The Dual Mechanisms of Cognitive Control Project

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Abstract

■ We describe an ambitious ongoing study that has been strongly influenced and inspired by Don Stuss's career-long efforts to identify key cognitive processes that characterize executive control, investigate potential unifying dimensions that define prefrontal function, and carefully attend to individual differences. The Dual Mechanisms of Cognitive Control project tests a theoretical framework positing two key control dimensions: proactive and reactive. The framework's central tenets are that proactive and reactive control modes reflect domain-general dimensions of individual variation, with distinctive neural signatures, involving the lateral prefrontal cortex as a central node within associated brain networks (e.g., fronto-parietal, cingulo-opercular). In the Dual Mechanisms of Cognitive Control project, each participant undergoes three separate imaging sessions, while performing theoretically targeted variants of multiple well-established cognitive control tasks (Stroop, Cued task-switching, AX-Continuous Performance Test, Sternberg working memory) in conditions that encourage utilization of different control modes, and also completes an extensive out-of-scanner individual differences battery. Additional key features of the project include a high spatio-temporal resolution (multiband) acquisition protocol and a sample that includes both a substantial subset of monozygotic twin pairs and participants recruited from the Human Connectome Project. Although data collection is still continuing (target $n = 200$), we provide an overview of the study design and protocol, along with initial results ($n = 80$) revealing evidence of a domain-general neural signature of cognitive control and its modulation under reactive conditions. Aligned with Don Stuss's legacy of scientific community building, a partial data set has been publicly released, with the full data set released at project completion, so it can serve as a valuable resource. ■

INTRODUCTION

The project described in this publication was strongly influenced and inspired by Don Stuss's career-long effort to understand frontal lobe function and to identify key cognitive processes that characterize executive control. By way of introduction, the following attempts to articulate this influence through personal reflections of the first author (T. S. B.). As a beginning graduate student in 1992, with primary interests in "big questions" related to self-control, consciousness, emotion–cognition interactions, and individual differences, it was immediately clear that *The Frontal Lobes* (Stuss & Benson, 1986) would be an essential reference for me, as it provided a comprehensive and eye-opening introduction to the mysteries of the PFC and executive function. Through that book, I was acquainted with Don Stuss's careful approach to both theorizing and research investigations. My appreciation for this approach only grew stronger as I began my own forays into this complex and thorny domain. Indeed, it is my hope that some of the principles outlined in Stuss, Shallice, Alexander, and Picton (1995) are embedded in the work described here:

> Determine a set of putative processes that are closely related and that are used in many different tasks… select a set of tasks, each of which loads differently on the[se]…processes…describe the tasks in the context of a theory of frontal lobe function that provides predictions about underlying cognitive processes and cerebral mechanisms…test individual subjects more than once to estimate reliability and variability…use different experimental methods to provide converging evidence for interpreting distinct frontal processes.

Indeed, another inspiring Stuss research principle that we have tried to adhere to closely in this project is to carefully attend to individual differences (Stuss, 2016, 2017).

Although my professional relationship with Don was mostly that of a distant admirer, I was lucky enough to have a few personal interactions with him. The most vivid one was when, as a newly minted PhD and junior assistant professor, I was thrilled to receive an invitation to the Rotman Research Institute Conference in Spring 2000, where I was able to mingle with organizers Don Stuss and Bob Knight, along with most of the world's luminaries on prefrontal function. Moreover, because my graduate mentor Jonathan Cohen had to decline his invitation, I had the privilege of getting to speak with this group on the work that we had done together. I can admit now that I was, of course, actually quite petrified by the prospect, as this would be my biggest talk to date and the most discerning audience that I had ever faced. Although I am sure my nervousness showed clearly, I vividly remember

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the interactions I had with Don before the talk session, as he helped me get my presentation set up and walked me through the session structure. Don's twinkling eyes and ready smile made me feel instantly more at ease, and his obvious enthusiasm and excitement for the session was infectious and energizing, turning my anxiety into anticipation. However, most memorable to me was Don's soothing, compassionate, and authentic manner—when he told me that he was really looking forward to my talk and that he was sure it would be terrific, I immediately could sense that he was not just saying it to be polite—he really meant it! I was not surprised to see that this first impression was strongly confirmed throughout my later interactions with Don at conferences and visits to the Rotman and by all the glowing words written about him in obituaries and eulogies, from those who knew him better than me. Moreover, I am quite proud of the chapter I wrote with Jonathan Cohen and Deanna Barch (Braver, Cohen, & Barch, 2002) for the seminal and highly influential book that came out of the conference: *Principles of Frontal Lobe Function* (Stuss & Knight, 2002).

It is the hope of all the authors that Don's intellectual spirit and legacy are clearly visible within the Dual Mechanisms of Cognitive Control (DMCC) project. The DMCC project is a large-scale longitudinal study that provides a systematic test of the Dual Mechanisms of Control (DMC) framework, a theoretical account of both interindividual and intraindividual variability in cognitive control mechanisms (Braver, 2012; Braver, Gray, & Burgess, 2007). The study has multiple components, which assess brain activity and behavioral performance via a newly developed task battery. This battery is designed to probe the two main control modes postulated in the framework, proactive and reactive, in terms of both experimental manipulations and individual differences. The target sample size of the DMCC project is to acquire data from 200 healthy young adults. It is worth noting that, although there have now been a number of larger-scope neuroimaging projects that share some similarity with the DMCC project (e.g., Human Connectome Project [HCP], Adolescent Brain and Cognitive Development [ABCD], Cam-Can, IMAGEN, PNC, UK Biobank; Casey et al., 2018; Miller et al., 2016; Satterthwaite et al., 2014; Shafto et al., 2014; Van Essen et al., 2013; Schumann et al., 2010), this project is somewhat unique in that it was designed to test a specific theoretical framework, and with a sufficient sample size for not only a robust and reliable estimation of group effects but also to provide sensitivity to individual difference effects, although subject to the constraints of what is financially and logistically feasible within an individual laboratory effort, headed by a single principal investigator. In that regard, it is well aligned and more akin to the "extensive sampling of individual brains" approach advocated in recent work (Naselaris, Allen, & Kay, 2021). Likewise, the sample is also somewhat unique, consisting of two informative participant subsets: (1) identical (monozygotic [MZ]) twin pairs, enabling phenotypic analyses of genetic and/or environmental similarity effects, and (2) participants recruited from the HCP, enabling integration of DMCC data with prior HCP data.

Funded by a National Institute of Mental Health (NIMH) MERIT award, primary data collection in the DMCC project began in late 2016. As of 2021, the project is still ongoing (thanks to a second round of NIMH funding), with data collection expected to continue until 2023 and beyond. Each participant takes part in at least one wave of testing, which includes an extensive out-of-scanner behavioral session and three fMRI neuroimaging sessions. In the neuroimaging sessions, high-resolution anatomical, resting-state fMRI and task fMRI data are collected. In total, a minimum of 300 min (5 hr) of task fMRI and 30 min of resting-state fMRI are collected for each participant. The out-of-scanner assessments include over 25 measures of cognitive ability and personality traits as well as psychological and physiological indices of health and well-being. In each fMRI session, participants perform the full DMCC task battery, in one of three conditions, namely, baseline, proactive, and reactive, with these conditions describing distinct variants of each task in the battery. Finally, the project also includes a longitudinal component, as a subset of participants return for multiple waves of retesting with the full task protocol, spaced months or even years apart. The purpose of this report is to describe the origin and current state of the DMCC project, including the underlying theoretical and conceptual backbone behind the DMCC protocol, the task paradigms that comprise the primary neuroimaging battery, and the analysis pipeline. In addition, we present a first set of initial results from the project, which provide new evidence of a domain-general neural signature of cognitive control and its modulation under reactive conditions.

Theoretical and Conceptual Goals of the DMCC Project

The DMCC project was explicitly designed to help achieve the goals of the Research Domain Criteria (RDoC), a major strategic initiative of the NIMH. The RDoC initiative aims for a reconceptualization of mental illness and neuropsychiatric disorders in terms of underlying dimensions that can be characterized at different levels of analysis, from behavioral profiles, to neural system and circuit abnormalities, all the way to genetic and molecular causes (Cuthbert & Insel, 2013). The DMCC project was structured to help achieve these goals, by providing a rigorous and systematic examination of the putative core dimensions and neural mechanisms that give rise to variation in cognitive control function.

Cognitive control, which refers to the ability to regulate, coordinate, and sequence thoughts and actions in accordance with internally maintained goals (Miller & Cohen, 2001), is one of the key domains or constructs of focus within the RDoC initiative. There is a strong consensus that cognitive control impairments are a critical component of a wide range of mental health and neuropsychiatric

disorders (e.g., schizophrenia, depression, attention deficit/hyperactivity disorder, Parkinson disease, Alzheimer disease). Yet, there is still a poor understanding of the underlying subcomponents and mechanisms that give rise to both normal and pathological variation in cognitive control function. In developing the DMCC project, we relied heavily on the DMC theoretical framework, which we believe provides critical experimental leverage and methodological tools for uncovering and characterizing the component mechanisms of cognitive control variation.

The DMC framework is a unifying and coherent theoretical account that explains three empirically observed sources of variation—within-individual (task and state related), between-individual (trait related), and between-groups (i.e., impaired populations with changes to brain function and integrity)—in terms of an underlying core dimension of variability related to the temporal dynamics of cognitive control. It is this emphasis on cognitive control variability and temporal dynamics that critically distinguishes the DMC framework from other theoretical accounts, which nonetheless posit similar computational mechanisms and neural architectures (Herd et al., 2014; Banich, 2009; Koechlin & Summerfield, 2007; Engle & Kane, 2003; Botvinick, Braver, Barch, Carter, & Cohen, 2001; Miller & Cohen, 2001; Miyake et al., 2000).

In the DMC framework, the key distinction is between two control modes that have contrasting dynamic neural signatures. Proactive control involves sustained and preparatory activation of cognitive goal representations within lateral PFC, enabled by phasic inputs (for goal updating) and tonic signals (for goal maintenance) arising from the mid-brain dopamine system (and associated components, i.e., dorsal and ventral striatum). In contrast, reactive control involves transient, stimulus-driven goal activation in these lateral PFC regions, based on signals arising from neural circuits that mediate interference/conflict detection (e.g., ACC, medial frontal cortex) and/or episodic/associative cueing (e.g., posterior parietal cortex, medial temporal lobe).

On the basis of a range of theoretical arguments (detailed in Braver, 2012; Braver et al., 2007), we have postulated that proactive and reactive control modes reflect computational trade-offs with complementary costs and benefits. Consequently, successful cognition depends on a variable mixture of proactive and reactive control strategies. Moreover, there are a variety of state, trait, and population factors that influence which control mode is dominant, including available cognitive resources and capacity, motivational salience of task performance and reward attainment, expectations for interference, and the integrity/efficacy of relevant neural systems and circuits.

A key tenet of the DMC framework is that proactive and reactive control modes appear to serve as meaningful constructs in the RDoC sense, in that they appear to (a) index coherent dimensions of both state- and trait-related variability in normal cognitive control function, (b) be useful for characterizing both age-related changes and clinical impairment in a variety of populations, and (c) exhibit unique and well-defined behavioral and neural signatures. Indeed, a tantalizing possibility is that proactive and reactive control might act as endophenotypes, in also reflecting meaningful dimensions of genetic variation (e.g., single-nucleotide polymorphisms, such as COMT; Furman et al., 2020; Green, Kraemer, DeYoung, Fossella, & Gray, 2012; Mier, Kirsch, & Meyer-Lindenberg, 2010). For example, we previously speculated that the complementary computational trade-offs of proactive and reactive control could each confer evolutionary advantages optimized for different environmental contexts (e.g., stable / predictable vs. rapidly changing / chaotic), leading to their stable expression in the population (Braver, Cole, & Yarkoni, 2010).

