed to greater control signalling from cortical to basal ganglia regions. In particular, the right IFG has been strongly linked to inhibitory control (Aron et

al., 2003; 2004; Forstmann et al., 2008b), suggesting that the tendency to be more conservative may be related to greater inhibitory signalling from this region to the basal ganglia, which results in slowed motor output.

Perhaps most intriguingly, our findings also showed a dissociation between two white matter regions within the striatum. The external capsule, a lateral region of the striatum, was associated with risky response threshold setting, whereas the anterior limb of the internal capsule, a medial region of the striatum, was associated with cautious response threshold setting. Probabilistic tractography analysis confirmed that these two regions were associated with distinct neural networks. Seeding the external capsule produced connections with the pre-SMA that were stronger for the risky group (see also Lehéricy et al., 2004). This supports the notion that participants who set a low response threshold have enhanced top-down signalling from the pre-SMA to the striatum, yielding a faster release of the basal ganglia from inhibition (Bogacz et al., 2010; Mink, 1996). In contrast, the anterior limb of the internal capsule produced connections with the anterior PFC and IFG within a network that corresponded closely to the anterior thalamic radiation. Connections to the IFG were stronger for the cautious group. This finding is consistent with the TBSS results and suggests that a preference for cautious responding is mediated by enhanced signalling from the right IFG to the basal ganglia, producing a slowing of motor output.

In sum, not only were the external capsule and anterior limb of the internal capsule found to be part of distinct fronto-striatal networks, but also the strength of connectivity within these networks varied according to whether participants adopted a cautious or risky response strategy.

8.5.2 Networks underlying trial-by-trial threshold adjustment vs. overall threshold setting

There were two noticeable discrepancies between our current and our previous findings that examined trial-by-trial threshold adjustments. Firstly, while Mansfield et al. (2011) showed that BOLD activation in a region between caudate and putamen was negatively related to response threshold, the current findings show that FA in the anterior limb of the internal capsule, which also lies between these two structures, was *positively* related to response threshold. This inconsistency highlights the complexity of striatal organisation (see Draganski et al., 2008) and suggests that the relationship between regions within the striatum and setting of response conservativeness is not straightforward. One possible reason for this discrepancy is that the cluster within the anterior limb of the internal capsule that was significant for the current study represented only a small, anterior segment of Mansfield et al.'s caudate-putamen junction (CPJ) mask. Hence, the effects observed in our previous study could have been driven by activation changes in another (perhaps more posterior) region between the caudate and putamen. These inconsistent findings may also be attributed to the nature of the measurements derived in each case – while BOLD represents changes in blood oxygenation in response to external events, FA is a static structural measure based on the diffusion properties of tissue. Therefore, the lack of a direct correspondence between these measures is not surprising, particularly given the complexity of brain structure-function relationships (see Damoiseaux & Greicius, 2009). These discrepant findings highlight the need for systematic analyses using high spatial-resolution measurements to examine how sub-regions within the striatum are related to setting of response threshold.

Second, based on Mansfield et al.'s (2011) finding that increased threshold setting in response to switch cues was associated with increased activation in the right STN, we

predicted an association between overall more cautious response threshold setting and white matter connectivity in the STN. However, TBSS analysis did not produce any significant correlations between threshold setting and FA within the vicinity of the STN, nor did we find evidence for stronger projections from the anterior limb of the internal capsule to the STN for the cautious group compared to the risky group. One possible explanation is that the right STN may be involved in dynamic trial-by-trial threshold changes based on cue information, but not in a more global preference for a cautious approach to responding. In contrast to this specialised role of the STN, the striatum appears to play a more general role in setting response threshold, responding dynamically to cue information to bring about threshold adjustments, while also determining the overall level of response caution.

8.5.3 ERP-response threshold relationships mediated by FA

A secondary aim of this study was to examine whether these fronto-striatal networks could explain individual differences in anticipatory control of threshold, that is, threshold adjustments that are carried out during the cue-target interval. Karayanidis et al. (2009) showed that a large cue-locked positivity for *switch-to* cues is associated with setting a low threshold, suggesting that response threshold is adjusted prior to target onset. In the current study, we combined DWI and ERP data to examine whether fronto-striatal regions underlie anticipatory control of response threshold.

