Immediate versus delayed control demands elicit distinct mechanisms for instantiating proactive control

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Abstract

Cognitive control is critical for dynamically guiding goal-directed behavior, particularly when applying preparatory, or proactive, control processes. However, it is unknown how proactive control is modulated by timing demands. This study investigated how timing demands may instantiate distinct neural processes and contribute to the use of different types of proactive control. In two experiments, healthy young adults performed the AX-Continuous Performance Task (AX-CPT) or Dot Pattern Expectancy (DPX) task. The delay between informative cue and test probe was manipulated by block to be short (1s) or long (~3s). We hypothesized that short cue-probe delays would rely more on a rapid goal updating process (akin to task-switching), whereas long cue-probe delays would utilize more of an active maintenance process (akin to working memory). Short delay lengths were associated with specific impairments in rare probe accuracy. EEG responses to control-demanding cues revealed delay-specific neural signatures, which replicated across studies. In the short delay condition, EEG activities associated with task-switching were specifically enhanced, including increased early anterior positivity ERP amplitude (accompanying greater mid-frontal theta power) and a larger late differential switch positivity. In the long delay condition, we observed study-specific sustained increases in ERP amplitude following control-demanding cues, which may be suggestive of active maintenance. Collectively, these findings suggest that timing demands may instantiate distinct proactive control processes. These findings suggest a reevaluation of AX-CPT and DPX as pure assessments of working memory and highlight the need to understand how presumably benign task parameters, such as cue-probe delay length, significantly alter cognitive control.

Keywords Cognitive control · Working memory · Task-switching · AX-Continuous Performance Task · EEG, Dot Probe Expectancy

Introduction

Cognitive control adaptively guides behavior, optimizing the balance between efficiently acting on existing rules and flexibly responding to new information. The dual mechanisms of control framework (Braver, Paxton, Locke, & Barch, 2009) divides control into proactive and reactive modes that are thought to be utilized reciprocally to enact goal-directed behavior. Proactive control utilizes context information to bias lower-level processes to prepare for an upcoming event,

maximizing efficiency over flexibility. Reactive control favors a later stimulus-evoked reactivation of task goals and results in slower and more variable responses (Braver, 2012; Braver et al., 2009). Although extensive work has distinguished proactive from reactive control (Braver, 2012; Braver et al., 2009; Cooper et al., 2015; Lesh et al., 2013), there has been little investigation of the electrophysiological processes that could underlie proactive control. Proactive control is generally characterized as a unitary construct, but it remains untested whether this predominant assumption of unitary proactive control is justified. Because one must not only plan “what,” but also “when,” we expect processes underlying proactive control to be sensitive to temporal information. To better understand the mechanisms facilitating proactive control, we evaluated the hypothesis that proactive control may comprise distinguishable subsets of processes that are elicited differently in accordance with the temporal dynamics of goal demands.

Cognitive control is costly (for review, see Shenhav, Botvinick, & Cohen, 2013), and different mechanisms for

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proactive control may offer cost savings. It may be optimal to adjust the proactive processes for updating and/or retaining the upcoming goal based on the temporal context. For example, when driving down a highway, you may react differently to a sign indicating that your desired exit will appear in half a mile than to a sign acknowledging that your desired exit is 10 miles away. It also remains to be known how elevated control demands (like a rare left exit sign) might interact with the length of time (1/2 or 10 miles) over which a control goal (exiting the highway) must be maintained. Although in each scenario, one must proactively update and retain this new goal, the timing demands on each are varied. We propose that these updating versus retention processes may be conducted differently and thereby express dissociable signals based on *when* the goal is to be acted upon.

In the present set of experiments, we investigated the hypothesis that the features contributing to proactive control vary systematically with the temporal delay over which goals need to be held in mind and can be at least partly dissociated into separable neural processes. This approach does not posit that proactive processes are necessarily binary nor mutually exclusive but instead tests whether some subprocesses may be more strongly elicited in the context of particular delay dynamics. We hypothesized that short temporal delays will require more of a goal-updating process (comparable to task-switching), where transient control processes immediately drive the rapid instantiation of a new state representation at the expense of the previous state (Medalla & Barbas, 2009; Stanley, Roy, Aoi, Kopell, & Miller, 2018). In contrast, we expect that long temporal delays will utilize more of an active maintenance process (comparable to working memory), where control processes elicit persistent activity patterns to maintain a sustained representation (Barak & Tsodyks, 2014; Jensen & Lisman, 2005; Vogel & Machizawa, 2004; Wang, 2010; Wasmuht, Spaak, Buschman, Miller, & Stokes, 2017; although also see Spaak, Watanabe, Funahashi, & Stokes, 2017; Stokes et al., 2013).

To interrogate the effects of temporal demands on proactive control processes, we manipulated delay length in two experiments, using common cued control tasks known to evoke proactive and reactive cognitive control: the AX-Continuous Performance Task (AX-CPT) (Barch et al., 1997; Cohen et al., 1997), and the Dot Probe Expectancy (DPX) task (Henderson et al., 2012; MacDonald et al., 2005). In both of these tasks (Fig. 1), a cue informs the participant of the common or rare (control-demanding) task to be performed after the cue-probe delay. By manipulating shorter versus longer cue-probe delays, we could elucidate how proactive control processes during the delay differ based on temporal demands. To maximize differences between the short and long delay conditions and the cognitive processes being tested, we used a static 1-second delay in the short delay condition and a jittered 3-second delay (± 0.5 seconds) in the long delay condition. In addition to

eliciting distinct timing processes across these different temporal delays (Buhusi & Meck, 2005; Morillon, Schroeder, Wyart, & Arnal, 2016), the predictability of a static versus jittered delay may further alter anticipatory processes, optimizing the ability for precise temporal preparation in the short condition while making temporal preparation more difficult in the long condition.

Applying a label to proactive control subprocesses is fraught with inevitable disagreement over semantics and operational definitions of the likely role of frontal cortex, but we attempted to dissociate proactive processes by their neural mechanisms and subsequent behavioral consequences. To define the most likely candidate processes, we quantified neural signals chosen *a priori* from well-established literatures in task switching and working memory maintenance. Critically, we are not inferring the existence of these exact constructs based on their neural signatures (e.g., reverse inference), but we aimed to utilize these signals as a foundation for dissociating between delay conditions. This is a more conservative form of inference and should be considered as the first step within a broader research program that will ultimately distill invariant features associated with distinct psychological processes. Task-switching has been characterized in the EEG literature with three well-replicated, event-related potential (ERP) components during prestimulus preparation: an early anterior positivity, a differential switch positivity and a sustained frontal negativity (Capizzi, Feher, Penolazzi, & Vallesi, 2015; Jamadar, Hughes, Fulham, Michie, & Karayanidis, 2010; Karayanidis, Provost, Brown, Paton, & Heathcote, 2011; Lenartowicz, Escobedo-Quiroz, & Cohen, 2010; Li, Wang, Zhao, & Fogelson, 2012; Nicholson, Karayanidis, Poboka, Heathcote, & Michie, 2005; Rushworth, Passingham, & Nobre, 2005).

The early anterior positivity is evoked early in the cue-probe interval during switch trials, primarily during N1 and P2 periods (Capizzi et al., 2015; Collins, Cavanagh, & Frank, 2014; Karayanidis et al., 2009) over anterior and mid-frontal electrodes (Astle, Jackson, & Swainson, 2008; Lavric, Mizon, & Monsell, 2008; Manzi, Nessler, Czernochowski, & Friedman, 2011). The early anterior positivity is suggested to reflect early context updating in the prefrontal cortex, before task-set reconfiguration. Task goal reconfiguration also is associated with the mid-frontal N2 ERP component (Di Russo et al., 2016; Gajewski, Kleinsorge, & Falkenstein, 2010), which is modulated by the need for cognitive control (for review, see Folstein & Van Petten, 2008). Together, these multiphasic aspects of the midfrontal ERP complex may reflect the operations of a generic mediofrontal theta-band process (Harper, Malone, & Bemat, 2014) that appears to be a marker of the need for control (Cavanagh & Frank, 2014). Notably, recent task switching investigations have described how switching is associated with enhanced frontal midline theta power (Cooper et al., 2015; Cooper, Darriba, Karayanidis, & Barceló, 2016; Cunillera et al., 2012).

Fig. 1 AX-CPT and DPX Task designs. Participants performed the AX-CPT for 10 blocks of 50 trials each, in which cue-probe delay varied by block set. Five blocks of short (1 sec) cue-probe delay were followed by five blocks of long (3 ± 0.5 sec) cue-probe delay, or vice versa, with delay order counter-balanced between participants. Participants responded to all cues by pressing the left index finger. Only X probes following A cues demanded a right index finger button press; this A-X combination

occurred on 70% of trials. All other cue-probe combinations (A-Y, B-X, B-Y) demanded a left index finger button press to the probe; these combinations were rare, each only occurring on 10% of trials. [Inset] In DPX, the task design was identical, except the cue and probe stimuli were dot combinations (see inset) instead of letters, and the cue-probe frequencies differed slightly from those used in AX-CPT (AX = 68.75%, AY = 12.5%, BX = 12.5%, BY = 5%)

The differential switch positivity is a positive-going waveform observed primarily at centroparietal sites, emerging as early as 200-ms post-cue and peaking between 300–700-ms post-cue, greater for switch relative to stay trials (Capizzi et al., 2015; Cunillera et al., 2012; Karayanidis et al., 2009; Li et al., 2012; Manzi et al., 2011; Nicholson, Karayanidis, Davies, & Michie, 2006; Nicholson et al., 2005). This component also has been referred to as a P3b (Kieffaber & Hetrick, 2005) and a late parietal positivity (Astle, Jackson, & Swainson, 2006; Gajewski & Falkenstein, 2011). The switch positivity is widely thought to be associated with anticipatory task-set reconfiguration that is normally specific to switch-to trials, in which the participant knows the exact task for which to prepare a response (Karayanidis et al., 2011; Nicholson et al., 2006).