A major aim of the DMCC project is to extend our understanding of proactive and reactive control, by conducting a comprehensive test of their construct validity. Although rigorous establishment of construct validity is a critically important endeavor (Cronbach & Meehl, 1955), particularly with respect to RDoC goals, it is still only infrequently attempted in investigations of cognitive (executive) control (Rey-Mermet, Gade, Souza, von Bastian, & Oberauer, 2019; Karr et al., 2018; Friedman & Miyake, 2017) and is even more rarely a focus of cognitive neuroscience research in this domain (Kragel et al., 2018; Derrfuss, Brass, & von Cramon, 2004; Sylvester et al., 2003). A first step is to establish convergent validity, which requires assessment of multiple distinct measures of proactive and reactive control in a within-participant design, to test for common cross-task relationships and patterns of activation. A second step is to establish divergent (discriminant) validity, by demonstrating that proactive and reactive control modes do in fact reflect dissociable constructs. This is actually quite challenging experimentally, in that proactive and reactive control modes are by definition temporally related, such that reduced utilization of proactive control will increase the demand on reactive control, and vice versa (which we have previously termed a "reactive–proactive shift"; Braver, Paxton, Locke, & Barch, 2009). The third step of construct validation is to properly situate proactive and reactive control within a nomological network of related constructs at different levels of mechanism and description, including other measures of individual difference (e.g., personality/motivation, intelligence, working memory [WM] capacity), brain function (e.g., anatomy, connectivity), and genetics (e.g., heritability, single-nucleotide polymorphisms). Finally, for the longer-term effort of evaluating the utility of proactive and reactive control as meaningful constructs in studies of health and disease, it will be necessary to determine their predictive validity for important functional outcomes (e.g., educational and career achievement, physical and mental health status and vulnerabilities). In this first stage of reporting on the project and its progress, we focus on the first step of construct validation, through the development of the cognitive control battery and the establishment of convergent validity.

The DMCC Task Battery

The DMCC task battery includes four well-established task paradigms frequently used in the cognitive control literature: Stroop, Continuous Performance Test (AX-CPT), Cued task-switching (TS), and Sternberg WM. Critically, however, each of the tasks is performed under three different conditions that encourage utilization of different cognitive control strategies: baseline, proactive, and reactive. Moreover, the variants of these paradigms adopted within the DMCC project are in some cases novel, without prior precedent in the literature. Consequently, here we provide an overview of each of the tasks in the battery, along with the rationale for their inclusion and the logic behind the different manipulations (see Figure 1). It is also worth noting that the full DMCC task battery is being explored in a parallel behavioral study (conducted on-line through Amazon Mechanical Turk), via a test–retest format, to evaluate psychometric properties. A report of behavioral findings from that study is forthcoming, so here we emphasize the basic behavioral effects, along with predictions for neuroimaging.

Stroop

The color–word Stroop is widely recognized as a canonical task of cognitive control, in which top–down selective attention is required to focus processing on the task-relevant font color of printed words, while ignoring the irrelevant but otherwise dominant word name. The primary index of cognitive control is thus the "Stroop interference effect," which contrasts incongruent (word name indicates a different color than the font color, e.g., BLUE in red font) and congruent (word name matches font color, e.g., BLUE in blue font) trials (see Figure 1A). A key dimension of the task that has often been used to manipulate cognitive control demands is that of probability congruence (PC; Bugg & Crump, 2012; Bugg, Jacoby, & Toth, 2008). Under high-PC conditions, congruent trials are frequent and incongruent trials are rare, such that cognitive control demands are on average low and intermittent. Consequently, the baseline condition utilizes high PC, as it produces robust Stroop interference and individual difference effects (Kane & Engle, 2003).

In contrast, the proactive condition utilizes a low-PC condition in which PC is decreased in a global or list-wide manner (Bugg, 2012; Bugg, McDaniel, Scullin, & Braver, 2011). In this case, proactive control is theoretically associated with sustained maintenance of the task goal to attend to the ink color dimension and ignore the word, which should be present in a consistent (i.e., on all trials) and persistent (i.e., engaged even before stimulus onset) manner. Thus, the key prediction is that Stroop interference should be reduced on all trials, relative to a baseline condition with high-PC conditions. Likewise, in terms of neural activity dynamics, the key prediction is that cognitive-control-related mechanisms should be engaged

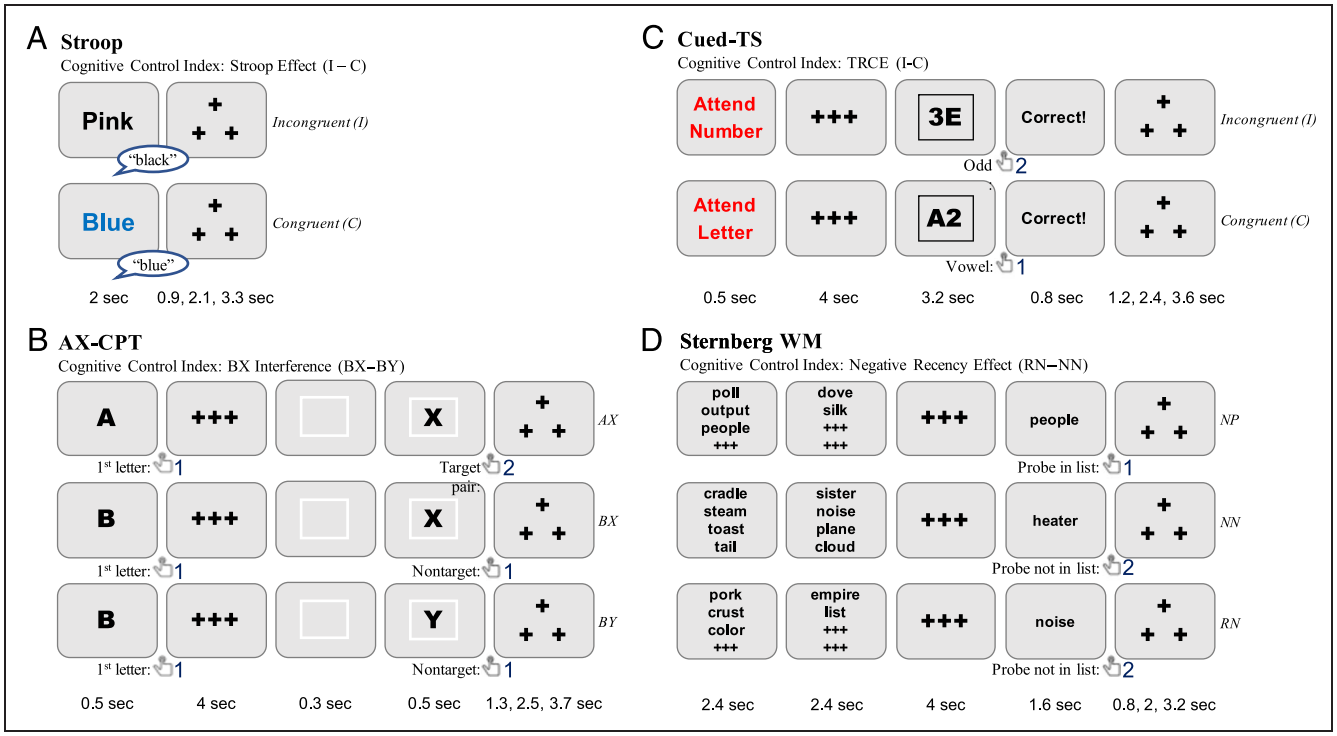

Figure 1. Diagram of cognitive control tasks used in the DMCC battery, highlighting key trial contrasts used to define cognitive control index. (A) Stroop task, illustrating contrast between incongruent and congruent trials. (B) AX-CPT, illustrating target (AX) trials as well as key contrast between BX and BY trials. (C) Cued-TS, illustrating contrast between incongruent and congruent trials. (D) Sternberg WM, illustrating target (NP) trials as well as key contrast between RN and NN trials. Diagram illustrates baseline condition, with stimulus timing information listed for each task, as well as the appropriate response button for each trial type.

before stimulus onset, potentially sustained across trials, and/or present globally on all trials.

The reactive condition also manipulates PC, but in an item-specific, rather than list-wide, fashion. In this case, specific colors occur with low PC (e.g., RED in green font is more frequent than RED in red font), whereas others occur with high PC (e.g., YELLOW in yellow font is frequent). This type of item-specific PC manipulation is theoretically predicted to enhance the utilization of reactive control when low-PC items are encountered. For these items, strong associations may develop between a critical feature (a specific ink color) and increased control demands (i.e., high interference), leading to this feature more effectively engaging goal retrieval and utilization (Bugg & Hutchison, 2013; Bugg, Jacoby, & Chanani, 2011; Jacoby, Lindsay, & Hessels, 2003). When this occurs, the engagement of cognitive-control-related neural activity would be expected to be transient, present only after stimulus onset, and primarily engaged by low-PC incongruent items (relative to low-PC congruent items).

A novel feature of the Stroop tasks included in the battery is that there are actually two distinct and intermixed set of items, namely, biased items, for which PC is manipulated across conditions, and unbiased items ("PC-50": 50% congruent, 50% incongruent). The unbiased items, which are included and equivalent across all three conditions, enable tighter comparisons and predicted dissociations among conditions. Specifically, in the proactive condition, changes in Stroop behavioral interference and neural activity, relative to baseline, should equivalently impact both types of items, whereas in the reactive condition, the cognitive-control-related changes should be specific to the biased items. Finally, it is worth noting that, because of the large numbers of different font colors (8) included in each of the conditions, the task is implemented with vocal rather than manual responding, using digitization and automated signal processing algorithms to extract response latencies from the noisy scanner environment. In our previous behavioral studies, we have used similar experimental manipulations to dissociate proactive and reactive control, using both picture–word (Gonthier, Braver, & Bugg, 2016) and color–word (Gourley, Braver, & Bugg, 2016) Stroop variants.

AX-CPT

The AX-CPT has become increasingly utilized as a task of context processing and cognitive control, given its simplicity, flexibility, and applicability in a wide range of populations (Chun, Ciceron, & Kwapil, 2018; Barch, Braver, Carter, Poldrack, & Robbins, 2009; Chatham, Frank, & Munakata, 2009; MacDonald, 2008; Paxton, Barch, Racine, & Braver, 2008). In the task, contextual cues constrain the appropriate response to probe items. As the name suggests, A-cues followed by X-probes require a target response and occur with a high frequency, leading to strong cue–probe associations. Cognitive control is postulated as the key process involved in maintaining and utilizing the contextual cue information, to minimize errors and response interference occurring on BX trials, which occur when the X-probe is presented but not preceded by an A-cue. Thus, a useful index of cognitive control for this task is the "BX interference effect," which contrasts the BX with the BY trial type (in BY, neither an A-cue nor an X-probe is presented, leading to low control; see Figure 1B). In prior work, shifts in the tendency to utilize proactive or reactive control have not only been observed when comparing different populations or groups but also been manipulated within participants (Braver et al., 2009).

The AX-CPT conditions included in the battery extend prior recent work, by using a task variant in which the A- and B-type contextual cues occur with equal frequency, thus eliminating confounds in earlier versions that could be because of the lower overall frequency of encountering B-cues (Gonthier, Macnamara, Chow, Conway, & Braver, 2016; Richmond, Redick, & Braver, 2015). Furthermore, these conditions also include no-go trials, in which the probe is a digit rather than a letter. Because of the increase in response uncertainty (i.e., three types of probe response are possible: target, nontarget, and no-go), the addition of no-go trials decreases the overall predictive utility of context information for responding, and as a consequence, was found to reduce the overall proactive control bias typically observed in healthy young adults. Thus, the baseline condition includes these no-go trials to produce a "low control" state, from which to more sensitively observe condition-related changes in control mode (Gonthier, Macnamara, et al., 2016).

The proactive condition replicates prior work using context strategy training to increase predictive preparation of responses after contextual cue information (Gonthier, Macnamara, et al., 2016; Edwards, Barch, & Braver, 2010; Paxton, Barch, Storandt, & Braver, 2006). Specifically, before performing this condition, participants are provided with explicit information regarding the frequencies of these cue–response associations and receive training and practice in utilizing them to prepare the dominant responses. In addition, during intertrial intervals, participants are provided with visual instructions to "remember to use the strategy." The key prediction is that the increased utilization of contextual cue information will lead to a bias to prepare a target response after an A-cue (analyzed in terms of both AX and AY trials) and a nontarget response after a B-cue, leading to reduced interference on BX trials. However, a side effect of this context-based strategy is increased interference on AY trials, which occurs when the A-cue is not followed by an X-probe. This translates into a prediction of increased cue-related neural activity, which might also be accompanied by sustained activation (in maintaining the instructed strategy) across the task block.