ERP data replicated the finding that cue-locked positivity amplitude for *switch-to* cues is negatively correlated with response threshold. We used an ROI approach to examine the structures which may explain this relationship, focusing on frontal and striatal white matter regions produced from the TBSS analysis that formed distinct networks associated

with threshold setting. Entering FA from either the external capsule or the anterior limb of the internal capsule as a covariate completely eliminated the relationship between the cue-locked positivity and response threshold. In contrast, entering FA from the pre-SMA region or the IFG region as a covariate produced only small changes in this relationship. The fact that neither of the two frontal regions mediated the relationship between cue-locked positivity and response threshold suggests that anticipatory setting of response threshold may be related to structural integrity specifically within the striatum. This indicates that a crucial aspect of the ability to flexibly shift response threshold in anticipation of an easy or a difficult trial lies in the efficiency with which gating mechanisms within the striatum can be engaged, rather than the efficiency of signalling from cortical regions to the striatum.

8.5.4 Conclusion

The results of the current study suggest that individual differences in the overall setting of response thresholds can be explained by structural integrity in some of the same networks that are engaged for trial-by-trial threshold adjustments based on external cues. These findings extend our understanding of fronto-striatal involvement in setting response caution, suggesting that these networks have a general role in setting thresholds, whether this is in response to external cues or a result of intrinsic trait-related tendencies. In addition, by combining the spatial resolution of DWI data and the temporal resolution of ERP data, we added temporal information to existing neural models of response threshold adjustment, showing that preparatory control of threshold adjustment is linked to the striatum. Taken together, our findings show that the striatum is instrumental in both global setting of response thresholds and transient adjustment of thresholds on the basis of external cue information.

Chapter 9: General Discussion

For decades now, there has been a great deal of interest in uncovering the processes underlying the switch cost - the decline in performance that occurs when switching to a different task compared to repeating the same task. Behavioral evidence has shown that multiple processes contribute to switch cost, including passive carry-over of interference, as well as active control processes that reconfigure the task-set (see Kiesel et al., 2010; Vandierendonck, Liefooghe & Verbruggen, 2010 for a review). It has also been shown that at least some of these active control processes can be completed proactively, in anticipation of target onset. However, it is still unclear whether preparation to switch tasks involves qualitatively distinct preparation compared to the more general task preparation required on all trials. The aim of this thesis was to examine the evidence for distinct switch-related preparation processes and to define the nature of this preparation.

We developed a task-switching paradigm that was designed to delineate distinct preparatory control processes. This paradigm represents a significant step forward from typical cued-trials task-switching paradigms that only include fully-informative switch and repeat cues. In these paradigms, switch cues signify not only a switch in task but also the upcoming task itself. Therefore, these paradigms do not allow us to differentiate between processes specifically elicited in preparation to switch task from more general preparation processes such as arousal or task expectancy processes, which we refer to below as task readiness. Our paradigm introduced partially informative switch cues, that is, cues that reliably predict a switch in task but do not specify the upcoming task. Hence, both fully-informative *switch-to* cues and partly-informative *switch-away* cues validly predict a change in task, but only the former provide reliable information about the identity of the

new task. Therefore, this paradigm dissects proactive control processes occurring during the cue-target interval into readiness to switch (*switch-to, switch-away*), uploading of new task-set (*switch-to*) and task readiness (*switch-to, repeat*). This paradigm was modeled on earlier work by Nicholson et al. (2006b), but included a critical *non-informative* cue condition, that did not allow either switch preparation or task-readiness.

We applied this paradigm in two studies using a select range of methodologies to define the spatial and temporal dynamics of these processes. These analyses revealed two switch-related preparation processes – one related to the signal to switch (which we refer to herein as *switch-specific preparation*, for simplicity) and another related to updating the task-set. Throughout the papers presented in this thesis, we examine switch-specific preparation from multiple perspectives in an attempt to define the nature of this process. Firstly, we used ERPs to examine whether this preparation could be temporally dissociated from more general task preparation and used formal cognitive modeling to examine whether switch-specific preparation is associated with a behavioural advantage (Karayanidis et al., 2009). We then used a novel multivariate pattern analysis of EEG data to examine whether these processes could be both temporally *and* spatially dissociated (Mansfield et al., 2012). The neural networks associated with this switch-specific preparation were examined using fMRI (Mansfield et al., 2011) and DWI (Mansfield et al., submitted). In addition, we combined these neuroimaging measures with parameters derived from formal cognitive modeling to make more specific inferences about the nature of this process (Karayanidis et al., 2009; Mansfield et al., 2011; submitted). This approach limits speculation about the relationship between patterns of neural activation and cognitive processes, as it attempts to first delineate the specific processes indexed in single end-state measures of performance (RT, accuracy) before linking these with neural activity. This