The sustained frontal negativity, also referred to as the frontal contingent negative variation (Astle et al., 2008; Lavric et al., 2008; Nicholson et al., 2005; Poljac & Yeung, 2014), is a late component associated with proactive preparation of overt response processes (i.e., with motor output) (Astle et al., 2008; Capizzi et al., 2015; Karayanidis et al., 2010). This sustained frontal negativity often is observed at centro-frontal electrodes (Barcelo, Escera, Corral, & Periañez, 2006), including AFz (Astle et al., 2008), Fz, and FCz (Capizzi et al., 2015).

Although the task-switching literature is rich with work comparing short (<200 ms) and longer (up to 1,000 ms) switch intervals, it is important to note that this literature does not sufficiently address how task switching differs over multisecond delays. In addition, prior work, to our knowledge, has not comprehensively analyzed task-switching components in the AX-CPT or DPX paradigms. In our experiments comparing activity over short (1 second) and long (~3 second) delays, we hypothesize that rare (control-demanding) cues in the short delay will instantiate increased amplitude of mid-frontal early anterior positivity, as well as corresponding increases in mid-frontal theta power. Similarly, we expect to find selective increases in differential switch positivity and sustained frontal negativity for short and rare cues.

The AX-CPT and DPX paradigms have most often been presumed to assess working memory (Barch et al., 2009; Cohen, Barch, Carter, & Servan-Schreiber, 1999; Kessler, Baruchin, & Bouhsira-Sabag, 2015; Redick, 2014), and this construct has been associated with distinct neural processes from those implicated in switching task sets. Activation in both posterior parietal (Kikumoto & Mayr, 2017) and lateral prefrontal regions has been implicated in working memory maintenance (for review, see Eriksson, Vogel, Lansner, Bergström, & Nyberg, 2015). However, the electrophysiological signatures of working memory are not yet well defined.

Recent findings have suggested that working memory can be instantiated with short-term synaptic plasticity (Christophel, Klink, Spitzer, Roelfsema, & Haynes, 2017; Polania, Paulus, & Nitsche, 2011), and there is ample evidence that slow wave activities also are associated with active maintenance (Freunberger, Werkle-Bergner, Griesmayr, Lindenberger, & Klimesch, 2011; Schmitt, Ferdinand, & Kray, 2014; Unsworth, Fukada, Awh, & Vogel, 2015; Vogel & Machizawa, 2004). Because reliable, generic EEG signatures of working memory have not been established, we hypothesize only that we will observe increased sustained, slow-wave activity for rare (control-demanding) cues during the long delay condition.

In summary, we hypothesized that proactive control is not a unitary construct and that the influence of distinct subprocesses could be parsed based on temporal demands. This is an important idea, because the AX-CPT and DPX paradigms have been run in healthy and patient populations, with delay length often treated as a trivial parameter. Cue-probe delay length varies widely between studies in the AX-CPT/DPX literature, with mixed behavioral (for a meta-analytic review, see Janowich & Cavanagh, 2018) and neural findings. Because the literature fails to substantively address the role of delay in proactive control processes, we set forth to examine empirically the behavioral consequences and neural manifestations of temporal delay. We tested our delay manipulation in two experiments using the AX-CPT or DPX paradigms, similar cued control tasks differing only on their use of verbalizable letter (AX-CPT) versus nonverbalizable dot stimuli (DPX) cues. By utilizing each of these widely used paradigms in separate within-subjects experiments, we want to establish a strong initial report on the generalizability and reliability of temporal effects on control. If delay dynamics do reliably alter behavior and/or neural mechanisms of proactive control, the field will need to reevaluate the findings and implications of cued control studies in light of their respective timing demands.

Methods

Participants

Seventy-five healthy young adults participated in either Experiment 1 (AX-CPT) or Experiment 2 (DPX). Thirty-five undergraduate students at the University of New Mexico (26 women, ages 18–42 years, mean $19.8 \pm \text{SD } 3.4$ years) participated in Experiment 1, and 40 undergraduate students at the University of New Mexico (26 women, ages 18–41 years, mean $21.3 \pm \text{SD } 5.0$ years) participated in Experiment 2. Demographic information is displayed in Table 1. Participants reported no current use of psychiatric or neurological medication, no history of head injury or

Table 1.

	AX-CPT (Exp. 1)	DPX (Exp. 2)
N	35	40
Age (yr)	19.83 (± 3.40)	21.3 (± 5.00)
Education (yr)	13.40 (± 1.27)	14.15 (± 1.99)
Gender	26 F, 9 M	26 F, 14 M
Handedness	35 R	40 R
Delay first	Short = 18; Long = 17	Short = 20, Long = 20

epilepsy, and normal or corrected-to-normal vision. All participants were right handed. Participants provided written, informed consent and received course credit for their participation. The University of New Mexico Institutional Review Board approved these experiments.

In Experiment 1, data from seven participants were excluded from EEG analyses: one due to technical problems with the EEG equipment, three due to excessive noise in the EEG data, and four due to sub-par behavioral performance (below 50% accuracy averaged between all conditions, or any one condition less than 25% accuracy).

In Experiment 2, data from three participants were excluded for excessive noise in the EEG data, and two participants were excluded for sub-par behavioral performance (below 50% accuracy averaged between all conditions, or any one condition less than 25% accuracy). This left a total of 28 participants in Experiment 1 and 35 participants in Experiment 2.

Cognitive/behavioral tasks

Experiment 1

The AX-Continuous Performance Task (AX-CPT) (Carter et al., 1998; Cohen et al., 1999; Cohen et al., 1997) is a standard cue-probe cognitive task in which variance in cue and probe expectancy are used to assess the impact of (cue-derived) context on cognitive control. The task flow and parameters are depicted in Fig. 1. In this task, a probe stimulus (X or Y) was presented following a paired cue stimulus (A or B) in target and nontarget combinations. In a two alternative-forced choice manner, participants were instructed to respond to both cue and probe stimuli with left or right trigger buttons on a joystick. In the target AX sequence, X probes following A cues demanded a right trigger press; all other cues and probes were to be responded to with the left trigger. Because 70% of trials were composed of A-X cue-probe target pairs, entailing a left-right cue-probe response sequence, and A-Y, B-X, and B-Y cue-probe nontarget pairs were much more rare (10% trials of each), a strong expectancy was generated to respond according to the “A-X” rule (Servan-Schreiber et al., 1996). Feedback was given for incorrect (“ERROR!”)

and nonresponse (“Too Slow!”) trials for 500 ms. Trials were separated by a jittered inter-trial interval of 750–1,000 ms.

A key feature of our variant of the AX-CPT paradigm is the block-wise manipulation of short versus long delays between cue (A or B) and probe (X or Y) stimuli. In the short delay condition, a static 1,000-ms delay separated the cue and probe stimulus. In the long delay condition, the probe was presented ~3,000 ms after the cue (randomly jittered between 2,500–3,500 ms in intervals of 50 ms). All participants completed both short and long delay blocks, with block order randomly counterbalanced between participants.

After being instructed in AX-CPT task rules by the experimenter, participants completed a practice session of 25 (short delay) trials. Participants were then given delay-specific instructions for the first delay condition and completed 5 blocks of 50 trials (total 250 trials) with short breaks offered between each block. Instructions for the second delay condition were then presented, followed by 5 blocks of 50 trials (total 250 trials), with short breaks offered between each block. Total task duration was 41.7 minutes (± 3.4 min). This task was written in Matlab using the Psychophysics Toolbox extensions (Brainard, 1997; Kleiner, Brainard, & Pelli, 2007; Pelli, 1997).

Experiment 2

While the AX-CPT continues to be used in many studies, more recent investigations have adapted a number of subtle alterations to the perceptive and probabilistic features of the original AX-CPT, engendering the emergence of the Dot Pattern Expectancy Task (DPX) (Barch et al., 2009; MacDonald et al., 2005). DPX follows similar experimental design and logic as AX-CPT, but differs in the stimuli used as A/B cues and X/Y probes, as well as using slightly different proportions of cue-probe combinations (MacDonald et al., 2005). We aimed to replicate our AX-CPT findings with the DPX task, which shares the same general structure of proactive control and hypothesized dependence on timing manipulation, even in the context of lower-level parameter changes. In Experiment 2, there were three differences from Experiment 1. First, in DPX, cues and probes were depicted as dot combinations instead of letters (Fig. 1 inset). Second, five unique B cues and five unique Y probes were used. Third, the cue/probe proportions were altered: A-X: 70%; A-Y: 12.5%; B-X: 12.5%; B-Y: 5%. The different cue-probe proportions in Experiment 2 were chosen due to the predominant use of these proportions in the DPX literature (MacDonald et al., 2005). All other timing, trial/block, and feedback parameters used in the AX-CPT experiment were replicated in the DPX experiment. To ease simultaneous discussion of AX-CPT and DPX studies, terms A/B and X/Y will be used throughout this manuscript.

Cue-based analyses

We compared behavioral and neural responses for A versus B cues to distinguish instantiation of common versus rare rule sets between delay lengths. Trials were divided into four conditions for each set of comparisons: short A, short B, long A, and long B. Two-way repeated measures ANOVAs were used to calculate main effects of cue type and delay length and cue-delay interactions; only the interactions are of theoretical interest for inferring different neural proactive control processes due to delay. Nonparametric correlations between neural and behavioral variables were computed with Spearman's rho. To assess statistical differences in correlations between short and long delay lengths, within-sample rho-to-z tests (Lee & Preacher, 2013; Steiger, 1980) were conducted; these tests incorporate a variable describing how the two tests are themselves correlated (Meng, Rosenthal, & Rubin, 1992) and are preferred for nonindependent correlations. In order to facilitate direct comparison of preparatory activity for short versus long delay, analyses and visualizations were conducted for only the first 1,000-ms post-cue (the length of the short delay).