The reactive condition utilizes a new manipulation that has not been examined in prior work. Specifically, in the reactive condition, item-specific probe cueing is present (similar to other cueing manipulations in tasks such as

the flankers; Braem et al., 2019; Bugg & Crump, 2012; Crump, Gong, & Milliken, 2006), such that on high-control-demand trials (AY, BX, no-go), the probe item appears in a distinct spatial location and with a distinct border color surrounding it (presented briefly before the onset of the probe). Critically, because these stimulus–control associations (i.e., between border color/spatial location and high control demand) only form at the time of probe onset, they are not hypothesized to modulate the utilization of proactive control strategies. Likewise, the probe features are insufficient to direct stimulus–response learning, because they do not directly indicate the appropriate response to be made (i.e., either a nontarget or no-go response could be required). In contrast, because probe features serve as cues signaling high control demand, they can drive more rapid and effective retrieval of contextual information to resolve the conflict. The key prediction is that utilization of probe features should reduce BX interference in the reactive condition. In terms of neural activity dynamics, reactive control effects should be observable as transient probe-triggered activation on BX trials (relative to BY trials).

Cued-TS

Cued-TS has long been recognized as a critical paradigm to assess a core component of cognitive control—the ability to update and activate task representations in an on-line manner to appropriately configure attention and action systems for processing the upcoming target (Kiesel et al., 2010; Vandierendonck, Liefooghe, & Verbruggen, 2010; Meiran, 1996). The key aspect of the paradigm is that two or more tasks randomly alternate in a trial-by-trial fashion, with target items typically being ambiguous, so that they can be processed according to multiple task rules. Consequently, the advance presentation of the task cue, before target onset, is what disambiguates the target and specifies the appropriate stimulus–response rules. An important index of cognitive control in TS paradigms is the "task-rule congruency effect" (TRCE; Meiran & Kessler, 2008), which refers to the increased interference (both errors and RT) when the target response required for the current task trial is incongruent to the response that would be required to the same target stimulus if a different task had been cued (see Figure 1C). For example, in letter–digit TS (also called consonant–vowel, odd–even; Minear & Shah, 2008; Rogers & Monsell, 1995), if in the letter task, a right button press is required for a consonant and a left button press for a vowel, but in the digit task, a right button press is required for odd and a left button press for even, the "3E" target stimulus would be incongruent (whereas the "A2" target stimulus would be congruent, because for either task, the left button press would be correct). Another cognitive control effect is the mixing cost, which occurs on all trials in TS blocks (relative to single-task blocks; Rubin & Meiran, 2005).

In prior work, it was found that including reward incentives on a subset of trials, with reward cues presented at the time of the task cue, led to a strong reduction in the mixing cost (interference on task-repeat vs. single-task trials)—and this was present even on the trials that were nonincentivized—but no effect on the TRCE (Bugg & Braver, 2016). This finding was interpreted as indicating that global performance enhancements are associated with proactive control, whereas reactive control primarily influences the TRCE and so is less impacted by advance reward incentive manipulations. The Cued-TS conditions included in the DMCC battery build on these prior findings, by using variants of the consonant–vowel, odd–even (letter/digit) paradigm that accentuate the robustness of the TRCE, as a putative marker of reactive control, while also incorporating advance task cues with a long cue-to-target interval, which enables effective utilization of proactive control.

In the baseline condition, target stimuli are list-wide mostly congruent, as prior work has found that mostly congruent conditions result in a large and robust TRCE (Bugg & Braver, 2016). The proactive condition follows Bugg and Braver (2016) in keeping the same list-wide mostly congruent structure as the baseline condition but adding reward incentives on a subset of trials. Specifically, on a third of the trials, reward cues are presented simultaneously with advance task cues (i.e., by presenting the task cue in green font) and indicate the opportunity to earn monetary bonuses if performance is accurate and fast (relative to baseline performance) on that trial. By only presenting reward cues on a subset of trials, the remaining subset of nonincentivized trials and target stimuli can be directly compared across the proactive and baseline conditions. A divergence from Bugg and Braver (2016) is that single-task conditions are not included as part of the battery (because of length constraints), which precludes direct calculation of mixing costs. Nevertheless, the key prediction is that enhanced proactive control will lead to global performance improvement (i.e., present on all trials) even on these nonincentivized trials. In terms of cognitive-control-related neural activity, the prediction is of increased cue-related activity, which might also be accompanied by sustained activation (in maintaining the reward incentivized motivational context) across the task block.

The reactive condition utilizes a new manipulation that has not been examined in prior work. Specifically, the reactive condition includes punishment (rather than reward) incentives, again on the same one third of trials that were incentivized in the proactive condition. However, in the reactive condition, the incentive cue is presented at the time of the target stimulus, rather than with the task cue (i.e., by presenting the target in green font), which prevents the use of incentive motivation in a preparatory fashion. Participants are instructed that they will lose a component of their potential monetary bonus if they make an error on these incentivized trials. Critically, the incentivized trials occur preferentially with incongruent target stimuli. This manipulation is intended to associate punishment-related motivation with these

high-conflict items, potentially leading to increased response monitoring and caution when incongruence is detected. As such, the key prediction is that enhanced reactive control should reduce the TRCE, even on the nonincentivized trials, when compared to baseline and proactive conditions. In terms of neural activity dynamics, reactive control effects should be observable as transient probe-triggered activation on incongruent trials (relative to congruent trials).

Sternberg WM

The Sternberg item-recognition task has been one of the most popular experimental paradigms used to assess STM/WM for over 50 years (Sternberg, 1966) but, more recently, has been adapted particularly for the study of cognitive control and in neuroimaging paradigms, with the "recent probes" variant (Jonides & Nee, 2006; Jonides, Smith, Marshuetz, Koeppe, & Reuter-Lorenz, 1998). Like standard versions of the paradigm, the recent probe variant presents participants with a memory set of various load levels (number of items), followed after a short delay (retention period) by a single item probe, which requires a target response if the probe was a part of the memory set. However, in the recent probe variant, the key manipulation is that the probe item can also be a part of the memory set of the previous trial, but not the current trial, which is termed a "recent negative" (RN) probe. On these RN trials, the probe is associated with high familiarity, which can increase response interference and errors, unless cognitive control is utilized to successfully determine that the familiarity is a misleading cue regarding probe status (target or nontarget). Thus, a key index of cognitive control in this Sternberg variant is the "negative recency effect" (Jonides & Nee, 2006; Monsell, 1978), which contrasts RN and novel negative (NN) trials (i.e., when the probe item is not a member of the current or previous trial's memory set; see Figure 1D).

The classic finding in the literature is that, as the memory set increases in size (i.e., WM load increases), performance declines accordingly (Sternberg, 1969). Under conditions in which the WM load is below capacity (three to four items), proactive control strategies can be utilized to keep the memory set accessible within WM and used as an attentional template from which to prospectively match against the probe. In contrast, when the WM load is above capacity (approximately seven items), reactive control strategies are likely to be utilized, with probe responses driven by retrieval-focused processes, such as monitoring of familiarity signals. The variants of the Sternberg WM included in the DMCC battery are adapted from prior studies, which utilized manipulations of both WM load expectancy (Speer, Jacoby, & Braver, 2003) and RN frequency (Burgess & Braver, 2010). Specifically, in all conditions, trials randomly vary in set size, with words used as stimuli, such that all items are novel on each trial, with the exception of RN probes. Under such conditions, Burgess and Braver (2010) found that strong RN interference effects are observed. Likewise, following Speer et al. (2003), the set size in a given trial is revealed sequentially, leading to unpredictability and reliance on WM load expectancies to engage control strategies.

In the baseline condition, most trials have high WM load (six to eight items) and RN frequency is low, which should reduce tendencies to engage either proactive or reactive control strategies. However, in the proactive condition, most trials have low WM load (two to four items), leading to the expectancy that active maintenance-focused and proactive attentional strategies will be effective, whereas RN frequency remains low (i.e., matched with the baseline condition), such that the utility of reactive control should be unchanged. The critical prediction concerns the five-item set size, which occurs equivalently in all conditions and thus can be compared between them. The key hypothesis is that use of proactive control strategies will improve performance, primarily for the target probe trials (termed novel positive, or NP, because they never overlap across trials). In terms of neural activity dynamics, the key prediction is of increased encoding-related activity (i.e., during presentation of the memory set) on all trials, which might also be accompanied by sustained activation (i.e., maintaining the attentional strategy) across the task block.

In the reactive condition, WM loads are identical to the baseline condition, whereas the frequency of RN trials is strongly increased. Thus, in the reactive condition, it is familiarity-based interference expectancy that increases, rather than WM load expectancy. On the basis of the increased interference expectancy, the theoretical hypothesis is that participants will not rely on familiarity as a cue for responding but will instead use familiarity cues to prompt evaluation of the probe match to items stored in WM. Consequently, the key prediction is that of reduced RN-related interference in the reactive condition. In terms of neural activity dynamics, reactive control effects should be observable as transient probe-triggered activation on RN trials (relative to NN trials).

Focus of the Current Report

Because of the rich nature of the DMCC data set and the ongoing state of data collection, many primary research questions of interest will be the focus of future papers. Most prominently, individual difference-focused analyses, which will examine the relationship between neural activity patterns associated with proactive and reactive control, and the other individual difference measures, will be most powerfully investigated after data collection is complete (estimated 2023), with a target sample size of 200. Here, we took advantage of the within-participant design and novel DMCC task battery, with four distinct tasks to focus initial analyses on event-related (i.e., transient) activation and cross-task relationships. We first examined the baseline condition, to examine questions related to the domain generality of cognitive control. In addition, we investigated the

effects of reactive control manipulations on these event-related responses and brain–behavior relationships. We chose to focus on reactive control in this analysis, because many of our reactive control conditions are novel; more generally, examination of reactive control has been somewhat neglected in ours and other researchers' prior work. Examination of proactive control effects is equally important; however, these are only briefly described here, as a comprehensive treatment would require a distinct set of analyses (e.g., sustained and multivariate) that are beyond the scope of the current work, and will instead be the focus of a forthcoming paper.

METHODS

Participants

Analyses were conducted on two subsets of healthy young adult participants. The first was a set of 55 unrelated individuals (age: mean = 31.7 years, *SD* = 5.9 years; female = 34, male = 21) for which data from the baseline condition have been described (Etzel et al., 2021) and publicly released as OpenNeuro Dataset ds003465 (named DMCC55B, openneuro.org/datasets/ds003465). The second subset was an enriched set of 80 participants (age: mean = 32.0 years, *SD* = 6.1 years; female = 47, male = 32, prefer not to answer = 1) that had high-quality data from both baseline and reactive conditions. This participant sample included both prior HCP participants (n = 43) and 24 twin pairs. As with the HCP, recruitment of twin participants was drawn from a database maintained by the Missouri Family Registry at Washington University, St. Louis. Sample participants had the following self-reported demographic breakdown: White/Caucasian (57), Black/African American = 11, Asian/Pacific Islander = 5, more than one race = 5, and prefer not to answer = 1. During recruitment, all participants were screened and excluded if they were outside the 18- to 45-year age range, were diagnosed with severe mental illness, had significant neurological trauma, has certain medication usage, or had failure to pass screening for MRI safety contraindications. Participants recruited from the HCP sample were screened and excluded for a significant change in their status with regard to these exclusion criteria from the time of their last HCP scan. A screening form with the full listing of exclusion criteria can be found at the following link (osf.io/6efv8/). All participants provided written informed consent in accordance with the institutional review board at Washington University, St. Louis, and received $450 compensation for the completion of all sessions (along with additional monetary bonuses for performance in the Cued-TS tasks).

Protocol

Participants underwent a series of four experimental sessions spaced with a minimum 2-day interval between each session to minimize fatigue. Sessions were scheduled according to scanner constraints but typically occurred over a 3-week window (median number of days between the first and third imaging session = 19). The first session was an out-of-scanner behavioral assessment, geared toward providing a comprehensive profile of individual difference characteristics, and included self-report measures related to personality and psychological health and well-being as well as cognitive tests of crystallized and fluid intelligence, processing speed, WM capacity, and attentional control. A full list and detailed description of these measures is beyond the scope of the current report but can be found at nda.nih.gov/edit_collection.html?id=2970 and Etzel et al. (2021). After the out-of-scanner behavioral session, participants underwent three imaging sessions, under which baseline, proactive, and reactive task conditions were performed. The baseline condition was always completed in the first neuroimaging session, whereas proactive and reactive condition order was counterbalanced across participants, in terms of session order. For twin pairs, both members of the pair experienced the same task and session order, to facilitate twin-based comparisons. Anatomical scans were typically collected during the first session (baseline condition); however, if scans were not rated of sufficient quality (structural rating scale and criteria following HCP protocols), they were repeated at the beginning of a later scanning session and the highest-rated scans were used. In addition to the anatomical and task fMRI scans, two resting state scans, each of 5-min duration, were collected in each imaging session, one before the first task-fMRI scan and the second after the fourth scan. A subset of participants (n = 40) returned for later retest waves, in which they performed the full DMCC protocol at least a month (and sometimes many months to years) after their initial session. Full test–retest analyses are beyond the scope of this paper, although an initial analysis is reported (designed to control for potential order effects) that includes retest data from the baseline condition.