allows for a more fine-grained examination of the function of neural activity associated with switch-specific preparation. Using this approach we were able to provide the first evidence for qualitatively distinct switch-specific preparation that appears to be related to conflict control.

9.1 Evidence in favour of switch-specific preparation

The current findings present compelling evidence in support of models that posit qualitatively distinct switch-specific preparation (e.g. Rogers & Monsell, 1995; Rubinstein et al., 2001). In Karayanidis et al. (2009; Chapter 4), we used converging evidence from ERPs and latent measures derived from drift-diffusion modeling to find support for switch-specific preparation that is associated with a behavioural advantage. ERPs showed evidence for an early component (D-Pos1) that was elicited by cues that signalled a certain change in task (*switch-to, switch-away*), but not by cues that did not (*non-informative* cues). This provides evidence for a mechanism that is engaged when the cue reliably predicts an upcoming switch in task, regardless of whether the upcoming task is specified. We also found a later positivity (D-Pos2) for *switch-to* trials that appears consistent with previous switch positivities from traditional task-switching paradigms (e.g. Karayanidis et al., 2003; Nicholson et al., 2005) and is in line with a task-set updating or goal activation process when the cue reliably predicts the upcoming task. Therefore, we showed novel evidence for a temporal distinction between two components of switch preparation – an early component that is elicited specifically in response to the signal to switch (i.e., switch-specific preparation) and a later task-set updating component. Further, these switch-related preparation components were distinct from a later pre-target negativity that differed in

amplitude between cues that reliably predicated the upcoming task (*repeat, switch-to*) and those that did not (*switch-away, non-informative*) and therefore appeared to index task readiness.

Interestingly, we did not find any RT advantage associated with switch-specific preparation. That is, *switch-away* cues (which defined an upcoming switch but not the task) did not differ in reaction time from *non-informative* cues (which did not define either a switch or the task). To understand the reasons for this discrepancy between ERP and behavioural data, we turned to formal models of cognition which define latent cognitive processes that characterize overt behavior. We selected the EZ2 diffusion model of two-choice decision making, as this model estimates both decision and nondecision processes. The latter index the time taken by cue encoding and response selection processes, and in the context of task-switching, active control processes. Therefore, increased preparation within the C-T interval should correspond to a reduction in nondecision time as there is reduced need for post-target control processes. In support of this notion, we found that nondecision time was lowest for *switch-to* and *repeat* trials that both allow preparation for the upcoming task. Crucially, consistent with a switch-specific preparation process, we also found a nondecision time advantage for *switch-away* cues relative to *non-informative* cues that resulted in a switch trial. This indicates that some preparation had taken place on these partially-informative switch trials, leading to a behavioral advantage over cues that did not allow for any preparation for the switch in task. However, this advantage did not translate into an RT advantage because it was counteracted by the fact that response threshold was set higher for *switch-away* relative to *non-informative switch* trials, resulting in slower but less error-prone responses. That is, *switch-away* trials had faster nondecision time but higher response threshold than *non-informative switch* trials, resulting in no net RT benefit

associated with foreknowledge of a switch in task. This study represents the first attempt to identify the underlying processes involved in task-switching using a model of two-choice decision making. This formal cognitive modeling provided important evidence that helped clarify apparent contradictions between behavioral and ERP effects, and provided the crucial evidence showing that foreknowledge of a task switch *is* associated with some behavioural advantage.