Behavioral analyses

Context activation/updating was quantified with the Behavioral Shift Index (BSI) (Braver et al., 2009) (used in Chiew & Braver, 2013; Edwards, Barch, & Braver, 2010; Lamm et al., 2013; Lucenet & Blaye, 2014; Morales et al., 2014; Schmitt et al., 2015), which indexes the proportional use of proactive versus reactive control based on task error rate or reaction time to “AY” relative to “BX” cue-probe pairs. The following formula generates a single proactive/reactive BSI value:

$$(aY - bX) / (aY + bX)$$

Higher BSI scores are associated with a greater use of proactive control, whereas lower BSI scores are associated with a greater use of reactive control. If context activation/updating abilities are intact, proactive control should bias responses based on context (Braver, Barch, & Cohen, 1999) and manifest in impaired performance on AY trials (Braver, Satpute, Rush, Racine, & Barch, 2005), during which a robust prepotent response must be inhibited. BSI operationalizes proactive control as a unitary construct. By considering the relationship between BSI and cue-locked neural activity, we can resolve whether different neural responses to cued task demands bias behavior toward proactive or reactive control.

EEG data acquisition

EEG data were acquired with a BrainVision 64-channel amp, with standard 10-20 configuration, and recorded with

PyCorder software. Data were recorded continuously across 0.1–100 Hz and sampled at 500 Hz. VEOG was recorded above and below the right eye. FPz was utilized as online ground, and CPz was the online reference.

EEG data pre-processing

Epochs were created surrounding cue onset (−2,000: 7,000 ms), from which associated cue and cue-probe delay activity were isolated. CPz was recreated by re-referencing the data to an average reference. Very ventral channels (FT9, FT10, TP9, TP10) were removed due to unreliability. Bad channels were identified using a combination of FASTER (Nolan, Whelan, & Reilly, 2010) and EEGLab's *pop_rejchan* (Delorme & Makeig, 2004) and were then interpolated. Bad epochs were identified by FASTER and then rejected. Independent components analysis (*runica.m*) was run, and VEOG activity and a Gaussian template around frontopolar channels were compared with components to help identify and remove blink activity.

After pre-processing, data were transformed to surface Laplacian (*laplacian_perrinX.m*) (Cohen, 2014; Perrin, Pernier, Bertrand, & Echallier, 1989). As a high-pass spatial filter, the Laplacian filters out spatially broad features, thereby minimizing the effects of volume-conduction, and highlights local topographical features. The surface Laplacian is reference-free and as such avoids confounds with the choice of reference electrode (Cohen, 2014; Kayser & Tenke, 2006).

ERP and time-frequency analyses

Event-related potentials (ERPs) were created to assess the early post-cue activity involved in instantiating proactive control. Cue-locked activity for each condition (see above) was calculated as an average of all trials with correct responses to both cue and probe, ensuring attention to the task and successful context processing. To equalize the signal to noise ratio, trial count was equated between conditions by randomly drawing A trials equal to the count of B trials. This resulted in approximately 40–50 trials for each cue x delay condition (48 ± 4 trials). Data were low-pass filtered at 20 Hz (*eegfilt.m*). Epochs for ERP analyses were created from −200:1000 ms peri-cue, and activity was baseline-corrected to −200:0 ms pre-cue.

The ERP and time-frequency components chosen for analysis were selected based on prior literature suggesting their involvement in task-switching or working memory processes and were evaluated at a priori regions and time windows of interest, as detailed below. Grand averages were collapsed between all conditions to derive analytic windows of interest (Cohen, 2014). For each ERP component of interest at each electrode of interest, individual peaks were identified from the across-condition time windows. For early components, windows were centered at 20 ms around the component peak. For

later sustained components, average activity was computed across the entire window of interest. Early anterior potential was computed at FCz as the P2–N2 difference for each participant, in which the minimum (trough) of the N2 was subtracted from the maximum (peak) of the P2. The differential switch positivity was quantified at Cz from 400–600 ms. The sustained frontal negativity was quantified at an average of mid-frontal electrodes (AFz, Fz, and FCz) from 400–600 ms. To investigate working memory-related sustained activity during the delay, two exploratory analyses were conducted based on a history of prefrontal and posterior parietal activations in the working memory literature, in conjunction with observations of our data. First, a left pre-frontal cluster (AF3, AF7, F3, F5, F7) of electrodes was evaluated from 150–400 ms post-cue. In addition, a cluster of bilateral posterior-parietal (PO3, PO4, PO7, PO8) electrodes was evaluated from 400–800 ms post-cue.

We conducted time-frequency analyses to follow-up the ERP findings, investigating only spectral phenomena immediately seen in ERPs. For time-frequency analyses, wavelet transforms (Cavanagh, Cohen, & Allen, 2009) were applied to cue-locked EEG data in the original −2,000:7,000 ms epochs. Utilization of these longer epochs allowed us to extract and analyze low-frequency bands. Because temporal smoothing from time-frequency decomposition may introduce temporal leakage of trial-related activity into the pretrial period (Cohen, 2014), all time-frequency analyses were conducted with a baseline time period of −300 to −100 ms pre-cue. Main and interaction effects were tested in two ways. First, for display, paired-samples *t*-tests were computed over the entire time-frequency spectrograph. Second, time-frequency regions of interest (tf-ROIs) were run in ANOVAs for direct comparison to the ERP activities. As time-frequency activities are smeared by wavelet convolution, time-frequency and ERP windows will not precisely overlap, but they are nonetheless reflective of frequency-related information underlying the ERPs (Cohen, 2014). In light of the relative prominence of theta (4–7 Hz) and delta (1–4 Hz) activity corresponding to early and later/sustained ERP activities, respectively (Harper, Malone, Bachman, & Bernat, 2016), theta was used to assess spectral phenomena seen in early delay periods (200–400 ms), and low-frequency delta-theta (1–7 Hz) power was used to investigate spectral properties of activities in later delay periods (200–600 ms). Thus, full spectra plots and band-specific topoplots are displayed in figures for visualization purposes only and do not represent hypothesis testing for all points shown.

Results

Accuracy

A repeated-measures 2 (Delay: short, long) * 2 (Cue: A,B) * 2 (Probe: X, Y) ANOVA was run for behavioral accuracy in

each of the AX-CPT and DPX tasks (Fig. 2; Tables 2 and 3). All main and interaction effects were significant in both studies (Table 3). Most critically, participants showed robust deficits in accuracy on aY trials in Short Delay relative to Long Delay. This result was found in Experiment 1 (AX-CPT) and replicated in an independent sample in Experiment 2 (DPX).

As detailed in the *Methods*, we are only interested in control-related interactions with delay. Motivated by the three-way interaction and *a priori* hypotheses on the relevance of aY and bX trials in the AX-CPT/DPX paradigms, we investigated delay effects on aY and bX trials specifically. A repeated-measures 2 (Delay: short, long) by 2 (Cue-Probe: aY, bX) ANOVA revealed main effects of delay, cue-probe combination, and delay*probe interaction for each of AX-CPT and DPX tasks. To follow-up this significant interaction, we ran paired *t*-tests for delay on aY and bX separately. aY accuracy was significantly different between delay lengths, whereas bX was not different. These patterns were fully replicated in the DPX study (Tables 2 and 3).

Response time

A 2 (Delay: short, long) * 2 (Cue: A,B) * 2 (Probe: X, Y) repeated-measures ANOVA also was run for probe RTs for both AX and DPX studies (Table 3). In AX-CPT, all major main effects were significant, but the interactions were not. In DPX, all major main effects were significant, and delay*cue, delay*probe, and cue*delay*probe interactions also were significant.

Early anterior potential following cues

In AX-CPT, the Early Anterior Potential at FCz (Fig. 3A) showed a simple main effect of cue ($B > A$; $F(1,27) = 22.31$, $p < 0.001$) with no main effect of delay length ($F(1,27) = 0.07$, $p = 0.800$) and a critical significant interaction between cue and delay length ($F(1,27) = 6.69$, $p = 0.015$), in which the greatest amplitude was observed for Short B cues. These effects were replicated in the DPX experiment (main effect of cue ($B > A$; $F(1,34) = 11.24$, $p = 0.002$); main effect of delay ($S > L$; $F(1,34) = 7.27$, $p = 0.011$; cue*delay interaction $F(1,34) = 13.86$, $p < 0.001$).

Time-frequency power was evaluated for AX-CPT and DPX at FCz (Fig. 3B); these findings indicate statistically significant main effects in the *a priori* theta band TF-ROI (as well as extending in both later time and broader frequency) from cue type as well as a cue*delay interaction, shown as the difference of differences plot. Topoplots (Fig. 3B inside) depict uncorrected statistical differences between conditions. Theta (4–7 Hz) tf-ROI power was calculated for AX-CPT (Experiment 1) and DPX (Experiment 2) from 200–400 ms at FCz with 2x2 repeated-measures ANOVAs. In AX-CPT, there was a significant main effect of cue ($B > A$; $F(1,27) = 20.83$, $p < 0.001$), a significant main effect of delay, ($S > L$; $F(1,27) = 25.30$, $p < 0.001$) and a critical significant cue*delay interaction ($F(1,27) = 14.17$, $p < 0.001$), in which the greatest power was observed for Short B cues. Similarly in DPX, there was a significant main effect of cue ($B > A$; $F(1,34) = 46.18$, $p < 0.001$), a significant main effect of delay ($S > L$; $F(1,34) =$

Fig. 2 AX-CPT and DPX Accuracy and Reaction Time to probe stimuli. Error bars represent standard error. Asterisks indicate significant Cue-Probe x Delay interactions ($p < 0.05$). aY accuracy was significantly worse in short delay blocks relative to long delay blocks for both AX-

CPT (A) and DPX (B) experiments. Main effects of delay on reaction time were found for all Cue-Probe pairs, but no delay x cue-probe type interactions were observed

Table 2.