Participants were included in analyses if they successfully completed all experimental sessions. Of the 80 participants meeting these criteria for the initial analyses, 10 participants did not have full imaging data for all baseline and reactive scans (most were missing one scanning run because of technical issues). In addition, 14 participants were missing behavioral data during at least one scanning run (again because of technical issues, typically related to button box or microphone malfunction). Because of the loss in statistical power, these participants were excluded from some analyses (i.e., those focused on the problematic task in the relevant session).

Imaging Data Acquisition

All imaging data were acquired on a Siemens 3-T PRISMA scanner using a 32-channel head coil and included both high-resolution magnetization prepared rapid gradient echo anatomical scans (T1- and T2-weighted with

0.8-mm^3 voxels) and BOLD functional scans using the CMRR multiband acceleration sequences initially developed for the HCP (Uğurbil et al., 2013; acceleration factor = 4, 2.4-mm^3 voxels, 1.2-sec repetition time [TR], with alternating anterior-posterior and posterior-anterior and PA encoding directions). Full details of the acquisition protocol and parameters can be found at osf.io/tbhfg/. In each of three imaging sessions, participants underwent eight BOLD scans runs of approximately 12 min in duration, during which they performed two consecutive runs of each of the four DMCC tasks.

Each scanning run followed a mixed, block/event-related format (Petersen & Dubis, 2012; Visscher et al., 2003), in which task trials were grouped into blocks separated by short resting fixation blocks. Each task block lasted approximately 3 min and was preceded and followed by a 30-sec fixation block, for runs of approximately 12 min. The precise trial and run durations varied slightly between tasks (see below and osf.io/48aet/). Trial duration and intertrial intervals were timed to synchronize with the scanner pulses to facilitate estimation of the event-related response.

Tasks

All DMCC tasks were programmed and presented to participants using E-Prime software (Version 2.0, Psychology Software Tools). All task scripts are available at pages .wustl.edu/dualmechanisms/tasks. In all tasks but the Stroop, participants responded with a custom-designed manual response box, using index and middle fingers of the right hand. In the Stroop, participants made vocal responses that were digitally recorded and later processed to automatically extract response latencies, using a MATLAB (The MathWorks) spectral filtering algorithm, with code available at github.com/ccplabwustl/dualmechanisms/tree/master/preparationsAndConversions/audio. These recordings were also manually inspected for quality control purposes and to code response errors.

In the Stroop task (see Figure 1A), participants named the font color of the word (red, purple, blue, yellow, white, pink, black, or green). The key contrast of interest is of biased incongruent versus biased congruent trials. In the AX-CPT task (Figure 1B), participants made target or nontarget button press responses to cue and target stimuli, with target trials defined as an A-cue followed by an X-probe. The key contrast of interest is BX versus BY trials. In the Cued-TS paradigm (see Figure 1C), participants made target or nontarget button press responses to letter–digit target stimuli, with the target defined by the task cue (letter or digit) and response mapping (letter: consonant or vowel; digit: odd or even). The key contrast of interest is nonincentive incongruent versus nonincentive congruent trials. In the Sternberg paradigm (see Figure 1D), participants made target or nontarget button press responses to probe word stimuli, deciding whether they had been one of the words previously presented in the memory set for that trial. The key contrast of interest is RN critical (five-item) trials versus NN critical (five-item) trials. Detailed information regarding stimulus parameters is available at osf.io/48aet/.

Data Analysis

For behavioral data, analyses focused on RT and error rates in the key contrasts of interest. These contrasts isolate interference effects associated with increased cognitive control demands or, in other words, the degree to which task performance declines in high-control relative to low-control trials. Second-level (i.e., group effect) statistical analyses were conducted using robust *t* tests (Yuen), which operate on trimmed means (0.1 trim) to reduce the effects of outliers (Yuen, 1974), or linear mixed-effect models, which enable task and dependent measures to be appropriately nested within participants, while also handling missing data (Bates, Mächler, Bolker, & Walker, 2015).

For imaging data, preprocessing was implemented with fMRIPrep (Esteban et al., 2019) and followed a standard, state-of-the-art pipeline for preprocessing. The fMRIPrep pipeline was implemented in a Singularity container (Kurtzer, Sochat, & Bauer, 2017) with additional custom scripts for file management (more details on the pipeline are available at osf.io/6p3en/; container scripts are available at hub.docker.com/u/ccplabwustl). The fMRIPrep pipeline includes the following preprocessing steps: anatomical brain extraction and reconstruction of the cortical surface, head-motion estimation and correction, estimation and correction of susceptibility-derived distortions, slice-timing correction, intrasubject registration, spatial normalization, and output of the functional BOLD data into cortical surface space and segmented subcortical nuclei, using FreeSurfer and the *fsaverage5* cortical template space (Fischl et al., 2002). After fMRIPrep preprocessing, additional preprocessing and task-related activation were estimated with AFNI software (Cox, 1996). Additional preprocessing steps included extraction of frame-wise motion censoring (framewise displacement > 0.9 mm) and image normalization (i.e., demeaning).

Task fMRI data were analyzed using a mixed blocked/event-related general linear model (GLM) estimation approach. Standard AFNI GLM procedures (*3dREMLfit*) were applied whole brain at the vertex level (including six-parameter motion and frame-wise censoring parameters, as well as polynomial detrending, using the *-polort* flag). Event-related activation was estimated using a piecewise linear spline deconvolution approach, implemented with the AFNI *TENTzero* function. This approach increases the flexibility of event-related time course estimation and is useful for multievent trials that were present in three of the four DMCC tasks (i.e., all but Stroop). Task regressors modeled various trial types of interest. In addition, nuisance regressors modeled block

onsets and offsets. A boxcar regressor (AFNI BLOCK) modeled the duration of each task block, to estimate sustained activity.

After GLM estimation, vertex-wise beta estimates were averaged into cortical parcels according to the Schaefer 400 atlas (Schaefer et al., 2018) and into subcortical parcels via the CIFTI FreeSurfer segmentation (19 nuclei; Glasser et al., 2013). For the primary analyses of interest, contrast time courses were computed and extracted around the 2-TR peak of the target event (allowing for the ~5-sec hemodynamic lag). These contrasts isolate interference effects associated with increased cognitive control demands or, in other words, the degree to which neural activity increases on high-control relative to low-control trials. Second-level (i.e., group effect) statistical analyses were performed to test whether a contrast was significant (i.e., greater than zero, indicating high control demand activity > lower control demand activity) using one-sample *t* tests. The full preprocessing and processing pipelines were implemented as semiautomated workflows. Schematic diagrams of these workflows along with associated documentation on standardized operating procedures, processing scripts, software tools, and example outputs are all available on OSF and can be accessed via osf.io/6jd9e/.

In addition to the primary univariate analyses, two multivariate analyses were conducted. The first examined activation pattern similarity across the four DMCC tasks, using the baseline condition data, and DMCC55B release (to eliminate any potential concerns regarding twin-similarity effects). To conduct this analysis, coefficient estimates of the high- and low-control-demand trial types in each task at the target event peak (described above) were extracted from each parcel of interest. These were formed into a set of eight vectors per participant × parcel (two per task). For each participant and parcel, pairwise activation pattern similarities were computed among these eight vectors, using the Pearson correlation coefficient (*r*) as the measure of similarity (Nili et al., 2014). Three types of cross-task correlations (i.e., between different tasks) were computed: correlations between high-control-demand trial types (Hi–Hi, six pairings), between high- and low-control-demand trial types (Hi–Lo, 12 pairings), and between low-control-demand trial types (Lo–Lo, six pairings). Correlation coefficients were converted to *z* values (using Fisher's *r*-to-*z* transformation) and then averaged by correlation type (Hi–Hi, Hi–Lo, and Lo–Lo) and then by participant (i.e., over parcels). These mean *z* values were then contrasted across the three pairings of interest. In particular, to test the hypothesis that high-control-demand trial types would be more similar across tasks than low-demand trial types, Hi–Hi was contrasted against Lo–Lo and against Hi–Lo.

The second multivariate analysis was conducted to determine whether the cross-task activation profile of the reactive condition was indeed dissociable from the proactive as well as baseline conditions. For this analysis, each participant's activation profile for a given condition was treated as a sample from a multivariate distribution within a space of 140 dimensions (35 ROIs × 4 tasks). If each condition truly drove a unique profile of activation, there should be three distinct "clouds" within this space, one per condition. That is, relative to the amount of within-condition (between-participant) variability, the group-mean profile of the reactive distribution should be discriminable from not only the baseline mean but also the proactive mean. To test these hypotheses, we used an unbiased measure of multivariate discriminability, a cross-validated (leave-one-participant-out) form of the Mahalanobis distance (Walther et al., 2016). For each fold, activity profiles were whitened using the within-condition covariance matrix estimated from held-out participants (optimally regularized toward zero, with separate shrinkage estimators for off-diagonals and diagonals; Schäfer & Strimmer, 2005). *t* Tests over participants were then used to assess whether condition distributions were discriminable (one-sided, one-sample) and whether a distribution was closer to one than another (two-sided paired). Finally, to visualize the arrangement of these activity profile distributions, a linear-discriminant-analysis-based projection procedure was used that was analogous to cross-validated Mahalanobis. Specifically, in leave-one-participant-out cross-validation, we used the training-set participants to compute the mean of each condition and then the two linear discriminants that spanned these three means (using the whitening procedure described above). The profile of the held-out participant was then projected onto these discriminants. By iterating this procedure through all participants, a set of cross-validated projections was obtained. Cross-validating in this manner ensured that whatever clustering is observed within the projected profiles is a property of the data, not of the linear discriminant analysis procedure (this was also verified by checking that this procedure does not generate separate clusters on pure noise). To illustrate within-condition variability, participants' projections were bootstrap resampled (with replacement, no subsampling, 10,000 times), and each resample was averaged over participants by condition.

All analyses were performed using R statistical software Version 3.1.3 (R Development Core Team, 2015). Code and input data for replicating the figures and statistics, as well as detailed reporting of Supplementary Results, are available at osf.io/xvzrf/.

RESULTS

Baseline Condition: Behavioral Performance

We examined the presence of interference effects in the baseline condition, associated with high versus low cognitive control demands, through the relevant contrast of interest for each task, in both RT and error rates. In all four tasks, and in both behavioral measures, these interference effects were highly robust (see Table 1): Stroop

Table 1. Behavioral Measures for High- and Low-Control-Demand Trials in DMCC Tasks

	Baseline				*Reactive*			
	High RT (msec)	*Low RT (msec)*	*High % Error*	*Low % Error*	*High RT (msec)*	*Low RT (msec)*	*High % Error*	*Low % Error*
Stroop	927 (15.3)	793 (15.2)	2.3 (0.5)	0.3 (0.1)	854 (17.8)	771 (15.9)	1.9 (0.4)	0.2 (0.2)
AX-CPT	607 (25.4)	465 (14.4)	16.3 (2.0)	2.6 (0.6)	584 (21.8)	429 (13.0)	10.3 (2.0)	3.3 (0.6)
Cued-TS	1161 (32.1)	1108 (31.6)	7.6 (1.1)	2.8 (0.4)	1078 (37.0)	1016 (33.1)	4.4 (1.0)	2.1 (0.3)
Sternberg	1109 (29)	946 (22.5)	26.6 (2.4)	5.5 (1.3)	1033 (24.9)	909 (19.5)	19.2 (1.9)	4.1 (1.6)

Left columns indicate baseline condition; right columns indicate reactive condition. Data reported are group means, with *SEM* in parentheses.

(incongruent–congruent; RT: $t = 18.67$, $p < .001$; error: $t = 4.59$, $p < .001$), AX-CPT (BX–BY; RT: $t = 8.78$, $p < .001$; error: $t = 7.53$, $p < .001$), Cued-TS (incongruent–congruent; RT: $t = 5.34$, $p < .001$; error: $t = 5.44$, $p < .001$), and Sternberg (RN–NN; RT: $t = 7.30$, $p < .001$; error: $t = 9.94$, $p < .001$). These results are consistent with the interpretation that the selected trial type contrasts index increased cognitive control demands.