In Mansfield, Karayanidis and Cohen (2012; Chapter 5), we sought converging evidence that early switch-specific preparation for *switch-to* and *switch-away* trials could be differentiated from later task readiness for *switch-to* and *repeat* trials using a novel multivariate pattern analysis of frequency-specific topographical patterns in EEG activity. This analysis provides an independent data-driven confirmation of these two preparation processes by targeting commonalities in topographical patterns across the different cue conditions to reveal core underlying processes. This was achieved by training a classifier to differentiate between *switch-to* cues (that inform of upcoming switch trial and task identity) and *non-informative* cues (that do not provide either type of information). The classifier was then forced to misclassify *switch-away* cues (that inform only of upcoming switch) and *repeat* cues (that inform only of upcoming task) using the same model. This produced evidence for two processes: one for cue types that reliably predicted an upcoming task switch (*switch-to* and *switch-away*) and the other for cue types that reliably identified the upcoming task (*repeat* and *switch-to*). Specifically, alpha-band activity for cues that reliably predicted an upcoming switch was similar over right IFC early in the cue-target interval. This is consistent with the ERP evidence for early switch-specific preparation common to both *switch-to* and *switch-away* trials. Moreover, this finding represents the first evidence that preparation to switch is associated with a frontal source. In contrast,

consistent with a later task readiness process, cues that identified the upcoming task showed similar patterns of activity late in the C-T interval over PPC. Therefore, these misclassifications provided crucial evidence that a switch-specific process could be distinguished not only temporally, but also spatially from general task readiness.

Taken together, these findings indicate that switch-specific preparation can be both temporally and spatially distinguished from later general task readiness processes. In addition, these findings further inform our understanding of the nature of switch-specific preparation. The fact that switch-specific preparation is elicited even when the upcoming task is not specified, suggests that this preparation cannot be associated with retrieval of the now-relevant task set. Instead, we speculated that this component is consistent with suppression of the previous-task set, which would ensure that the rules associated with the now-irrelevant task-set do not interfere with upcoming performance of the relevant task (see Rubinstein et al., 2001). The multivariate pattern classification analysis provided converging evidence consistent with this argument, showing that the common activation for *switch-to* and *switch-away* cues was associated with activation over right inferior frontal cortex, a region previously associated with response inhibition (e.g. Aron et al., 2004 for a review). However, it is important to note that these inferences are still quite indirect, as there is no way of directly measuring cognitive inhibition. Hence, the interpretation that this cue-locked early switch positivity reflects inhibition of the now irrelevant task-set remains speculative and the process by which such inhibition may be implemented remains undefined.

As discussed above, we showed that formal cognitive modeling provided the crucial evidence that foreknowledge of a switch in task provided a behavioural advantage over not having foreknowledge that the task would switch. In addition, the diffusion model

analysis allowed us to more directly measure the specific cognitive processes that contributed to switch cost. This approach provided an alternative explanation regarding the nature of switch-specific preparation. Specifically, we showed that response threshold (an index of response caution) is adjusted on a trial-by-trial basis depending on whether the cue provides certainty of an easy repeat trial, or certainty of a more difficult switch trial. Specifically, response threshold was set higher when the cue predicted with certainty a switch in task (i.e., *switch-to* and *switch-away* cues) relative to when the cue predicted a repeat in task, or was equally likely to result in a switch or repeat trial (ie., *non-informative*). Therefore, when participants were informed in advance that the previously relevant task-set would no longer be relevant, they shifted their response threshold up so as to allow for more careful responding. These findings present the first evidence that changes in response threshold contribute to performance decrements for switch relative to repeat trials.

Two pieces of evidence support the suggestion that threshold adjustment is carried out in a preparatory manner within the C-T interval. One piece of evidence comes from the finding that response threshold, although set higher for informative (*switch-to*) and partially informative switch cues (*switch-away*) relative to informative *repeat* cues, did not differ between *non-informative* cues leading to a repeat or a switch trial. If response threshold adjustment occurs following target onset, then we would have expected a higher response threshold for *non-informative switch* relative to *non-informative repeat* trials. The fact that response threshold adjustment did not differ between these two trial types suggests that it was set prior to the onset of the target that revealed whether the task would switch or repeat. The other piece of evidence comes from the finding that the amplitude of the cue-locked switch positivity was correlated with threshold setting on *switch-to* trials, suggesting

that threshold setting was carried out within the C-T interval. Therefore, these findings indicate that not only is response threshold adjusted on a trial-by-trial basis, but that this adjustment is carried out as part of advance preparation. These findings suggest an alternative explanation for the switch-specific component of preparation – that it may be related to threshold control rather than an inhibitory process.