Experiment 1: AX-CPT				
ACC (SD)	aX	aY	bX	bY
Short delay	0.957 (0.035)	0.738 (0.169)	0.893 (0.121)	0.972 (0.059)
Long delay	0.965 (0.035)	0.886 (0.120)	0.897 (0.129)	0.981 (0.035)
RT (SD)	aX	aY	bX	bY
Short delay	0.305 (0.034)	0.377 (0.053)	0.276 (0.096)	0.270 (0.083)
Long delay	0.454 (0.093)	0.545 (0.093)	0.442 (0.151)	0.431 (0.128)
Experiment 2: DPX				
ACC (SD)	aX	aY	bX	bY
Short delay	0.947 (0.048)	0.665 (0.181)	0.905 (0.112)	0.953 (0.077)
Long delay	0.963 (0.036)	0.804 (0.135)	0.907 (0.101)	0.971 (0.072)
RT (SD)	aX	aY	bX	bY
Short delay	0.312 (0.050)	0.417 (0.064)	0.248 (0.090)	0.252 (0.089)
Long delay	0.477 (0.110)	0.660 (0.200)	0.413 (0.151)	0.408 (0.129)

Table 3

Experiment 1 AX-CPT	Delay	Cue	Probe	Delay x cue	Delay x probe	Delay x cue x probe
Probe accuracy F(1,27)	F = 21.724; $p < 0.001$	F = 11.262; $p = 0.002$	F = 5.243 $p = 0.030$	F = 9.722 $p = 0.004$	F = 14.393; $p = 0.001$	F = 18.224; $p < 0.001$
Probe RT F(1,27)	F = 63.201; $p < 0.001$	F = 27.537; $p < 0.001$	F = 51.988; $p < 0.001$	F = 0.109; $p = 0.743$	F = 0.482; $p = 0.493$	F = 1.291; $p = 0.266$
Probe accuracy (aY vs. bX)	F=17.48; $p < 0.001$		F = 7.16; $p = 0.012$		F = 13.48; $p < 0.001$	
<i>t</i> -test probe accuracy (aY)	$p < 0.001$					
<i>t</i> -test probe accuracy (bX)	$p = 0.890$					
<i>t</i> -test probe accuracy (short)			$p < 0.001$			
<i>t</i> -test probe accuracy (long)			$p = 0.980$			
Probe RT (aY vs. bX)	F = 74.74; $p < 0.001$		F = 34.10; $p < 0.001$		F = 0.204; $p = 0.654$	
Experiment 2 DPX	Delay	Cue	Probe	Delay x cue	Delay x Probe	Delay x Cue x Probe
Probe accuracy F(1,34)	F = 11.796; $p = 0.002$	F = 61.755; $p < 0.001$	F = 57.225; $p < 0.001$	F = 12.303 $p = 0.001$	F = 13.153; $p = 0.001$	F = 8.804; $p = 0.005$
Probe RT F(1,34)	F = 88.147; $p < 0.001$	F = 116.468; $p < 0.001$	F = 76.311; $p < 0.001$	F = 8.012; $p = 0.008$	F = 7.105; $p = 0.012$	F = 9.809; $p = 0.004$
Probe accuracy (aY vs. bX)	F = 11.95; $p = 0.002$		F = 68.92; $p < 0.001$		F = 13.98; $p < 0.001$	
<i>t</i> -test probe accuracy (aY)	$p < 0.001$					
<i>t</i> -test probe accuracy (bX)	$p = 0.905$					
<i>t</i> -test probe accuracy (short)			$p < 0.001$			
<i>t</i> -test probe accuracy (long)			$p < 0.001$			
Probe RT (aY vs. bX)	F = 68.16; $p < 0.001$		F = 139.89; $p < 0.001$		F = 11.41; $p = 0.002$

Fig. 3 Early anterior potential and early theta power at FCz. **A.** Cue-locked ERPs by delay length and cue type for AX-CPT (left) and DPX (right) experiments. Colored dots indicate average cue RT for each color-coded condition; a priori region of interest indicated by yellow highlight. Insets display the P2-N2 cross-over interaction for each cue by delay type. **B.** Time-frequency main effects displayed as subtractions of short and

long delay and the interaction displayed as the difference of differences. Outlined time-frequency areas highlight statistically significant differences. Topoplots show theta (4–7 Hz) power differences 200–400-ms post-cue at each delay length between cue types. Black dots indicate statistically significant differences between cue types at that delay length for that electrode

31.73, $p < 0.001$) and a significant cue*delay interaction ($F(1,34) = 4.90$, $p = 0.034$). These findings suggest that early mid-frontal activities during proactive control can be differentiated by delay length, in particular activities previously associated with task switching during short delay.

Differential switch positivity following cues

The differential switch positivity (Fig. 4) was quantified as the average amplitude at Cz between 400–600 ms. In AX-CPT, there was a significant main effect of cue ($B > A$; $F(1,27) = 5.01$, $p = 0.034$), a significant main effect of delay ($S > L$; $F(1,27) = 17.72$, $p < 0.001$) and a critical significant interaction of cue*delay ($F(1,27) = 6.07$, $p = 0.021$), where the greatest amplitudes were observed following Short B cues. Similarly, in DPX we observed a significant main effect of

cue ($B > A$; $F(1,34) = 11.60$, $p = 0.002$), a significant main effect of delay ($S > L$; $F(1,34) = 6.44$, $p = 0.016$), and a cue*delay interaction ($F(1,34) = 6.04$, $p = 0.019$) with greater amplitudes following Short B cues.

To follow-up these ERP findings, time-frequency power was evaluated for AX-CPT and DPX at Cz, and statistics were computed on low-frequency delta-theta (1–7 Hz) band activity at Cz (Fig. 4B outside). Topoplots (Fig. 4B inside) depict uncorrected delta-theta band differences between conditions to demonstrate the spatial selectivity of these findings. In AX-CPT, there was a significant main effect of cue ($B > A$; $F(1,27) = 21.49$, $p < 0.001$), but no main effect of delay ($F(1,27) = 0.33$, $p = 0.552$) and no cue*delay interaction ($F(1,27) = 2.16$, $p = 0.153$). Similarly in DPX, there was a significant main effect of cue ($B > A$; $F(1,34) = 19.87$, $p < 0.001$) but no main effect of delay ($F(1,34) = 0.29$, $p = 0.596$) or cue*delay

Fig. 4 Differential switch positivity and early-mid delta-theta power at Cz. **A.** Cue-locked ERPs by delay length and cue type for AX-CPT (left) and DPX (right) experiments. Colored dots indicate average cue RT for each color-coded condition; a priori region of interest indicated by yellow highlight. Insets display the mean 400–600-ms cross-over interaction for each cue by delay type. **B.** Time-frequency main effects displayed as

subtractions of short and long delay and the interaction displayed as the difference of differences. Outlined time-frequency areas highlight statistically significant differences. Topoplots show delta-theta (1–7 Hz) power differences 200–600-ms post-cue at each delay length between cue types. Black dots indicate statistically significant differences between cue types at that delay length for that electrode

interaction ($F(1,34) = 0.29, p = 0.592$). These findings suggest that later midline activities during proactive control can be differentiated by cue rarity and delay length, at least in ERP amplitudes. The preferential finding of differential switch positivity for short rare cues lends further support to the hypothesis that short delays during proactive control are most similar to this established task switching component.

Sustained frontal negativity following cues

The sustained frontal negativity was assessed as the average amplitude at midline frontal electrodes AFz, Fz, and FCz between 400–600 ms. Nonsignificant results are reported in the supplement.

Sustained posterior-parietal activity following cues

Late sustained activity at posterior parietal electrodes was computed by averaging amplitude from 400–800 ms post-

cue at an average of bilateral posterior-parietal electrodes (PO3, PO4, PO7, PO8). In AX-CPT, a significant main effect of cue was observed ($B > A$; $F(1,27) = 17.26, p < 0.001$), with no main effect of delay ($F(1,27) = 2.42, p = 0.131$), but a critical significant delay*cue interaction ($F(1,27) = 4.80, p = 0.037$), with greatest sustained amplitude for rare cues during long delay (Fig. 5A). Because this ERP feature was slow and sustained, we did not investigate it with time-frequency methods due to limited resolution of sub-1 Hz activity. This ERP effect did not replicate in DPX (Cue $F(1,34) = 0.30, p = 0.586$; Delay $F(1,34) = 0.19, p = 0.671$; Cue*Delay Interaction $F(1,34) = 2.26, p = 0.146$).

Left prefrontal activity following cues

In an exploratory analysis in the DPX experiment, we observed a different interaction of delay*cue in left prefrontal areas. Left prefrontal activity was computed by averaging amplitude from 150–400 ms post-cue at an average of left frontal

Fig. 5 Posterior-parietal and left frontal sustained activity. Cue-locked ERPs by delay length and cue type. Colored dots indicate average cue RT for each color-coded condition; time region of interest indicated by yellow highlight. **A.** AX-CPT average of posterior parietal electrodes

(PO3, PO4, PO7, PO8). Insets display the mean 400–800-ms cross-over interaction for each cue by delay type. **B.** DPX average of left frontal electrodes (AF3, AF7, F3, F5, F7). Insets display the mean 150–400-ms cross-over interaction for each cue by delay type

electrodes (AF3, AF7, F3, F5, F7). In DPX (Fig. 5B), we observed a significant main effect of delay ($L > S$; $F(1,34) = 5.52$, $p = 0.027$), no main effect of cue type ($F(1,34) = 0.43$, $p = 0.517$), and a critical significant delay*cue interaction ($F(1,34) = 9.13$, $p = 0.006$), where the greatest amplitude was observed following Long B cues. These left frontal findings did not replicate in the AX-CPT, which had a significant main effect of delay ($L > S$; $F(1,27) = 6.90$, $p = 0.015$), no main effect of cue type ($F(1,27) = 1.21$, $p = 0.283$), and no delay*cue interaction ($F(1,27) = 1.06$, $p = 0.315$). These findings suggest that late, slow activities that may be reflective of active maintenance can differentiate proactive control specifically during long delays, but the lack of specificity in working memory signatures and the lack of direct replication between studies suggest that this hypothesis remains incompletely resolved.