Baseline Condition: Neural Activity

We conducted whole-brain parcel-wise analyses to identify regions showing robust effects of cognitive control demand. These analyses were based on event-related time courses for the high–low cognitive control demand contrast in each task, isolating a 2-TR peak window around the target event (assuming a ~5-sec hemodynamic lag and with the peak selected based on visualization of initial pilot data; see Figure 5). A two-stage conjunction analysis approach was then utilized to reveal regions showing consistent control demands across all four tasks. In the first stage, a linear mixed-effect statistical model was employed on each parcel to test for the fixed effect of high > low control demand, including the four tasks and participant as random effects. For this first stage, to control for multiple comparisons, a Bonferroni correction was used to control for the number of cortical parcels. Thus, the significance level was set at $p \leq .0001$. In the second stage, each task was interrogated individually, for the significance of the contrast, using $p \leq .05$ uncorrected significance levels. We counted a parcel as robust and consistently activated by control demand if it not only passed the first stage but was also significant for each of the four tasks, in the second stage.

From these analyses, we identified a set of 35 cortical parcels. These parcels are shown in Figure 2, with contrast time courses shown in Figure 5. The identified parcels were fully localized to fronto-parietal and cingulo-opercular regions associated with brain networks typically linked to cognitive control (Dosenbach, Fair, Cohen, Schlaggar, & Petersen, 2008; Vincent, Kahn, Snyder, Raichle, & Buckner, 2008; Cole & Schneider, 2007). Indeed, 31 of the 35 regions are located in parcels labeled in the Schaefer atlas as belonging to either the control (15), salience/ventral attention (8), or dorsal attention (8) networks (note that the remaining four parcels were labeled as belonging to the default mode network but were also located within the lateral PFC; see Table 2). The most robustly activated regions were bilateral, within dorsolateral PFC (Parcels 139, 140, 141, 346, 347, 349, and 350), dorsal anterior cingulate/pre-SMA (Parcels 110, 148, 311, and 361), and anterior insula/frontal operculum (Parcels 99, 101, 306, and 340). These results imply that this set of regions may function as a core network consistently responsive to cognitive control demands, across a wider set of task conditions, similar to findings from related work (Assem, Glasser, Van Essen, & Duncan, 2020; Fedorenko, Duncan, & Kanwisher, 2013).

Baseline Condition: Neural Pattern Similarity

We conducted a follow-up analysis to further explore the issue of domain generality in cognitive control task

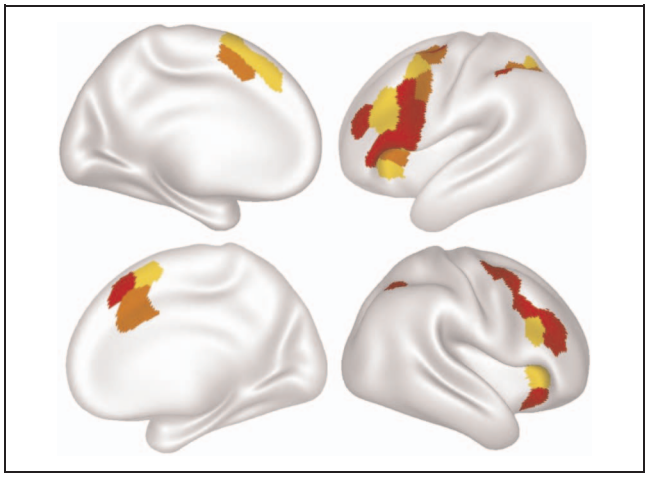

Figure 2. Brain regions identified showing a consistent effect of cognitive control demand in each of the four DMCC tasks. Regions are shown as surface-based parcels in the Schaefer 400 atlas (Schaefer et al., 2018) shown on medial (left side) and lateral (right side) surfaces, for the left (top) and right (bottom) hemispheres. Color scale indicates contrast significance in each of the four tasks: red ($p \leq .05$), orange ($p \leq .01$), and yellow ($p \leq .005$). Regions are localized to fronto-parietal and cingulo-opercular networks (see Table 2 for anatomical locations).

Table 2. The 35 Parcels Identified as Showing a Consistent Effect of Cognitive Control Demand across DMCC Tasks

Parcel Number	*Hemisphere*	*Network*	*ROI*	*x*	*y*	*z*
77	Left	Dorsal attention	Post_9	−33	−46	41
78	Left	Dorsal attention	Post_10	−29	−58	50
86	Left	Dorsal attention	FEF_1	−40	−3	51
87	Left	Dorsal attention	FEF_2	−25	−1	55
88	Left	Dorsal attention	FEF_3	−30	−8	52
90	Left	Dorsal attention	PrCv_1	−49	6	26
91	Left	Dorsal attention	PrCv_2	−50	3	38
99	Left	Salience/ventral attention	FrOperIns_3	−33	25	−1
101	Left	Salience/ventral attention	FrOperIns_5	−33	19	8
103	Left	Salience/ventral attention	FrOperIns_7	−43	12	2
105	Left	Salience/ventral attention	FrOperIns_9	−52	9	13
110	Left	Salience/ventral attention	Med_4	−5	9	48
127	Left	Control	Par_1	−29	−74	42
130	Left	Control	Par_4	−35	−62	48
132	Left	Control	Par_6	−45	−41	47
139	Left	Control	PFCl_5	−42	38	22
140	Left	Control	PFCl_6	−45	20	27
141	Left	Control	PFCl_7	−39	7	34
148	Left	Control	PFCmp_1	−4	28	47
172	Left	Default	PFC_7	−48	28	0
175	Left	Default	PFC_10	−53	19	11
185	Left	Default	PFC_20	−42	7	48
189	Left	Default	PFC_24	−6	10	65
290	Right	Dorsal attention	FEF_1	39	−3	53
306	Right	Salience/ventral attention	FrOperIns_5	37	23	5
311	Right	Salience/ventral attention	Med_1	7	19	35
314	Right	Salience/ventral attention	Med_4	6	11	58
337	Right	Control	Par_6	41	−55	48
340	Right	Control	PFCv_1	34	21	−8
346	Right	Control	PFCl_6	50	30	18
347	Right	Control	PFCl_7	48	18	23
349	Right	Control	PFCl_9	47	29	28
350	Right	Control	PFCl_10	39	11	34
353	Right	Control	PFCl_13	43	7	51
361	Right	Control	PFCmp_2	5	28	48

Parcel numbers, names, networks, and centroid coordinates (Montreal Neurological Institute) are those provided in the 400-parcel, seven-network resolution Schaefer atlas (Schaefer et al., 2018). For additional information, see github.com/ThomasYeoLab/CBIG/tree/master/stable_projects/brain_parcellation/Schaefer2018_LocalGlobal.

activation patterns. For this, we focused on multivariate pattern similarity, as it provides a complementary test to univariate analyses, addressing the question of whether common control-related activation patterns are evoked across tasks (He et al., 2021; Kragel et al., 2018). Furthermore, we conducted this analysis on the publicly released subset of 55 unrelated participants, to make this analysis maximally useful to the wider scientific community. Specifically, using the 35 parcels identified in the previous analysis, we computed three sets of cross-task pairwise activation pattern similarities: (1) high-control-demand trials in Task A with high-control-demand trials in Task B (six pairings, termed Hi–Hi), (2) low-control-demand trials in Task A with low-control-demand trials in Task B (six pairings, termed Lo–Lo), and (3) high-control-demand trials in Task A with low-control-demand trials in Task B (12 pairings, termed Hi–Lo). We hypothesized that the Hi–Hi would show significantly greater cross-task pattern similarity than either Lo–Lo or Hi–Lo, because only in Hi–Hi would a common cognitive control process be engaged (Nili et al., 2014). As predicted, the Hi–Hi similarity was significantly greater than either Lo–Lo (Figure 3; mean contrast $m = .12$, $p < .0001$) or Hi–Lo ($m = .08$, $p < .0001$). This finding supports the hypothesis that the high-cognitive-control-demand trial types exhibit a similar activation topography that is reflective of a cross-task domain-general cognitive control representation, which is distinct from that observed in the low-demand trial types.

Baseline: Brain–Behavior Relationships

Given that both behavioral performance and parallel neural activity measures showed consistent effects of control demand across the four tasks, we next tested whether these effects were associated. In particular, we hypothesized that individuals showing larger behavioral interference effects would also show larger neural activity effects of control demand, that is, a positive correlation. To test this hypothesis, and reduce dimensionality, we created a composite behavioral index of performance, by z score normalizing the data across participants and then combining RT and error measures across the four tasks to create a summed z score value for each participant, with larger values indicating higher interference. Likewise, to create a single neural activity index, we treated the 35 parcels as a "megaparcel," averaging contrast activity values (betas) across the set. In addition, we z score normalized and then summed these megaparcel values across the four tasks for each participant. We then correlated the neural activity index against the behavioral composite index. This correlation was significantly positive ($r = .26$, Pearson's $p = .03$, Spearman's $p = .03$; see Figure 6A), supporting our hypothesis.

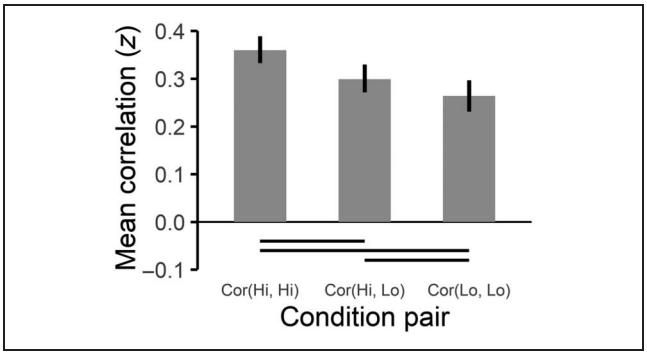

Figure 3. Different tasks drove similar patterns of activation within control-related fronto-parietal brain regions (DMCC35) on control-demanding trials [Cor(Hi, Hi)]. This pattern similarity was heightened relative to trials with low [Cor(Lo, Lo)] or differing [Cor(Hi, Lo)] levels of control demand. Error bars are 95% confidence intervals of between-participant variability (bootstrapped). Significant pairwise comparisons between similarity contrasts (paired two-tailed t test) are indicated by horizontal line segments.

Reactive Effects: Behavioral Performance

We next examined whether the experimental manipulations designed to encourage utilization of reactive control were effective in enhancing behavioral performance by reducing interference effects. Paired robust (Yuen) t tests were conducted to compare RT and errors across the baseline and reactive conditions, for each of the tasks. In each task, at least one of the behavioral metrics showed a statistically significant effect: Stroop (RT: $t = 7.84$, $p < .001$; error: $t = 1.18$, $p > .1$), AX-CPT (RT: $t = -1.22$, $p > .1$; error: $t = 3.31$, $p = .002$), Cued-TS (RT: $t = 0.2$, $p > .1$; error: $t = 2.2$, $p = .03$), and Sternberg (RT: $t = 1.67$, $p = .1$; error: $t = 2.32$, $p = .02$). Thus, behavioral data support the hypothesis of enhanced task performance (reduced interference) via increased utilization of reactive control (see Figure 4). To support this interpretation, we conducted a paired robust (Yuen) t test on the behavioral composite index aggregated across the four tasks, which was computed separately for reactive as well as baseline, for each participant. This analysis confirmed the hypothesis of a robust decrease in interference (improved cognitive control utilization) in reactive, relative to baseline ($t = 5.64$, $p < .001$). In addition, we repeated the analysis, but as a linear mixed-effects model, which jointly modeled error and RT (both z normalized, included as separate observations), with fixed effects of condition (baseline, reactive) and task as well as by-participant random slopes and intercepts for condition. An advantage of this model is that it incorporated the nested structure of the data (using random intercepts and slopes for the effect of condition), while also enabling inclusion of participants who had some missing data. Even using this model, the main effect of Condition was still highly significant ($z = 4.63$, $p < .001$).