In a recent study, Schmitz and Voss (2012) found further support for preparatory changes in response caution contributing to switch costs. For one group, an advance cue validly predicted a task switch or task repeat (predictable transition group; CTI 600ms), while for another group the task cue appeared simultaneously with the target (unpredictable transition group). Consistent with our findings, the former set a higher threshold for switch than repeat trials. However, interestingly, the latter group set response caution equally high for both switch and repeat trials. As response threshold only showed a difference between switch and repeat trials when the upcoming task transition was predictable, this provides further support for the notion that response threshold can be adjusted preemptively based on cue information.

In sum, the first two experimental chapters provide evidence in support of two distinct switch preparation processes – one that is specifically elicited in response to the cue to switch and another that is elicited when the upcoming task is additionally specified. The early switch-specific preparation was shown to be spatially and temporally distinct from later task-set updating and task-readiness processes. The conditions under which such switch-specific preparation is elicited led us to speculate that this process may reflect inhibition of the now-irrelevant task set. However, formal cognitive modeling allowed us to relate this preparation to switch task with preemptive adjustment of response threshold in anticipation of a more difficult switch trial.

9.2 Neural basis of switch-specific preparation

We proceeded to further characterize the nature of this process by examining the neural correlates of trial-by-trial adjustment in response threshold. Guided by neural models of speed-accuracy tradeoff, we first investigated whether threshold adjustments on switch and repeat trials are associated with fMRI activation in distinct neural networks (Mansfield et al., 2011; Chapter 7). We then examined whether these networks are in fact related to *preparatory* adjustment of response threshold (Mansfield et al., submitted; Chapter 8).

So far fMRI studies of task-switching have been unable to provide unambiguous evidence for switch-specific preparation. Using a model-based approach, we were able to link brain activation to a distinct switch-specific process – an increase in threshold setting – and show that this pattern of activation was distinct from patterns of activation associated with decreasing response threshold on repeat trials. Specifically, we showed that increased activation in right STN was associated with setting a higher response threshold on switch trials (Mansfield et al., 2011; Chapter 7). In contrast, greater activation in the medial striatum was associated with setting a lower response threshold on repeat trials. Therefore, we found evidence that activation in distinct basal ganglia regions is associated with setting a higher response threshold for more difficult switch trials and setting a lower response threshold for easier repeat trials, respectively.

The STN has been previously related to response inhibition (Aron & Poldrack, 2006) as well as conflict-induced slowing (Aron et al., 2007). In addition, Aron et al. (2007) found that this region forms part of a broader network incorporating pre-SMA and IFC that is associated with the efficiency of slowing under response conflict. According to this account, frontal regions send input to the STN to stop or temporarily slow the output of

the basal ganglia. We found that STN activation was associated with an increase in response threshold, suggesting that this process may rely on the same or similar conflict-control mechanisms to those engaged for response inhibition and conflict-induced slowing. Therefore, the switch-specific preparatory increase in response threshold appears to be closely related to other conflict control mechanisms that are employed to stop or slow response output.

This ROI analysis did not include the right IFC, one of the regions hypothesised to provide input to the STN under conditions of increased conflict. However, EEG topographical pattern analysis produced evidence for a right IFC source associated with switch-specific preparation (i.e., differentiating between cues that provide switch certainty and those that do not). Future work is needed to examine whether this activation is specifically related to adjustment of response threshold. Therefore, while we have shown evidence for both right IFC and STN involvement in switch-specific preparation, our findings do not provide unequivocal evidence that these components of the response inhibition network work together to increase response threshold. Whole brain analyses or ROI analyses targeting both the IFC and STN regions may assist in further clarifying the role of these regions in switch-specific preparation.

Also, interestingly, pre-SMA, which has been shown to form part of the network responsible for response inhibition, did not appear to be involved in switch-specific preparation. Instead, increased pre-SMA activation was associated with lower response threshold for *both* switch and repeat trials, suggesting that is involved in individual differences in overall threshold control. While previous evidence suggests that dorsomedial prefrontal regions play a prominent role in initiating control processes under decision conflict and uncertainty (e.g. Ridderinkhof et al., 2004), there is also some evidence to

suggest that this region is involved in the activation of action-sets (Cunnington et al., 2005; Rushworth, Walton, Kennerley & Bannerman, 2004). Therefore, it is possible that this region plays a more general role in cognitive control that changes depending on the current task context.