Brain-behavior correlations

While delay effects on behavior were robust, and several neural features were enhanced differentially in short or long delay, it is not clear whether these cue-locked EEG features are intimately related to probe behavior. We tested whether the behavioral shift index accuracy metric was differently correlated with our EEG measures for short versus long delay (Supplemental Figure 1). Several nonsignificant correlations are reported in the supplement. In summary, weak statistical differentiation of BSI by delay-related neural activity suggests that these cue-locked components offer only modest evidence of brain-behavior associations.

Discussion

To understand how upcoming temporal demands modulate proactive control, we manipulated timing-related task demands in two experiments and compared within-subjects behavior and electrophysiological signals associated with goal updating and active maintenance. Critically, our findings suggest a temporally guided fractionation in the construct of proactive control, which has typically been evaluated as a unitary construct. Two specific major findings emerged from these experiments. First, within-subjects accuracy to rare aY probes was selectively impaired during short delay, implicating specific difficulty in inhibiting a pre-potent aX response. Second, we observed significant within-subjects differences in ERP and time-frequency signatures associated with task-switching, cognitive control, and active maintenance based on delay length and cue type. Both of these major findings were observed in Experiment 1 (AX-CPT) and replicated in a separate sample in Experiment 2 (DPX). This serves as the first study to attempt to dissociate different subtypes of proactive control and provides novel evidence that temporal demands can elicit behavioral differences and neurophysiological distinctions in proactive processes. Again, we operationalized these distinct features as 1) a goal updating process in which transient control immediately drives the rapid instantiation of a new state at the expense of a previous state, in contrast to 2) an active maintenance process where control processes elicit persistent activity patterns to maintain a sustained representation (Barak & Tsodyks, 2014; Jensen & Lisman, 2005; Vogel & Machizawa, 2004; Wang, 2010; Wasmuht, Spaak, Buschman, Miller, & Stokes, 2017; although also see Spaak,

Watanabe, Funahashi, & Stokes, 2017; Stokes et al., 2013). Of course, we do not expect that active maintenance would occur in isolation; even a distant goal must be updated at some point in time. We posit that this active maintenance process stores one's new goals, preceding a later or more gradual reconfiguration to the new state (Frohlich, Bazhenov, Timofeev, Steriade, & Sejnowski, 2006).

Dissociating proactive control

For the past several years, the dual mechanisms of control framework has divided cognitive control into proactive and reactive cognitive control (Braver, 2012), with proactive control instantiated to actively maintain goal-relevant information ahead of cognitively demanding events (Miller & Cohen, 2001), and reactive control called upon as a late correction mechanism utilized as needed, and only after a high-interference event occurs (Jacoby et al., 1999). Proactive control has been described and studied as a unitary construct, but this present work attempts to highlight how different subprocesses within proactive control are utilized based on known temporal differences as to when the cognitively demanding event will occur.

In the current study, within-subjects EEG activity was analyzed during the cue-probe delay to reveal how cues were processed to proactively (ahead of the probe) instantiate cognitive control. If there are dissociable neural processes underlying different types of control instantiation ("A" vs. "B" rules) during different known delay durations, it is reasonable to deduce that participants are using different "types" (or subprocesses) of proactive control according to temporal demands.

Accuracy was impaired specifically to rare aY probes in the short cue-probe delay condition (Fig. 2). This finding not only indicates difficulty in inhibiting the aX response that is demanded on 80% of A trials, but highlights that this prepotency is significantly stronger and/or more difficult to overcome with a predictable, short cue-probe delay.

Dissociating proactive control: "goal-updating" or "active maintenance" subtypes

We expected short delay demands to evoke a rapid, goal-updating type of cognitive control to B cues, where control is needed to immediately alter task goals. Neural differences were observed for short B over long B cues in early evaluative components (early anterior positivity) and later preparatory components (differential switch positivity). Due to the specificity to goal updating trials and short-delay context, this post-cue neural activity can be characterized as a delay-sensitive marker of goal updating (Cacioppo & Tassinari, 1990).

In the task-switching literature, it has been observed that participants often fail to proactively reconfigure task sets

when there is a long cue-probe interval (de Jong, 2000). In these long delay scenarios where proactive task set reconfiguration is not triggered, it is likely that a different process is used to maintain changing task goals. We expected long delay cues to evoke a slower active maintenance process following rare B cues to hold the new stimulus-response mappings over a long and uncertain delay. In the AX-CPT experiment, instantiation of proactive control during the long delay was uniquely characterized by a sustained increase in ERP amplitude at a cluster of bilateral posterior-parietal electrodes post-cue. In DPX, we observed a sustained increase in left prefrontal electrodes selectively for rare cues during long delay, providing a plausible mechanism for maintenance of the rare cued rule in long, but not short delay. However, the current experiments are not suited to definitely declare this sustained activity as working memory maintenance. First, the characterization of electrophysiological markers of working memory is widely variable (Brookes et al., 2011; Jensen & Tesche, 2002; Polanía et al., 2011; Vogel & Machizawa, 2004). Furthermore, the working memory literature has predominantly focused on maintenance of concrete visuo-spatial or auditory items, as opposed to retention of abstract rules. To better understand how rule retention might relate to item maintenance, it will be important for future work to compare more directly these constructs and their underlying mechanisms.

Temporal prediction

In the short delay and long delay blocks, participants prepared goals ahead of either an entirely predictable 1,000-ms delay or a jittered 3,000 (± 500)-ms delay, respectively. In addition to cognitive retention or updating processes utilized to manage control information over the delay, temporal prediction processes will likely have been employed. The hazard function describes the continual tracking of the conditional likelihood for an event to occur at that particular moment in time (for review, see Nobre, Correa, & Coull, 2007) and has been associated with electrophysiological activity localized to the supplementary motor area (Herbst, Fielder, & Obleser, 2018; Coull, 2009).

These premotor preparatory activities are a possible target for the preparation of cognitive control. Indeed, reaction times were generally slower during the jittered, long delay condition. It is unclear whether this was driven by temporal unpredictability (Herbst & Obleser, 2017), temporal duration, or the combination of duration and variability (Bertelson & Boons, 1960), and it remains unknown how distinct control processes interact with motor preparatory activities (Gulbinaite, van Rijn, & Cohen, 2014).

Differences between AX-CPT and DPX paradigms

Despite the procedural differences between studies (cue type, single vs. multiple stimuli, cue-probe percentages) nearly all brain and behavioral effects were replicated between

experiments, demonstrating generalizability. Prior studies comparing AX-CPT and DPX paradigms in healthy young adults have observed similar behavioral performance between the two studies (Barch et al., 2009), as well as many common areas of fMRI activation for goal maintenance (Lopez-Garcia et al., 2015). This generalizability is important, because both AX-CPT and DPX tasks are widely used to assess working memory in various patient and healthy control groups, as well as in translational work (Blackman et al., 2016; Blackman, Macdonald, & Chafee, 2013).

Yet, several subtle but potentially important distinctions between the AX-CPT and DPX paradigms must be noted, because these distinctions may evoke different strategies for proactive control. First, AX-CPT utilizes verbalizable letters as cues, whereas DPX uses nonverbalizable dot combinations. The need for intermediate translation from dot stimuli to task identity may impose at least some additional cognitive demand. It is unclear how proactive control instantiation might differ with these greater demands on working memory and/or task switching in the Dot Pattern Expectancy (Henderson et al., 2012; MacDonald et al., 2005; Otto, Skatova, Madlon-kay, & Daw, 2015). Because these tasks were run in separate samples, we are unable to provide a formal (within-subjects) test of potential task differences.

Limitations and future directions

the current studies have several limitations, each of which invite questions to be addressed by future research. First, both studies used assessed two cue-probe delay lengths: 1,000 ms and $3,000 \pm 500$ ms. Although a 1,000-ms cue-probe delay is commonly used in AX-CPT and DPX studies, the next most common delay frequency in the published literature is between 4,500 and 6,000 ms (Janowich & Cavanagh, 2018). It is unclear whether delay-related differences in control instantiation would change significantly with an increase in delay from 3 to 5 seconds, for example. Future studies could explore the full range of AX-CPT/DPX delay lengths used (5–10 seconds). In addition, this short delay was fixed at 1,000 ms, whereas the long delay was jittered between 2,500 and 3,500 ms, conflating expectancy and delay. The increased reaction times in long delay, for instance, may be due in part to the cue-probe jitter. These parameters were set in the present experiment to maximize the chance of generating a maximal prepotent response in the short delay, but future replications could systematically parse these parametric choices.