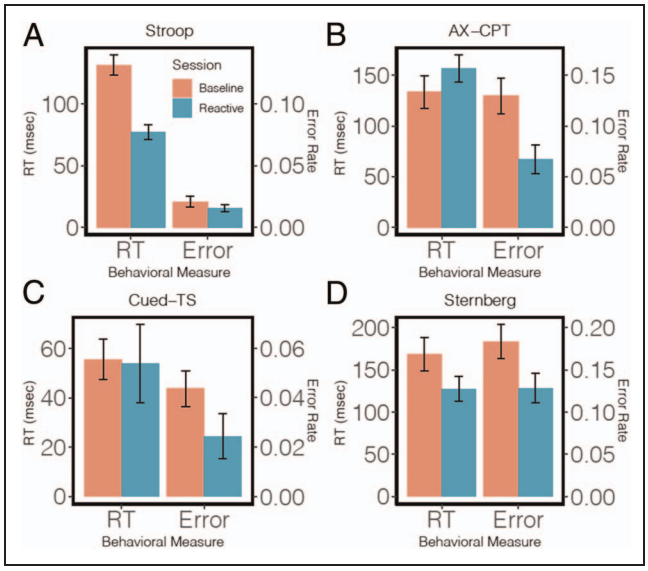

Figure 4. Effects of reactive condition on behavioral performance in DMCC cognitive control indices. Data are shown in terms of RT (left side/axis) and error rate (right side/axis) for each of the four DMCC tasks: (A) Stroop, (B) AX-CPT, (C) Cued-TS, and (D) Sternberg. Baseline (red bars) and reactive (green bars) data shown separately. Reductions in cognitive control indices indicate decreased interference in each task, consistent with enhanced control in the reactive condition.

Reactive Effects: Neural Activity

We examined whether performing the four tasks under reactive control conditions would be associated with parallel neural activity effects similar to what was observed in terms of behavioral performance. Visualization of the event-related contrast time courses for each task suggested a reduction in activation in reactive, relative to baseline (see Figure 5), in the 35-megaparcel. Paired robust (Yuen) t tests were conducted to statistically compare neural activity during the target period across the baseline and reactive conditions, for each task, in the 35-megaparcel. In all four tasks, we found that activity was numerically reduced in the reactive condition, and this reduction effect was statistically significant in three of the four tasks: Stroop ($t = 4.45$, $p < .001$), AX-CPT ($t = .79$, $p > .1$), Cued-TS ($t = 2.11$, $p = .039$), and Sternberg ($t = 2.58$, $p = .012$). Thus, the neural data support the interpretation of reduced activation associated with increased utilization of reactive control. To support this interpretation, we conducted a paired robust (Yuen) t test on the megaparcel, by again computing a neural activity index averaging across the four tasks. This analysis strongly supported the pattern of a robust decrease in activation in reactive, relative to baseline ($t = 4.97$, $p < .001$). In addition, we repeated the analysis, but as a linear mixed-effects model, which included fixed effects of condition (baseline, reactive) and task as well as by-participant random slopes and intercepts for condition. An advantage of this model is that it enabled proper consideration of the nested structure of the data (using random intercepts and slopes for the effect of condition), while also enabling inclusion of participants who had some missing data. Even using this model, the main effect of Condition was still highly significant ($z = 3.78$, $p < .001$).

Reactive Effects: Brain–Behavior Relationships

We hypothesized that the reactive-related enhancement of task performance (reduced interference effects) might be functionally linked to the parallel reduction of neural activity observed in fronto-parietal regions (35-megaparcel). To test this hypothesis, we first computed the brain–behavior correlation within the reactive condition by itself, using the behavioral composite index and neural activity index. Interestingly, within the reactive condition, we did not observe a significant brain–behavior relationship ($r = .15$, Pearson's $p > .1$, Spearman's $p > .1$; see Figure 6B). We next computed baseline–reactive change scores on these indices. Here, the brain–behavior correlation between these change scores was significant ($r = .31$, Pearson's $p = .01$, Spearman's $p = .001$; see Figure 6C). A more formal test of the hypothesis was conducted as a within-participant statistical mediation analysis, according to the procedures outlined in Judd,

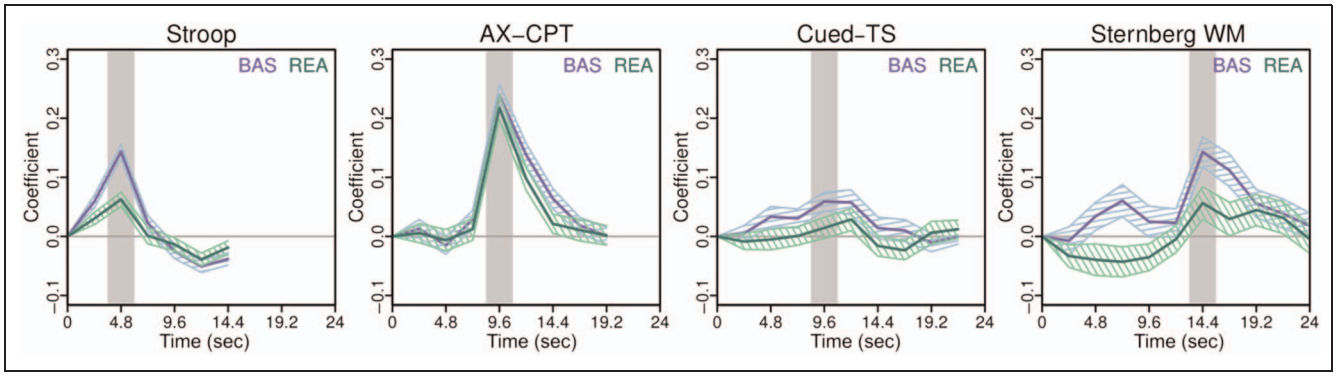

Figure 5. Event-related contrast effects for the DMCC tasks in the baseline and reactive conditions. Data are shown for the 35-megaparcel as contrast time courses (i.e., high–low control demand differences), with the key target period (2-TR window) shaded in gray. In the baseline condition (blue lines), there is a clear peak for each of the four DMCC tasks. This peak is consistently reduced across tasks in the reactive condition (green lines).

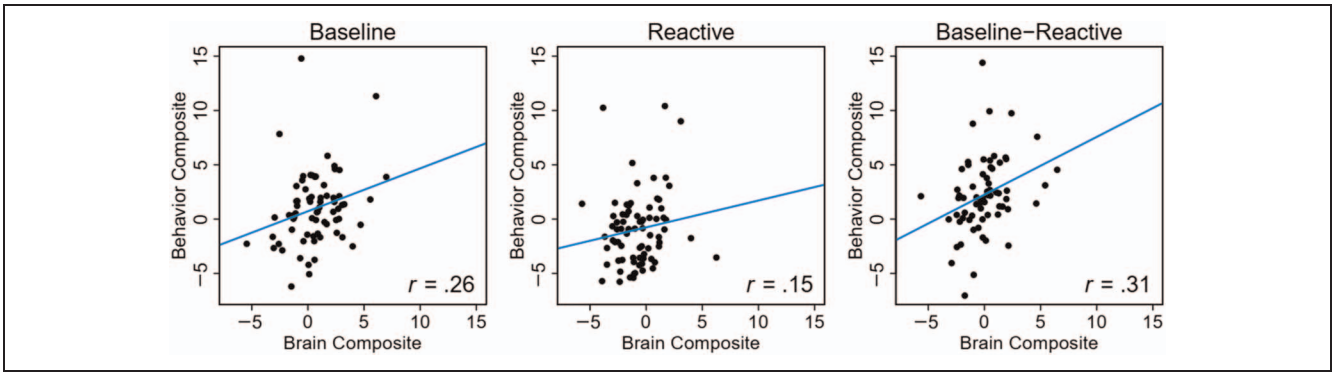

Figure 6. Brain–behavior correlations in the baseline and reactive conditions. Scatterplot data show each participant in terms of their neural activity index (*z*-normalized beta coefficient for the 35-megaparcel summed across the four tasks) and behavioral composite index (high–low demand cognitive control indices for RT and error *z* normalized and summed across the four tasks). The significant positive correlation in baseline (A) indicates that individuals showing greater control-related activity also showed more behavioral interference. This relationship was not significant in the reactive condition (B) but was significant in terms of the baseline–reactive change score (C). The positive correlation in the change score indicates that individuals showing a larger reactive-related reduction in activity also tended to show a larger reactive-related reduction in behavioral interference (i.e., enhanced control).

Kenny, and McClelland (2001). That is, we tested whether the effect of the reactive experimental manipulation on behavioral performance was statistically mediated (or moderated) by its effect on reducing neural activity. This analysis did find evidence of statistically robust mediation (estimate = 0.44, t = 2.95, p = .004) as well as moderation (estimate = −0.27, t = −2.11, p = .04).

Control Analyses

We conducted follow-up analyses to rule out potential alternate explanations of the findings, which are reported in detail in Supplemental Results (osf.io/xvzrf/), and briefly summarized here. First, because we initially identified candidate ROIs through baseline effects only, the activation patterns could be biased toward higher baseline activity and a greater difference between baseline and reactive. To address this issue, we identified high > low cognitive control demand effects using the same two-step procedure described above, but in a whole-brain analysis that included both baseline and reactive conditions, to minimize bias. This analysis identified a set of 20 parcels, of which 17 overlapped with the original 35 identified in baseline only. As expected, given the high degree of overlap, when these parcels were aggregated and treated as a set, the same pattern of baseline > reactive emerged. We also conducted an additional analysis of this type, but focusing on the reactive condition only, using the two-step procedure to identify high > low demand effects. In this analysis, two regions were identified, both of which overlapped with the original 35-parcel set and which again also showed the same baseline > reactive pattern. Finally, we conducted a whole-brain analysis that explicitly tested for the reverse reactive > baseline pattern in each parcel. No parcels were identified that exhibited a consistent pattern of this type across the four tasks, regardless of statistical threshold. Even when focusing on each task individually, only one task—AX-CPT—identified any parcels that met whole-brain statistical significance with the reactive > baseline pattern. In this task, four parcels were identified, which were all located in the visual cortex (Parcels 19, 24, 202, and 223).

A second set of analyses addressed a potential concern related to condition order. In particular, because of the nature of the task conditions, as well as our interest in individual differences, all participants performed the baseline conditions in their first imaging session. Consequently, the observed pattern of baseline > reactive might have been related to practice effects, because of reactive always being performed after baseline. Fortunately, a subset of participants returned for a second wave of testing, which occurred a minimum of 1 month after the first wave, during which the same DMCC tasks and conditions were performed in the same order. Although a full analysis of the test–retest data is beyond the scope of the present paper, it provided the opportunity to examine order counterbalancing. In particular, for 40 participants without retest, we used their first (and only) wave of testing with the baseline/reactive order. For the other 40 participants, with retest data, we combined their second wave of baseline data with their first wave of reactive data, to produce a reactive/baseline condition order. We then reanalyzed the data with this counterbalanced set of conditions, within the 35-parcel set using the mixed-level modeling approach described above (fixed effects of condition and task, by-participant random slopes and intercepts for condition). Indeed, the same pattern of results was obtained, including a highly significant condition effect (p < .001), with baseline > reactive in all four tasks.

A third set of analyses addressed the fact that a subset of participants were members of an identical twin pair, with both members included in the analysis, which may have created dependencies (i.e., reduced the effective degrees of freedom), and impacted the results. To accurately account for this dependency, the data were

reanalyzed using a different linear mixed-effect model that, in addition to including the fixed effects of condition, task, and parcel, also included a random effect of participant nested within family. For twin pairs, both co-twins were included as members of a single family, whereas for singletons, the family factor only included a single individual. Even when rerunning the analysis in this fashion, the main effect of Condition was still highly significant ($p < .001$). Finally, all of the analyses reported above were recomputed with the DMCC55 data subset, for which all participants are unrelated. Again, all of the key results were consistent, even when considering this subset. Thus, when considered together, the results suggest that the baseline > reactive pattern observed in the 35-parcel fronto-parietal regions appears to be quite robust and not driven by confounding factors.

Relationship to Proactive

Our primary focus in this report was to present initial analyses on the baseline condition as well as to examine the relationship with the reactive condition, as this condition has been understudied. In contrast, a detailed comparison with the proactive condition is beyond the scope of the current work and would require a separately focused analysis, given that proactive conditions are hypothesized to involve qualitatively distinct effects from reactive conditions (i.e., sustained, cue related). Nevertheless, we did conduct an analysis, using linear mixed-effect modeling, to compare the reactive and proactive conditions. We observed that there was no significant main effect of Condition ($p = .48$), but there was a highly reliable Condition × Task crossover interaction ($p < .001$), as two of the tasks showed increased activity in the proactive condition (Cued-TS, Sternberg) whereas the other two were increased in the reactive condition.