Our finding that a network previously shown to be associated with conflict-induced slowing is also activated on switch trials is compatible with Brown, Reynolds and Braver's (2007) computational model of conflict-control in task-switching. According to this model, different control loops are engaged depending on the type of conflict encountered. In particular, our findings support Brown et al.'s change control loop that is engaged for conflict arising at the level of task-sets. According to their model, this loop biases responding towards accuracy (over speed) and exploitation (over exploration), with the net effect of this control process being a 'braking' of response output. However, while Brown et al. argued that the change control loop is engaged when a new task-set becomes coactivated with a previous task set, we found that this type of control is engaged even when the cue does not identify the upcoming task (i.e., on *switch-away* trials). Therefore, this suggests that conflict between an upcoming task and a now-irrelevant task is not a necessary condition for change detection to be engaged and the system to be prepared to reduce conflict.

However, our findings from Mansfield et al. (submitted) question the role of this network in *preparatory* threshold adjustment. Specifically, we showed that structural integrity within the right striatum, rather than the STN, mediated the relationship between the amplitude of the cue-locked switch positivity and response threshold for *switch-to* trials. This suggests that the right striatum may be more directly associated with preparing the system to for change. Moreover, it is important to note that fMRI data cannot

unambiguously disentangle cue-related from target-related processing, and therefore the conclusion that the relationship between STN activation and threshold setting is temporally situated within the cue-target interval needs to be considered with caution. Further work is required to understand whether the STN pathway that has been previously been linked to response inhibition and conflict-induced slowing is also activated *proactively* in anticipation of conflict on switch trials.

In sum, using a model-based neuroscience approach, we have moved beyond simple identification of switch-specific preparation and developed some plausible hypotheses about what this preparation might entail. Specifically, we show that preparation for a switch in task is related with an increase in response threshold and that this is associated with the early switch positivity, suggesting that threshold regulation occurs in an anticipatory manner. Further, we showed that threshold adjustment on switch trials engages a cortico-basal ganglia network that has previously been linked to conflict control and that is distinct from another cortico-basal ganglia network engaged on repeat trials. Therefore, by pinpointing a specific control process that can explain switch cost and relating this to a specific pattern of neural activation, we were able to provide a new perspective on the nature of processes involved in preparation to switch task. This conceptualization of switch-specific preparation moves away from the notion of 'reconfiguration' of task-set and instead suggests that at least one part of preparation to switch tasks involves readying the system to deal with upcoming conflict.

9.3 Implications for neural models of response threshold adjustment

Our findings are consistent with neural models of the speed-accuracy tradeoff in two-choice decision-making, suggesting that the threshold adjustment in task-switching closely parallels that carried out in simpler two-choice decision making. Further, these findings inform the debate about the level of the cortico-basal ganglia-thalamic network at which the speed-accuracy tradeoff is controlled (see Chapter 6 for a review). According to the striatal theory, under conditions that are less risky, the striatum receives top-down input from the pre-SMA so that the output nuclei of the basal ganglia can be released from inhibition (Forstmann et al., 2008a). In Mansfield et al. (2011; Chapter 7), we found that the pre-SMA/striatal network showed increased activation under low-risk conditions and for individuals who were more risky responders. Further, in Mansfield et al. (submitted; Chapter 8), we showed that the relationship between the amplitude of the cue-locked switch positivity and response threshold estimates was mediated by structural integrity within the striatum. These findings support the theory that the striatum plays a pivotal role in adjusting response threshold according to cue information.

We also found some evidence that the striatal theory may account for individual differences in preference for an overall more risky response strategy. In Mansfield et al. (submitted; Chapter 8), we showed that individuals who set lower threshold across all conditions showed increased structural integrity within a network incorporating the pre-SMA and external capsule of the striatum. In contrast, individuals who set overall higher thresholds showed increased structural integrity in a network incorporating the anterior limb of the internal capsule – another striatal region. These findings suggest that while the striatal theory provides a plausible account of neural control of response threshold adjustment in response to external information, more complex models may be required to

account for individual differences in preference for a more risky or more cautious response strategy.