With the current setup of these AX-CPT and DPX tasks, remembering the A or B cue involves a relatively low working memory load, especially for our sample of healthy college students, which may explain the limited individual differences in accuracy and reaction time. As such, our brain-behavior correlations trended in the expected direction, but were non-significant. Finally, the ability to infer cognitive processes

based on different neural activities is limited by the lack of specificity between common EEG activities and presumably distinct cognitive processes. The centro-parietal P3, for instance, has been associated with task-switching (Gajewski & Falkenstein, 2011), as well as working memory (Polich, 2007). Consequently, it is difficult for correlations with any one brain signal to characterize definitively a certain type of behavior. Moreover, any psychological definition of an ERP or time-frequency component is likely imprecise, as the actual neural operation it indexes is unlikely to map directly onto a large-scale construct, such as “task-switching” or “working memory.” To reiterate our earlier point, our goal was not to use abductive (reverse) inference to parse definitively the distinct cognitive processes in this study. Our goal was a more modest approach that provides suggestive cognitive labels for our observed dissociations in neural activity. We hope to use experimental and quantitative constraints in the future to provide more definitive labels for these processes (Cavanagh & Castellanos, 2016; Hutzler, 2014; Poldrack, 2006; Yarkoni, Poldrack, Nichols, Van Essen, & Wager, 2011); however that is clearly outside the scope of the current report.

Conclusions

We have described how temporal delay, an otherwise arbitrarily controlled parameter in a popular assessment of cognitive control, has an important influence over of the type of cognitive control utilized. We suggest that timing demands may tap into distinct mechanisms for goal updating versus active maintenance. This proactive adaptation to temporal context is likely useful to balance optimally the costs of sustained control with the need to execute behavior successfully. Given the prevalence of this task for assessing cognition in psychiatric samples, it is critical to consider whether a given group is deficient in one or both of these dissociated aspects of control. Accordingly, researchers must preemptively weigh whether short and/or long delays best tax the cognitive constructs under consideration. Compounding this issue, fMRI studies tend to use long delays to facilitate the hemodynamic response function, whereas behavioral and EEG studies tend to use shorter delays (Janowich & Cavanagh, 2018). This pattern of differences in delay parameters suggests that there is a previously unappreciated problem generalizing findings between these techniques.

The temporal dissociation of two subtypes of proactive control merits further critical discussion of the common conceptualization of proactive control as a unitary construct. Altogether, our results suggest that cued continuous performance tasks tap into different cognitive features depending on seemingly arbitrary timing parameterization choices.

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References

- Astle, D. E., Jackson, G. M., & Swainson, R. (2006). Dissociating neural indices of dynamic cognitive control in advance task-set preparation: an ERP study of task switching. *Brain Research*, 1125(1), 94–103. <https://doi.org/10.1016/j.brainres.2006.09.092>
- Astle, D. E., Jackson, G. M., & Swainson, R. (2008). Fractionating the cognitive control required to bring about a change in task: a dense-sensor event-related potential study. *Journal of Cognitive Neuroscience*, 20(2), 255–267. <https://doi.org/10.1162/jocn.2008.20015>
- Barak, O., & Tsodyks, M. (2014). Working models of working memory. *Current Opinion in Neurobiology*, 25, 20–24. <https://doi.org/10.1016/j.conb.2013.10.008>
- Barcelo, F., Escera, C., Corral, M. J., & Periañez, J. a. (2006). Task switching and novelty processing activate a common neural network for cognitive control. *Journal of Cognitive Neuroscience*, 18, 1734–1748. <https://doi.org/10.1162/jocn.2006.18.10.1734>
- Barch, D. M., Berman, M. G., Engle, R., Jones, J. H., Jonides, J., MacDonald, A., ... Sponheim, S. R. (2009). CNTRICS final task selection: Working memory. *Schizophrenia Bulletin*, 35(1), 136–152. <https://doi.org/10.1093/schbul/sbn153>
- Barch, D. M., Braver, T. S., Nystrom, L. E., Forman, S. D., Noll, D. C., & Cohen, J. D. (1997). Dissociating working memory from task difficulty in human prefrontal cortex. *Neuropsychologia*, 35(10), 1373–80.
- Bertelson, P. & Boons, J.P. (1960). Time uncertainty and choice reaction time. *Nature*, 187, 531–532.
- Blackman, R. K., Crowe, D. A., DeNicola, A. L., Sakellaridi, S., MacDonald, A. W., & Chafee, M. V. (2016). Monkey Prefrontal Neurons Reflect Logical Operations for Cognitive Control in a Variant of the AX Continuous Performance Task (AX-CPT). *Journal of Neuroscience*, 36(14), 4067–4079. <https://doi.org/10.1523/JNEUROSCI.3578-15.2016>
- Blackman, R. K., Macdonald, A. W., & Chafee, M. V. (2013). Effects of ketamine on context-processing performance in monkeys: a new animal model of cognitive deficits in schizophrenia. *Neuropsychopharmacology : Official Publication of the American College of Neuropsychopharmacology*, 38(11), 2090–100. <https://doi.org/10.1038/npp.2013.118>
- Brainard, D. H. (1997). The Psychophysics Toolbox. *Spatial Vision*, 10(4), 433–436. <https://doi.org/10.1163/156856897X00357>
- Braver, T. S. (2012). The variable nature of cognitive control: A dual mechanisms framework. *Trends in Cognitive Sciences*, 16(2), 106–113. <https://doi.org/10.1016/j.tics.2011.12.010>
- Braver, T. S., Barch, D. M., & Cohen, J. D. (1999). Mechanisms of cognitive control: Active memory, inhibition, and the prefrontal cortex. *Pittsburgh (PA): Carnegie Mellon University*. Retrieved from ftp://46.13.242.59/IMATION_HDD/Documents/Work/Archives/2008/CIANS2008/2ndset/literatura/var/COGNITIVNI_FUNKCE.PDF
- Braver, T. S., Paxton, J. L., Locke, H. S., & Barch, D. M. (2009). Flexible neural mechanisms of cognitive control within human prefrontal cortex. *Proceedings of the National Academy of Sciences of the United States of America*, 106(15), 7351–7356. <https://doi.org/10.1073/pnas.0808187106>
- Braver, T. S., Satpute, A. B., Rush, B. K., Racine, C. A., & Barch, D. M. (2005). Context processing and context maintenance in healthy aging and early stage dementia of the Alzheimer's type. *Psychology and Aging*, 20(1), 33–46. <https://doi.org/10.1037/0882-7974.20.1.33>
- Brookes, M. J., Wood, J. R., Stevenson, C. M., Zumer, J. M., White, T. P., Liddle, P. F., & Morris, P. G. (2011). Changes in brain network activity during working memory tasks: a magnetoencephalography study. *NeuroImage*, 55(4), 1804–15. <https://doi.org/10.1016/j.neuroimage.2010.10.074>
- Buhusi, C. V., & Meck, W. H. (2005). What makes us tick? Functional and neural mechanisms of interval timing. *Nature Reviews Neuroscience*, 6(10), 755–765. <https://doi.org/10.1038/nrn1764>
- Cacioppo, J. T., & Tassinary, L. G. (1990). Inferring psychological significance from physiological signals. *The American Psychologist*, 45(1), 16–28. <https://doi.org/10.1037/0003-066X.45.1.16>
- Capizzi, M., Feher, K., Penolazzi, B., & Vallesi, A. (2015). Task-switching preparation across semantic and spatial domains: An event-related potential study. *Biological Psychology*, 110, 148–158. <https://doi.org/10.1016/j.biopsycho.2015.06.011>
- Carter, C. S., Braver, T. S., Barch, D. M., Botvinick, M. M., Noll, D., & Cohen, J. D. (1998). Anterior cingulate cortex, error detection, and the online monitoring of performance. *Science (New York, N.Y.)*, 280(May), 747–749. <https://doi.org/10.1126/science.280.5364.747>
- Cavanagh, J. F., & Castellanos, J. (2016). Identification of canonical neural events during continuous gameplay of an 8-bit style video game. *NeuroImage*. <https://doi.org/10.1016/j.neuroimage.2016.02.075>
- Cavanagh, J. F., Cohen, M. X., & Allen, J. J. B. (2009). Prelude to and resolution of an error: EEG phase synchrony reveals cognitive control dynamics during action monitoring. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience*, 29(1), 98–105. <https://doi.org/10.1523/JNEUROSCI.4137-08.2009>
- Cavanagh, J. F., & Frank, M. J. (2014). Frontal theta as a mechanism for cognitive control. *Trends in Cognitive Sciences*, 18(8), 414–421. <https://doi.org/10.1016/j.tics.2014.04.012>
- Chiew, K. S., & Braver, T. S. (2013). Temporal dynamics of motivation-cognitive control interactions revealed by high-resolution pupillometry. *Frontiers in Psychology*, 4(January), 15. <https://doi.org/10.3389/fpsyg.2013.00015>
- Christophel, T. B., Klink, P. C., Spitzer, B., Roelfsema, P. R., & Haynes, J.-D. (2017). The Distributed Nature of Working Memory. *Trends in Cognitive Sciences*, xx, 1–14. <https://doi.org/10.1016/j.tics.2016.12.007>
- Cohen, J. D., Barch, D. M., Carter, C., & Servan-Schreiber, D. (1999). Context-processing deficits in schizophrenia: converging evidence from three theoretically motivated cognitive tasks. *Journal of Abnormal Psychology*, 108(1), 120–133. <https://doi.org/10.1037/0021-843X.108.1.120>
- Cohen, J. D., Perstein, W. M., Braver, T. S., Nystrom, L. E., Noll, D. C., Jonides, J., & Smith, E. E. (1997). Temporal dynamics of brain activation during a working memory task. *Nature Publishing Group*.
- Cohen, M. X. (2014). *Analyzing Neural Time Series Data: Theory and Practice*. MIT Press. Retrieved from <https://books.google.com/books?id=jTSkAgAAQBAJ>
- Collins, A. G. E., Cavanagh, J. F., & Frank, M. J. (2014). Human EEG Uncovers Latent Generalizable Rule Structure during Learning. *Journal of Neuroscience*, 34(13), 4677–4685. <https://doi.org/10.1523/JNEUROSCI.3900-13.2014>
- Cooper, P. S., Darriba, Á., Karayanidis, F., & Barceló, F. (2016). Contextually sensitive power changes across multiple frequency bands underpin cognitive control. *NeuroImage*, 132, 499–511. <https://doi.org/10.1016/j.neuroimage.2016.03.010>
- Cooper, P. S., Wong, A. S. W., Fulham, W. R., Thienel, R., Mansfield, E., Michie, P. T., & Karayanidis, F. (2015). Theta frontoparietal