In addition, we used dimensionality reduction to visualize in two dimensions the multivariate relationships between baseline, proactive, and reactive conditions (i.e., including all four tasks and 35 parcels). As shown in Figure 7, the three conditions each evoked a discriminable profile of activity across parcels and tasks. As expected, reactive and baseline profiles were highly discriminable ($b = 6.33, p < .0001$), but so were the reactive and proactive profiles ($b = 5.8, p < .0001$). Importantly, the reactive profile was no less distant from the baseline profile than it was from the proactive profile ($\Delta b = 0.522$, $p = .43$). Thus, although the univariate contrast did not reveal a simple main effect of Condition between reactive and proactive, these conditions were nevertheless qualitatively distinct.

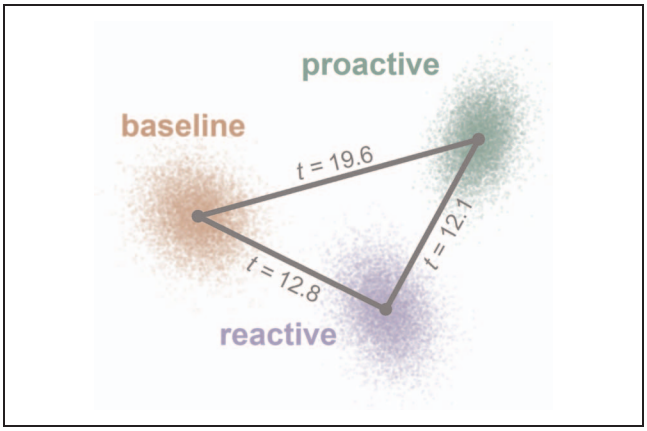

Figure 7. The reactive condition resulted in a consistent profile of activity that was discriminable from both baseline and proactive condition profiles. For each condition, each participant's profile of activity across 35 parcels and four tasks was considered as samples from a multivariate distribution (see Methods). Cross-validated dimensionality reduction was used to visualize the arrangement of these distributions within a 2-D space. Gray circles illustrate the group-mean profile associated with each condition, whereas the surrounding scatter of colored points illustrates between-participant variability (estimated via bootstrap). *t* Values along gray connecting lines correspond to an unbiased multivariate contrast between condition distributions (testing against the null hypothesis that two condition distributions are not discriminable). All distributions are well separated (all corresponding $ps < 10^{-22}$).

DISCUSSION

The focus of this report is twofold. First, we provide an overview of the DMCC project, inspired by the approach advocated by Don Stuss, to investigate executive function in a theoretically driven and experimentally rigorous manner, with a focus on individual differences and brain–behavior relationships. Second, we highlight the promise and potential of this project for researchers interested in the neural mechanisms of cognitive control, by reporting initial analyses of DMCC data that reveal a domain-general neural signature of cognitive control and its modulation under reactive conditions, which is reflected in decreased stimulus-triggered activity within a set of fronto-parietal brain regions. We elaborate on each of these dimensions in turn.

DMCC Project Features

The primary feature of the DMCC study is its within-participant design, in which each participant undergoes over 5 total hours of task fMRI, performing four distinct but theoretically targeted cognitive control paradigms (Stroop, AX-CPT, Cued-TS, and Sternberg) under three different control modes (baseline, reactive, and proactive). There are now a number of other studies, utilizing much larger sample sizes than the DMCC, in which each participant undergoes fMRI scanning while performing multiple cognitive tasks (e.g., HCP, ABCD, IMAGEN, PNC; Casey et al., 2018; Satterthwaite et al., 2014; Van Essen et al., 2013; Schumann et al., 2010), as well as smaller studies that have collected comparable task fMRI data on each individual (Nakai & Nishimoto, 2020; Gordon et al., 2017). However, to our knowledge, the DMCC project is the first collect this much task-fMRI data

within the domain of cognitive control, using theoretically targeted experimental paradigms. Indeed, using the terminology of Naselaris et al. (2021), the DMCC project is already close to the 1000 iso-hour contour that has been achieved by very few studies. Moreover, the use of a multitask approach aligns well with psychometric and measurement model perspectives, in which the use of multiple task indicators assessing the same theoretical construct provides the foundation for more statistically valid extraction of latent variables (Cooper, Jackson, Barch, & Braver, 2019; Friedman & Miyake, 2017; Conway & Kovacs, 2013; Kievit et al., 2011). In other words, by collecting data on each participant from multiple cognitive control tasks, the DMCC project provides a more psychometrically valid and meaningful basis for determining whether neural and behavioral markers reliably tap into cognitive control, in showing a consistent pattern across tasks. Moreover, from a construct validation perspective, it can be argued that the DMCC data most strongly demonstrate the generalizability of behavioral and neural markers of cognitive control constructs, by minimizing the impact of measurement error or anomalous/spurious effects that might be observed within single tasks.

A second key aspect of the DMCC design is that not only do participants perform multiple cognitive control tasks under multiple experimental contexts but that these contexts were also theoretically designed to manipulate the mode of cognitive control being deployed. In particular, the DMC framework suggests a meaningful distinction between proactive and reactive control modes, in that these can be distinguished in terms of operating characteristics, temporal dynamics, and neural coding schemes. The DMCC project provides an unprecedented opportunity to systematically test this theoretical framework, by examining the neural activity and behavioral profiles of individuals performing each of the four tasks in the DMCC battery under proactive and reactive as well as baseline conditions. Moreover, each of the individual tasks provides a rich set of data regarding the effects of different experimental manipulations on cognitive control modes and mechanisms, such as interference expectancy, instructed strategies, motivational incentives, and WM load. Conversely, when examined in combination, the data set enables a test of whether consistency in control mode shifts occur even across these heterogenous tasks and experimental contexts. As such, the DMCC project can also be construed as a large test–retest design, from which state-dependent components of cognitive and neural activation profiles can be uncovered and disentangled from the state-independent processes that are engaged as individuals perform demanding cognitive tasks. As discussed further below, here we provide the first analysis of this type, leveraging the advantages of the DMCC to demonstrate the presence of consistent state-dependent changes in neural activity profiles occurring during reactive control.

A third key aspect of the DMCC design is its focus on individual differences, enabling examination of cognitive control variation in relation to other established sources of individual variation. Because of the broad range of individual difference measures collected outside the scanner, it will be possible to relate variation in cognitive control function and control modes with a range of related constructs, including personality traits (e.g., anxiety, neuroticism, impulsivity, reward and punishment sensitivity, need for cognition), as well as with closely linked cognitive dimensions such as fluid intelligence, WM capacity, and processing speed. Another source of individual difference information is the HCP, because a large subset of DMCC participants also took part in the HCP. Consequently, it is possible to leverage the set of task fMRI paradigms used in the HCP, as well as its larger sample size (>1000 participants), to draw inferences and connections regarding neural substrates. Moreover, the larger sample size and genotyping available in the HCP make it possible to link neural and behavioral cognitive control profiles identified in the DMCC with relevant dimensions of genetic variation. In addition, the subset of MZ twins within the DMCC sample makes it possible to examine the effects of heritability and shared environmental on cognitive control variation in a manner that is more systematic and theoretically driven than has been possible in prior investigations within this domain (Tang, Etzel, Kizhner, & Braver, 2021).

A final key feature of the DMCC design is its longitudinal component, as this enables both individual-differences-focused and other theoretically valuable investigations of cognitive control function. Specifically, within the DMCC, many participants, including most of the MZ twin pairs, return for multiple waves of testing, during which the full experimental protocol is repeated. This aspect of the design provides a test of the longer-term (i.e., multiple month intervals) stability versus change present in behavioral and neural cognitive control profiles. Combined with the multitask, multiple-context nature of the design, these longitudinal data will enable richer and more rigorous investigations that can uncover latent sources of stability and change decoupled from task-specific effects and other sources of measurement error. Moreover, for the subset of DMCC participants in the HCP, there is also the possibility of relating cognitive control function with stability versus change in resting-state connectivity patterns over even longer intervals (years). We provided an initial example of the utility of this longitudinal design, as we were able to utilize the retest data from a subset of participants to control for potential condition order effects. Finally, we note another unique component of the design, in which some DMCC participants receive mindfulness skills training intervention occurring between testing waves. This component of the project will provide a novel means of testing the relationship between mindfulness and cognitive control function—a relationship that has been hypothesized in many theoretical treatments (Malinowski, 2013; Teper, Segal, & Inzlicht, 2013; Tang & Posner, 2009).

We describe these key features of the DMCC project in the hopes of making other interested investigators aware of the possibilities available with the data set. Aligned with the spirit of Don Stuss in building scientific communities, and with the current push toward open science and reproducibility, we have a strong commitment to make the DMCC data set publicly available. Although the project is still ongoing, we have recently released a subset of DMCC data (from the baseline condition in 55 unrelated participants; openneuro.org/datasets/ds003465) along with a technical description of data components (Etzel et al., 2021). A full release will occur after data collection is complete (estimated 2023).

Initial DMCC Findings

To provide a first demonstration of the promise of the DMCC data set, we conducted analyses that focused on reactive control, particularly whether there was a consistent behavioral and neural signature of this control mode. The reactive control mode has tended to receive less investigation than that of proactive control (Braver, 2012), and as such, the characteristics of reactive control have been more difficult to describe, sometimes even confused or conflated with a reduction in proactive control. Thus, one of the design goals of the DMCC battery was to provide task conditions, across a set of well-established cognitive control paradigms, that manipulated the utilization of reactive control, distinct from proactive control. In particular, we hoped to demonstrate that utilization of the reactive control mode can be linked with enhanced cognitive control function and improved task performance (i.e., reduced interference effects). In this respect, the results clearly supported our hypotheses. In all four tasks, we observed behavioral evidence of task performance improvements under reactive conditions, observable as reductions in interference relative to baseline.

We found a parallel and novel pattern when examining the fMRI data, in that a set of fronto-parietal brain parcels, defined by their consistent transiently increased activation to high-control-demand target items during the baseline condition, also showed a consistent reduction in this transient response in the reactive condition. Three aspects of this finding are particularly noteworthy. First, because we identified the set of 35 fronto-parietal parcels based solely on their baseline activation profiles, the activity reduction we observed in these same parcels under reactive conditions was unbiased. Moreover, additional control analyses demonstrated that the reactive-related activity reduction was the dominant feature of the data, regardless of how parcels were identified. Second, the set of fronto-parietal regions that we identified here is consistent with prior work, which described a similar canonical cognitive control network (Dosenbach et al., 2008; Vincent et al., 2008; Cole & Schneider, 2007). This network has also been referred to as the multiple-demand network (Camilleri et al., 2018; Duncan, 2010; Duncan & Owen, 2000), in that it exhibits consistent responsivity to increasing control demands across a range of task contexts (Assem et al., 2020; Shashidhara, Mitchell, Erez, & Duncan, 2019; Fedorenko et al., 2013). This set is primarily bilateral and includes not only midlateral PFC and parietal cortex but also other regions linked to cognitive control, such as the anterior insula/frontal operculum and medial frontal cortex/dorsal anterior cingulate. Our use of a standardized atlas and parcellation scheme (Schaefer et al., 2018) facilitates identification of these regions in multiple data sets and across laboratories, which will promote stronger tests of cross-study consistency in anatomical localization and naming conventions. Third, because of the multitask nature of the DMCC design, we were able to demonstrate a consistent pattern, not only for the baseline control demand effect but also for the reactive activation reduction effect. This consistency increases confidence in the interpretation that the reactive pattern is a generalizable one, occurring across different task contexts and experimental manipulations.

Indeed, reactive manipulations implemented across the four tasks were somewhat variable and, in some cases, novel. In the Stroop task, we used an item-specific proportion congruency manipulation that has been repeatedly shown in prior work (Gonthier, Braver, et al., 2016; Bugg & Hutchison, 2013; Bugg, Jacoby, et al., 2011). In the AX-CPT, the manipulation was similar, in that we used a context-specific proportion conflict manipulation (spatial location and border color of probe items predicted the likelihood that they would be high or low conflict). To our knowledge, this is the first time that both item-specific and context-specific manipulations have been studied together in a within-participant multitask design. In the Sternberg task, the reactive manipulation also involved interference expectancies but was related to familiarity, rather than congruency or conflict. Finally, in the Cued-TS paradigm, the reactive manipulation involved a punishment-related motivational context and so was quite different from the other tasks. Yet even with these heterogeneous manipulations, we observed a similar fronto-parietal neural profile for reactive control. As such, it seems warranted to refer to this fronto-parietal pattern of reduced transient activation as a consistent neural modulation that may in fact be a hallmark of reactive control engagement.