The STN theory (see Chapter 6) suggests that, under conditions associated with increased risk, the STN is activated to slow the output of the basal ganglia (e.g. Frank et al., 2007). Our findings from Mansfield et al. (2011; Chapter 7) are compatible with this, as we found that the right STN showed increased activation for individuals who were more cautious in response to switch cues. This finding is novel, as previous studies of response threshold control (e.g. Forstmann et al., 2008a; Forstmann et al., 2010a) did not show an association between threshold setting and activation or structural integrity within this region. However, in Mansfield et al. (submitted; Chapter 8) we did not find evidence that structural integrity within the STN was associated with setting an overall higher response threshold. Therefore, like the striatal theory, the STN theory may be able to explain trial-by-trial threshold adjustment, but may not account for individual differences in overall threshold setting.

Alternatively, the discrepancies between the networks associated with trial-by-trial threshold adjustment and those associated with individual differences in preference for an overall more risky or cautious response strategy may have arisen from the fact that we used different methodologies and different analysis strategies to investigate each type of threshold control. Specifically, trial-by-trial adjustment was analysed using an fMRI ROI approach, while overall threshold setting was analysed using DWI and a combined whole-brain and ROI approach. Perhaps if a whole brain analysis had been used in our fMRI study then this may have provided a more comprehensive picture of the neural basis of threshold control. Conversely, the use of a whole-brain approach in the DWI analysis combined with a relatively small sample size may have resulted in a lack of sensitivity to detect effects in

smaller structures such as the STN. Therefore, the difference in neural mechanisms supporting trial-by-trial threshold control and overall threshold setting need to be further clarified using a more systematic comparison of these two types of threshold control using a common analysis approach.

It is also pertinent to point out the limitations of using measures such as fMRI to delineate the neural mechanisms associated with transient control processes such as threshold adjustment. In particular, the temporal resolution of fMRI makes it difficult to determine how components of the observed networks interact to control the speed-accuracy tradeoff. Moreover, recent evidence using single-unit recordings during a visual search task in primates challenges the notion that the speed-accuracy tradeoff is mediated by the distance from baseline to threshold. For example, Heitz and Schall (2012) showed that integrated activity in movement neurons immediately prior to movement initiation did not differ between speed and accuracy instructions, suggesting that this integration terminates at a fixed threshold. Furthermore, firing rate excursion was larger under instructions to be fast compared to instructions to be accurate. In summary, there remain inconsistencies between neural mechanisms of speed-accuracy tradeoff and evidence accumulation model accounts of this process, suggesting that further work is required to reconcile behavioural and neural data.

9.4 Implications for understanding the organization and temporal characteristics of cognitive control processes

Our understanding of the organization and nature of cognitive control processes has come a long way since initial formulations of a single ‘homuncular’ control centre that

somehow orchestrates all goal-directed behaviour. We now know that such a conceptualisation is far too simple, as many studies have shown evidence that cognitive control processes can be fractionated into distinct components (Lehto, 1996; Stuss & Alexander, 2000; Stuss et al., 2002). Even so, factor analysis approaches have shown that while separate cognitive control processes can be distinguished, there is still some degree of commonality across these different functions (Miyake et al., 2000). Recent modeling work has also begun to focus on the temporal characteristics of cognitive control processes, in particular focusing on differentiating between cognitive control strategies that can be carried out *proactively* vs. *reactively* (e.g. Braver et al., 2007). The paradigm used in this thesis allowed the examination of component processes of proactive and reactive control in task-switching, further informing models of the organization and temporal ordering of cognitive control.

Taking task-switching as our control process of interest, we have presented convincing evidence that a conflict control process involving an increase in response caution ensures efficient transition to a new task-set. The fact that we found evidence that this process was associated with similar neural regions to those engaged in paradigms requiring inhibition of prepotent responses suggests that there may be a common conflict control mechanism underlying many cognitive control functions. By using strategies to reduce conflict one can ensure that the potential for interference from irrelevant task goals on the current task goal is reduced. This ability appears particularly important when faced with the high degree of complexity and competing demands inherent in our everyday environment. Future research may examine the extent to which this adjustment of response caution is exclusive to conflict control in the task-switching paradigm, or whether its role extends to other cognitive control functions.