- connectivity associated with proactive and reactive cognitive control processes. *NeuroImage*, 108(September 2015), 354–363. <https://doi.org/10.1016/j.neuroimage.2014.12.028>
- Coull, J.T. (2009). Neural substrates of mounting temporal expectation. *PLOS Biology* 7(8): e1000166. doi:<https://doi.org/10.1371/journal.pbio.1000166>.
- Cunillera, T., Fuentemilla, L., Periañez, J., Marco-Pallarès, J., Krämer, U. M., Càmar, E., ... Rodríguez-Fornells, A. (2012). Brain oscillatory activity associated with task switching and feedback processing. *Cognitive, Affective, & Behavioral Neuroscience*, 12(1), 16–33. <https://doi.org/10.3758/s13415-011-0075-5>
- Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, 134(1), 9–21. <https://doi.org/10.1016/j.jneumeth.2003.10.009>
- Di Russo, F., Lucci, G., Sulpizio, V., Berchicci, M., Spinelli, D., Pitzalis, S., & Galati, G. (2016). Spatiotemporal brain mapping during preparation, perception, and action. *NeuroImage*, 126, 1–14. <https://doi.org/10.1016/j.neuroimage.2015.11.036>
- Edwards, B. G., Barch, D. M., & Braver, T. S. (2010). Improving prefrontal cortex function in schizophrenia through focused training of cognitive control. *Frontiers in Human Neuroscience*, 4(April), 32. <https://doi.org/10.3389/fnhum.2010.00032>
- Eriksson, J., Vogel, E. K., Lansner, A., Bergström, F., & Nyberg, L. (2015). Neurocognitive Architecture of Working Memory. *Neuron*, 88(1), 33–46. <https://doi.org/10.1016/j.neuron.2015.09.020>
- Folstein, J. R., & Van Petten, C. (2008). Influence of cognitive control and mismatch on the N2 component of the ERP: A review. *Psychophysiology*, 45(1), 152–170. <https://doi.org/10.1111/j.1469-8986.2007.00602.x>
- Freunberger, R., Werkle-Bergner, M., Griesmayr, B., Lindenberger, U., & Klimesch, W. (2011). Brain oscillatory correlates of working memory constraints. *Brain Research*, 1375, 93–102. <https://doi.org/10.1016/j.brainres.2010.12.048>
- Frohlich, F., Bazhenov, M., Timofeev, I., Steriade, M., & Sejnowski, T. J. (2006). Slow State Transitions of Sustained Neural Oscillations by Activity-Dependent Modulation of Intrinsic Excitability. *Journal of Neuroscience*, 26(23), 6153–6162. <https://doi.org/10.1523/JNEUROSCI.5509-05.2006>
- Gajewski, P. D., & Falkenstein, M. (2011). Diversity of the P3 in the task-switching paradigm. *Brain Research*, 1411, 87–97. <https://doi.org/10.1016/j.brainres.2011.07.010>
- Gajewski, P. D., Kleinsorge, T., & Falkenstein, M. (2010). Electrophysiological correlates of residual switch costs. *Cortex*, 46(9), 1138–1148. <https://doi.org/10.1016/j.cortex.2009.07.014>
- Gulbinaite, R., van Rijn, H., Cohen, M.X. (2014). Fronto-parietal network oscillations reveal relationship between working memory capacity and cognitive control. *Frontiers in Human Neuroscience*, 8(761), 1–13. <https://doi.org/10.3389/fnhum.2014.00761>
- Harper, J., Malone, S. M., Bachman, M. D., & Bernat, E. M. (2016). Stimulus sequence context differentially modulates inhibition-related theta and delta band activity in a go/no-go task. *Psychophysiology*, 53, <https://doi.org/10.1111/psyp.12604>
- Harper, J., Malone, S. M., & Bernat, E. M. (2014). Theta and delta band activity explain N2 and P3 ERP component activity in a go/no-go task. *Clinical Neurophysiology*, 125(1), 124–132. <https://doi.org/10.1007/978-1-62703-673-3>
- Henderson, D., Poppe, A. B., Barch, D. M., Carter, C. S., Gold, J. M., Ragland, J. D., ... MacDonald, A. W. (2012). Optimization of a goal maintenance task for use in clinical applications. *Schizophrenia Bulletin*, 38(1), 104–113. <https://doi.org/10.1093/schbul/sbr172>
- Herbst, S.K., Fielder, L., & Obleser, J. (2018). Tracking temporal hazard in the human electroencephalogram using a forward encoding model. *eNeuro* 5(2), ENEURO.0017-18.2018. [10.1523/ENEURO.0017-18.2018](https://doi.org/10.1523/ENEURO.0017-18.2018)
- Herbst, S.K. & Obleser, J. (2017). Implicit variations of temporal predictability: Shaping the neural oscillatory and behavioral response. *Neuropsychologia* 101, 141–152. <https://doi.org/10.1016/j.neuropsychologia.2017.05.019>
- Hutzler, F. (2014). Reverse inference is not a fallacy per se: Cognitive processes can be inferred from functional imaging data. *NeuroImage*, 84, 1061–1069. <https://doi.org/10.1016/j.neuroimage.2012.12.075>
- Jacoby, L. L. (1999). Ironic effects of repetition: Measuring age-related differences in memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 25(1), 3–22.
- Jamadar, S., Hughes, M., Fulham, W. R., Michie, P. T., & Karayanidis, F. (2010). The spatial and temporal dynamics of anticipatory preparation and response inhibition in task-switching. *NeuroImage*, 51(1), 432–449. <https://doi.org/10.1016/j.neuroimage.2010.01.090>
- Janowich, J. R., & Cavanagh, J. F. (2018). Delay knowledge and trial set count modulate use of proactive versus reactive control: A meta-analytic review. *Psychonomic Bulletin and Review*. <https://doi.org/10.3758/s13423-018-1502-1>
- Jensen, O., & Lisman, J. E. (2005). Hippocampal sequence-encoding driven by a cortical multi-item working memory buffer. *Trends in Neurosciences*, 28(2), 67–72. <https://doi.org/10.1016/j.tins.2004.12.001>
- Jensen, O., & Tesche, C. D. (2002). Frontal theta activity in humans increases with memory load in a working memory task. *Neuroscience*, 115(8), 1395–1399. <https://doi.org/10.1046/j.1460-9568.2002.01975.x>
- de Jong, R. (2000). An intention-activation account of residual switch costs. In *Control of Cognitive Processes: Attention and Performance XVIII* (pp. 357–376).
- Karayanidis, F., Jamadar, S., Ruge, H., Phillips, N., Heathcote, A., & Forstmann, B. U. (2010). Advance preparation in task-switching: converging evidence from behavioral, brain activation, and model-based approaches. *Frontiers in Psychology*, 1(July), 25. <https://doi.org/10.3389/fpsyg.2010.00025>
- Karayanidis, F., Mansfield, E. L., Galloway, K. L., Smith, J. L., Provost, A., & Heathcote, A. (2009). Anticipatory reconfiguration elicited by fully and partially informative cues that validly predict a switch in task. *Cognitive, Affective & Behavioral Neuroscience*, 9(2), 202–215. <https://doi.org/10.3758/CABN.9.2.202>
- Karayanidis, F., Provost, A., Brown, S., Paton, B., & Heathcote, A. (2011). Switch-specific and general preparation map onto different ERP components in a task-switching paradigm. *Psychophysiology*, 48(4), 559–568. <https://doi.org/10.1111/j.1469-8986.2010.01115.x>
- Kayser, J., & Tenke, C. E. (2006). Principal components analysis of Laplacian waveforms as a generic method for identifying ERP generator patterns: II. Adequacy of low-density estimates. *Clinical Neurophysiology*, 117(2), 369–380. <https://doi.org/10.1016/j.clinph.2005.08.033>
- Kessler, Y., Baruchin, L. J., & Bouhsira-Sabag, A. (2015). Working memory updating occurs independently of the need to maintain task-context: accounting for triggering updating in the AX-CPT paradigm. *Psychological Research*. <https://doi.org/10.1007/s00426-015-0717-2>
- Kieffaber, P. D., & Hetrick, W. P. (2005). Event-related potential correlates of task switching and switch costs. *Psychophysiology*, 42(1), 56–71. <https://doi.org/10.1111/j.1469-8986.2005.00262.x>
- Kikumoto, A., & Mayr, U. (2017). The Nature of Task Set Representations in Working Memory. *Journal of Cognitive Neuroscience*. <https://doi.org/10.1162/jocn>
- Kleiner, M., Brainard, D. H., & Pelli, D. (2007). What's new in Psychtoolbox-3? Retrieved January 2, 2016, from <http://www.perceptionweb.com/abstract.cgi?id=v070821>
- Lamm, C., Pine, D. S., & Fox, N. A. (2013). Impact of negative affectively charged stimuli and response style on cognitive-control-