The functional relevance of this neural modulation was supported by the finding of a clear brain–behavior relationship, highlighting individual differences among participants. In particular, the individuals who showed the strongest reactive-related reduction in transient activity were the ones showing the largest behavioral benefits. The relationship was confirmed through formal statistical mediation analyses, which suggest that the impact of the reactive experimental manipulations on task performance was at least partially mediated by their associated impact on neural activity. Likewise, the significant

moderation effect means that the reactive-related reduction in fronto-parietal activity and behavioral interference was strongest for participants showing the largest effects (strongest activity and interference) in the baseline condition. Thus, we interpret the findings as indicating that the reactive-related reduction in transient activity is functionally related (or even more provocatively, a causal factor tied) to the improvement in performance.

There were some potentially surprising aspects of these reactive control findings. First, the more intuitive prediction might be that an increase in cognitive control utilization would be associated with increased activation in the neural substrates that implement control functions. Yet, here we found the opposite pattern, in which we attribute enhanced utilization of reactive control with a transient decrease in event-related activation. In the neuroimaging literature, decreased activity patterns co-occurring with improvements in behavioral performance markers are often referred to as reflecting enhanced efficiency in neural computation. That is, the computation may take less time or require less resources. Indeed, efficiency-related activation patterns have been attributed to enhanced cognitive control in prior work (Gold, Kim, Johnson, Kryscio, & Smith, 2013; Luna, Padmanabhan, & O'Hearn, 2010; Gray et al., 2005) and, in particular, in item-specific proportion conditions that reflect utilization of reactive control, in tasks such as the Stroop (Chiu, Jiang, & Egner, 2017; Grandjean et al., 2013; Blais & Bunge, 2010). Thus, in some ways, the findings are consistent with the prior literature. Nevertheless, computational and mechanistic accounts of how enhanced cognitive control can give rise to reduced activation are still somewhat lacking. Thus, a fuller understanding of the neural mechanisms of reactive control will still require further work, as elaborated further below.

Another potential issue related to the interpretation of the current results is that, frequently, evidence of reduced activation occurs with practice or repetition of items. This effect is so common in the memory and object recognition literature that it is referred to as the repetition suppression effect (Larsson & Smith, 2012; Horner & Henson, 2008; Grill-Spector, Henson, & Martin, 2006; Gonsalves, Kahn, Curran, Norman, & Wagner, 2005; Henson & Rugg, 2003). Similarly, increasing practice or experience with task conditions is also well established to lead to reductions in task-related activation (Chein & Schneider, 2005; Kelly & Garavan, 2005; Petersen, van Mier, Fiez, & Raichle, 1998). Finally, reactive control has been frequently interpreted as related to the learning of stimulus–response or stimulus–control state associations (Chiu & Egner, 2019), potentially via conflict-triggered learning mechanisms (Abrahamse, Braem, Notebaert, & Verguts, 2016; Verguts & Notebaert, 2008, 2009). These associations will build up with repeated exposures to stimulus trials and features. Thus, it is a possible concern that, in the DMCC study design, the reactive session always occurred after the baseline session. As a consequence, one alternative interpretation of the reactive-related reductions in activity is that they merely reflect the increased practice that occurs with the general task conditions during the reactive session relative to baseline, rather than anything specific or selective regarding the engagement of reactive control. In follow-up control analyses, we examined this concern by including the retest baseline data from a subset of participants who returned for longitudinal testing waves. For these participants, retest baseline data included in the analyses were substituted for the initial baseline condition, so that baseline (retest) was performed after reactive (test). Yet even with these analyses, which were effectively counterbalanced for order, the same pattern of results (a reactive-related reduction in activity) was obtained. Thus, the results suggest that the reactive effects cannot be attributed purely to order or practice.

Limitations and Future Directions

Although beyond the scope of the current paper, a key next step in the DMCC project will be to focus on determining whether a distinct neural signature of proactive control can be identified. A central claim of the DMC framework and a primary focus of the DMCC project is to test whether proactive and reactive control modes are implemented by distinct and dissociable neural mechanisms. In particular, the current findings are supportive of DMC framework tenets that reactive control is associated with transient neural mechanisms that are stimulus triggered and linked to key features of target items (e.g., conflict, familiarity, punishment). Likewise, through a multidimensional scaling approach, we demonstrated that the reactive and proactive conditions were clearly dissociable in terms of their multivariate activity profiles, even when focusing on these stimulus-triggered, transient activation patterns.

In addition, proactive control is postulated to recruit distinct neural mechanisms that are sustained or cue related and that become activated ahead of, and in anticipation of, control-demanding events. To most strongly confirm the presence of these independent neural control mechanisms, it will be critical to determine whether a double dissociation can be established, such that the proactive condition is selectively associated with consistent changes in sustained or cue-related activity across the four tasks in the battery, whereas the reactive condition is selectively associated with transient event-related effects. Moreover, establishment of such a double dissociation will be highly important for ruling out alternative interpretations of the findings, such as those related to differential task difficulty or cognitive control engagement.

Even without a contrasting focus on proactive control, the findings reported here can also be advanced by further explication and convergent evidence regarding underlying mechanisms. In particular, one intriguing hypothesis is that the reactive-related reduction in transient activity

may reflect more efficient signaling and propagation of control-related information among fronto-parietal regions. Furthermore, recent work has pointed to fronto-striatal pathways, particularly involving the dorsal striatum and caudate nucleus, in mediating the learning and storage of stimulus–control associations (Chiu & Egner, 2019). Thus, one important direction for future work will be to complement the activation-focused analyses conducted here, with those aimed at understanding whether reactive control is also linked to systematic changes in functional or effective connectivity, among fronto-parietal and fronto-striatal regions.

Another important direction will be to exploit both the twin-based and test–retest components of the DMCC study design to further explore and support reactive (and proactive) control findings. For example, a powerful means by which to demonstrate the robustness and generalizability of the reactive control pattern would be to test whether it is stable across repeated waves of testing. Another way to establish the functional importance of the reactive control signature would be test whether the individual-difference-related brain–behavior relationships we observed were also highly similar within MZ twin pairs. If such a pattern were observed, it would clearly support the interpretation that the reactive control signature reflects a meaningful and heritable dimension of individual variation, rather than a purely state-dependent activation pattern. This type of inference would also be supported by findings that the observed reactive control patterns were linked to other sources of individual differences. For example, in prior work, we and others have suggested that reactive control might be associated with increased trait anxiety (Fales et al., 2008), risk aversion (Brown & Braver, 2007), and punishment sensitivity (Savine, Beck, Edwards, Chiew, & Braver, 2010). Testing for these associations represents a rich and promising direction of exploration within the DMCC data set, once the sample size permits such investigations to be conducted with sufficient statistical power.

Another potential limitation of the current work, and also a key direction for future analyses, relates to the constraints imposed by a univariate, as opposed to multivariate, statistical modeling approach to the DMCC data. Indeed, univariate approaches only provide information about the intensity of brain activation (i.e., increasing or decreasing) and, as such, are of limited utility for understanding the computations that are more likely to be encoded in activation patterns. In contrast, multivariate approaches, such as multivariate pattern analysis (MVPA), provide richer information regarding the representational coding schemes that are implemented in different brain regions, which might be critical for disentangling and dissociating cognitive control dimensions, such as proactive and reactive. In particular, reactive and proactive control may be most strongly dissociated in terms of the neural coding of distinct control dimensions (Freund, Etzel, & Braver, 2021). For example, reactive control might be more strongly identified in terms of the neural coding of congruency information or stimulus–control associations, whereas proactive control is likely to be associated with the coding of task rules or goal-related information. Our group has started to explore MVPA approaches, such as representational similarity analysis (RSA), with the DMCC data set, as a means to better understand neural coding within the Stroop task (Freund, Bugg, & Braver, 2021) and similarity among twins (Tang et al., 2021). As such, we believe that these approaches are highly promising for more systematic exploration.

A related and critical question within the DMCC project is to more firmly establish the domain generality of reactive and proactive control. Although domain generality can be explored with univariate approaches as well, such as through conjunction analysis and composite indices, as utilized in this report, such methods are less powerful, because they are susceptible to measurement error and other sources of noise. Indeed, there has been quite a bit of recent controversy and debate regarding whether univariate behavioral and neural measures of cognitive functioning are sufficiently reliable to be treated as individual difference measures and included in cross-task analyses (Elliott et al., 2020; Rouder & Haaf, 2019; Whitehead, Brewer, & Blais, 2019; Hedge, Powell, & Sumner, 2018; Dubois & Adolphs, 2016; Bennett & Miller, 2010). One solution to this problem is to use latent variable approaches, which are especially well adapted to the multitask, multicondition approach utilized in the DMCC project. Because latent variable approaches examine relationships between latent factors, estimated in shared variance across tasks or conditions, they are less prone to measurement error and, as such, may be more sensitive and selective in revealing the domain generality of cognitive control dimensions. Indeed, our group has begun exploring the use of latent variable approaches to neuroimaging analyses, in large-sample data sets such as the HCP, and found them to be quite effective (Cooper et al., 2019). However, one of the main drawbacks of such approaches is that they are "data-hungry" and are likely not to be sufficiently powerful in data sets such as the DMCC until data collection is complete, with sample sizes in the range of 200 individuals.

This is again an issue for which MVPA approaches might represent an alternative and more efficient solution (Dubois & Adolphs, 2016). A key advantage of MVPA approaches is that they provide richer and more targeted descriptions of neuroimaging data, by more effectively pooling voxel-wise patterns, which also enables both signal and noise to be modeled more accurately (Bejjanki, da Silveira, Cohen, & Turk-Browne, 2017; Cohen et al., 2017; Norman, Polyn, Detre, & Haxby, 2006). In particular, RSA measures focus on the similarity in neural activation patterns and, as such, can enable examinations of second-order relationships (Haxby, Connolly, & Guntupalli, 2014; Kriegeskorte & Kievit, 2013; Kriegeskorte, Mur, & Bandettini, 2008). Prior work has shown the utility of this

approach within the domain of cognitive control as well (Freund et al., 2021; He et al., 2021; Kragel et al., 2018). Here, we provided an initial demonstration of this approach with the DMCC data set, demonstrating the increased relative similarity of high control conditions, relative to low control demand across tasks within the baseline condition. Future work can build upon this approach to focus on cross-condition as well as cross-task similarity structures and test whether the neural coding of reactive and proactive control also shows the theoretically predicted forms of domain generality suggested by the DMC framework.

Conclusion

The DMCC project represents an ambitious and rigorous attempt to reveal key neural mechanisms of cognitive control, which also follows key research strategies and principles for the study of executive function that were outlined by Don Stuss over 25 years ago (Stuss et al., 1995). In particular, it tests the key theoretical tenets of the DMC framework, which postulate reactive and proactive modes as meaningful and distinct dimensions of cognitive control that serve as important sources of both intraindividual and interindividual variation. Towards that end, we have provided initial support for these DMC tenets, by identifying a domain-general neural signature of cognitive control, that it is (a) consistently engaged across multiple tasks, (b) involves a focal set of frontoparietal regions, (c) contributes to behavioral performance enhancements observed under those conditions that encourage utilization of reactive control, and (d) is subject to significant individual differences. Our goal is to inform investigators interested in individual differences and cognitive control of the advantageous design features of the DMCC project, with the hope that they will be encouraged to make use of the data set. In that spirit, we hope to continue the legacy and example set by Don Stuss in building a strong community of researchers working together to advance our understanding of frontal lobe function, the neural underpinnings of cognitive control, and individual differences in these domains.

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Diversity in Citation Practices

A retrospective analysis of the citations in every article published in this journal from 2010 to 2020 has revealed a persistent pattern of gender imbalance: Although the proportions of authorship teams (categorized by estimated gender identification of first author/last author) publishing in the *Journal of Cognitive Neuroscience* (*JoCN*) during this period were M(an)/M = .408, W(oman)/M = .335, M/W = .108, and W/W = .149, the comparable proportions for the articles that these authorship teams cited were M/M = .579, W/M = .243, M/W = .102, and W/W = .076 (Fulvio et al., *JoCN*, 33:1, pp. 3–7). Consequently, *JoCN* encourages all authors to consider gender balance explicitly when selecting which articles to cite and gives them the opportunity to report their article's gender citation balance. The authors of this article report its proportions of citations by gender category to be as follows: M/M = .69, W/M = .17, M/W = .08, and W/W = .06.

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