These findings also support and extend on models of the temporal organization of cognitive control processes (e.g., Braver et al., 2007). Using a paradigm that included cues of varying information value, we were able to show the conditions under which cognitive control can be carried out proactively. When cues were fully informative about the task transition (i.e., switch or repeat) as well as the identity of the upcoming task, we found strong evidence for the engagement of proactive control processes. However, we also found evidence for the engagement of proactive control even when the cue did not provide all of the information required to complete the upcoming task. In particular, reduced nondecision time for *switch-away* relative to *non-informative switch* trials suggests that participants engaged in at least some preparation even when they did not know what the upcoming task would be. Therefore, providing only some information about the upcoming target appears sufficient to elicit proactive control strategies. This finding suggests that participants are biased to adopt more proactive control strategies given any opportunity for advance preparation. Given this, future studies may further explore the minimum information required to elicit this bias towards proactive control.

Braver et al. (2007) also predicted that proactive control would be associated with a distinct pattern of neural activation. Specifically, it was argued that proactive control should be associated with sustained activity in the IFC, indexing the sustained activation and maintenance of task goals. The current findings extend on this model, showing that proactive control may involve more than just the maintenance of the task goal within the preparation interval. In fact, it appears that, depending on task parameters, proactive control can be comprised of multiple components. For example, providing foreknowledge that the task will switch invokes strategies to deal with upcoming conflict. If the cue additionally specifies the upcoming task, this allows for task-related preparation processes related to

task-set updating (switch trials) or task readiness (both switch and repeat trials). These components of proactive control appear to be supported by complex neural networks involving a broad range of fronto-parietal and fronto-striatal regions. Further research is required to clarify the extent to which these networks are engaged across other paradigms designed to target proactive cognitive control.

9.5 Future directions and final comments

The goal of this thesis was to examine whether switch-specific preparation processes could be distinguished from general task preparation processes. Further, we aimed to understand the nature of switch-specific preparation. We used a paradigm that was designed to isolate specific control processes, along with a multi-modal approach combining evidence from cognitive modeling, electrophysiological, haemodynamic and structural measures. Cognitive modeling allowed for the nature of underlying processes to be defined with greater specificity, while neuroimaging modalities were able to uncover the spatial and temporal characteristics of these processes. Therefore, as each of these methodologies contributes unique information to model building, this approach allows for the development of more comprehensive and fine-grained models of cognitive control in task-switching.

In particular, the studies in the current thesis highlight the value of using techniques that go beyond traditional measures of behavioural and neuroimaging data, and delve deeper into the underlying core processes that may be contributing to observable effects. For example, our novel multivariate pattern classification approach identified common EEG topographical patterns across conditions that indicated the existence of core

underlying processes. We were also able to extract the underlying process contributing to observable behavioural performance using evidence accumulation modeling. When combined with a paradigm that is designed to isolate specific control processes, these approaches represent a powerful way of extracting the core processes that underlie task-switching performance measures. Given the almost 20-year-long debate over the nature of cognitive control processes engaged on switch trials, these approaches appear to offer a great deal of promise in resolving ambiguity over what the switching process entails.

I expect that the findings presented in this thesis will stimulate further research into how the brain flexibly deals with an increasingly stimulating and demanding everyday environment. The complexity of higher-order cognitive control processes makes work in this area challenging but exciting, as we continue to build an understanding of the ways in which the brain allows us to function in our day-to-day lives. With creative approaches to targeting specific processes, as well as the rapid development of sophisticated and innovative analysis methods, I look forward to seeing just how far we can go in uncovering the intricacies of cognitive control.

Chapter 10: References

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Appendix

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Date: 19-2-2013
Springer reference: Cognitive, Affective, & Behavioral Neuroscience June 2009, Volume 9, Issue 2, pp 202-215 Anticipatory reconfiguration elicited by fully and partially informative cues that validly predict a switch in task Frini Karayanidis, Elise L. Mansfield, Kasey L. Galloway, Janette L. Smith, Alexander Provost, Andrew Heathcote

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