- related neural activation: an ERP study. *Brain and Cognition*, 83(2), 234–43. <https://doi.org/10.1016/j.bandc.2013.07.012>
- Lavric, A., Mizon, G. a., & Monsell, S. (2008). Neurophysiological signature of effective anticipatory task-set control: A task-switching investigation. *European Journal of Neuroscience*, 28(5), 1016–1029. <https://doi.org/10.1111/j.1460-9568.2008.06372.x>
- Lee, I. A., & Preacher, K. J. (2013, September). Calculation for the test of the difference between two dependent correlations with one variable in common [Computer software]. Available from <http://quantpsy.org>.
- Lenartowicz, A., Escobedo-Quiroz, R., & Cohen, J. D. (2010). Updating of context in working memory: an event-related potential study. *Cognitive, Affective & Behavioral Neuroscience*, 10(2), 298–315. <https://doi.org/10.3758/CABN.10.2.298>
- Lesh, T. A., Westphal, A. J., Niendam, T. A., Yoon, J. H., Minzenberg, M. J., Ragland, J. D., ... Carter, C. S. (2013). Proactive and reactive cognitive control and dorsolateral prefrontal cortex dysfunction in first episode schizophrenia. *NeuroImage. Clinical*, 2, 590–9. <https://doi.org/10.1016/j.nicl.2013.04.010>
- Li, L., Wang, M., Zhao, Q.-J., & Fogelson, N. (2012). Neural mechanisms underlying the cost of task switching: an ERP study. *PloS One*, 7(7), e42233. <https://doi.org/10.1371/journal.pone.0042233>
- Lopez-Garcia, P., Lesh, T. A., Salo, T., Barch, D. M., MacDonald, A. W., Gold, J. M., ... Carter, C. S. (2015). The neural circuitry supporting goal maintenance during cognitive control: a comparison of expectancy AX-CPT and dot probe expectancy paradigms. *Cognitive, Affective, & Behavioral Neuroscience*, (December), 10.3758/s13415-015-0384-1
- Lucenet, J., & Blaye, A. (2014). Age-related changes in the temporal dynamics of executive control: a study in 5- and 6-year-old children. *Frontiers in Psychology*, 5(July), 1–11. <https://doi.org/10.3389/fpsyg.2014.00831>
- MacDonald, A. W., Goghari, V. M., Hicks, B. M., Flory, J. D., Carter, C. S., & Manuck, S. B. (2005). A convergent-divergent approach to context processing, general intellectual functioning, and the genetic liability to schizophrenia. *Neuropsychology*, 19(6), 814–821. <https://doi.org/10.1037/0894-4105.19.6.814>
- Manzi, A., Nessler, D., Czernochowski, D., & Friedman, D. (2011). The Development of anticipatory cognitive control processes in Task-Switching: An ERP Study in Children, Adolescents and Young Adults. *Psychophysiology*, 48(9), 1258–1275. <https://doi.org/10.1111/j.1469-8986.2011.01192.x>
- Medalla, M., & Barbas, H. (2009). Synapses with inhibitory neurons differentiate anterior cingulate from dorsolateral prefrontal pathways associated with cognitive control. *Neuron*, 61(4), 609–20. <https://doi.org/10.1016/j.neuron.2009.01.006>
- Meng, X.-L., Rosenthal, R., & Rubin, D. B. (1992). Comparing correlated correlation coefficients. *Psychological Bulletin*, 111(1), 172–175. <https://doi.org/10.1037/0033-2909.111.1.172>
- Miller, E. K., & Cohen, J. D. (2001). An integrative theory of prefrontal cortex function. *Annual Review of Neuroscience*, 24, 167–202.
- Morales, J., Yudes, C., Gómez-Ariza, C. J., & Bajo, M. T. (2014). Bilingualism modulates dual mechanisms of cognitive control: Evidence from ERPs. *Neuropsychologia*, 66, 157–169. <https://doi.org/10.1016/j.neuropsychologia.2014.11.014>
- Morillon, X. B., Schroeder, C. E., Wyart, X. V., & Arnal, X. L. H. (2016). Temporal Prediction in lieu of Periodic Stimulation, 36(8), 2342–2347. <https://doi.org/10.1523/JNEUROSCI.0836-15.2016>
- Nicholson, R., Karayanidis, F., Davies, A., & Michie, P. T. (2006). Components of task-set reconfiguration: Differential effects of “switch-to” and “switch-away” cues. *Brain Research*, 1121(1), 160–176. <https://doi.org/10.1016/j.brainres.2006.08.101>
- Nicholson, R., Karayanidis, F., Poboka, D., Heathcote, A., & Michie, P. T. (2005). Electrophysiological correlates of anticipatory task-switching processes. *Psychophysiology*, 42(5), 540–54. <https://doi.org/10.1111/j.1469-8986.2005.00350.x>
- Nobre, A. C., Correa, A., & Coull, J. T. (2007). The hazards of time. *Current Opinion in Neurobiology*, 17(4), 465–470. <https://doi.org/10.1016/j.conb.2007.07.006>
- Nolan, H., Whelan, R., & Reilly, R. B. (2010). FASTER: Fully Automated Statistical Thresholding for EEG artifact Rejection. *Journal of Neuroscience Methods*, 192(1), 152–162. <https://doi.org/10.1016/j.jneumeth.2010.07.015>
- Otto, A. R., Skatova, A., Madlon-kay, S., & Daw, N. D. (2015). Cognitive Control Predicts Use of Model-based Reinforcement Learning. *Journal of Cognitive Neuroscience*, 27(2), 319–333. <https://doi.org/10.1162/jocn>
- Pelli, D. G. (1997). The VideoToolbox software for visual psychophysics: transforming numbers into movies. *Spatial Vision*. <https://doi.org/10.1163/156856897X00366>
- Perrin, F., Pernier, J., Bertrand, O., & Echallier, J. F. (1989). Spherical splines for scalp potential and current density mapping. *Electroencephalography and Clinical Neurophysiology*, 72(2), 184–187. [https://doi.org/10.1016/0013-4694\(89\)90180-6](https://doi.org/10.1016/0013-4694(89)90180-6)
- Polanía, R., Paulus, W., & Nitsche, M. A. (2011). Noninvasively Decoding the Contents of Visual Working Memory in the Human Prefrontal Cortex within High-gamma Oscillatory Patterns. *Journal of Cognitive Neuroscience*, 24(2), 304–314. <https://doi.org/10.1162/jocn>
- Poldrack, R. A. (2006). Can cognitive processes be inferred from neuroimaging data? *Trends in Cognitive Sciences*, 10(2), 59–63. <https://doi.org/10.1016/j.tics.2005.12.004>
- Polich, J. (2007). Updating P300: An Integrative Theory of P3a and P3b. *Clinical Neurophysiology*, 118(10), 2128–2148. <https://doi.org/10.1016/j.clinph.2007.04.019>
- Poljac, E., & Yeung, N. (2014). Dissociable neural correlates of intention and action preparation in voluntary task switching. *Cerebral Cortex*, 24(February), 465–478. <https://doi.org/10.1093/cercor/bhs326>
- Redick, T. S. (2014). Cognitive control in context: Working memory capacity and proactive control. *Acta Psychologica*, 145(1), 1–9. <https://doi.org/10.1016/j.actpsy.2013.10.010>
- Rushworth, M. F. S., Passingham, R. E., & Nobre, A. C. (2005). Components of Attentional Set-switching. *Experimental Psychology (Formerly “Zeitschrift Für Experimentelle Psychologie”)*, 52(2), 83–98. <https://doi.org/10.1027/1618-3169.52.2.83>
- Schmitt, H., Ferdinand, N. K., & Kray, J. (2014). Age-differential effects on updating cue information: Evidence from event-related potentials. *Cognitive, Affective & Behavioral Neuroscience*, 1115–1131. 10.3758/s13415-014-0268-9
- Schmitt, H., Ferdinand, N. K., & Kray, J. (2015). The influence of monetary incentives on context processing in younger and older adults: an event-related potential study. *Cognitive, Affective, & Behavioral Neuroscience*, 15(2), 416–434. <https://doi.org/10.3758/s13415-015-0335-x>
- Servan-Schreiber, D., Cohen, J. D., & Steingard, S. (1996). Schizophrenic deficits in the processing of context: A test of a theoretical model. *Archives of General Psychiatry*, 53(12), 1105–1112. <https://doi.org/10.1001/archpsyc.1996.01830120037008>
- Shenhav, A., Botvinick, M., & Cohen, J. (2013). The expected value of control: An integrative theory of anterior cingulate cortex function. *Neuron*, 79(2), 217–240. <https://doi.org/10.1016/j.neuron.2013.07.007>
- Spaak, E., Watanabe, K., Funahashi, S., & Stokes, M. (2017). Stable and dynamic coding for working memory in primate prefrontal cortex longer time scales stable and dynamic epochs activity returns to baseline. *Journal of Neuroscience*, 37(27), 6503–6516. <https://doi.org/10.1523/JNEUROSCI.3364-16.2017>
- Stanley, D. A., Roy, J. E., Aoi, M. C., Kopell, N. J., & Miller, E. K. (2018). Low-Beta Oscillations Turn Up the Gain During Category Judgments. *Cerebral Cortex*, 28(1), 116–130. <https://doi.org/10.1093/cercor/bhw356>
- Steiger, J. H. (1980). Tests for comparing elements of a correlation matrix. *Psychological Bulletin*. <https://doi.org/10.1037/0033-2909.87.2.245>

- Stokes, M. G., Kusunoki, M., Sigala, N., Nili, H., Gaffan, D., & Duncan, J. (2013). Dynamic coding for cognitive control in prefrontal cortex. *Neuron*, 78(2), 364–75. <https://doi.org/10.1016/j.neuron.2013.01.039>
- Unsworth, N., Fukada, K., Awh, E., & Vogel, E. K. (2015). Working memory delay activity predicts individual differences in cognitive abilities. *Journal of Cognitive Neuroscience*, 27(5), 853–865. <https://doi.org/10.1162/jocn>
- Vogel, E. K., & Machizawa, M. G. (2004). Neural activity predicts individual differences in visual working memory capacity. *Nature*, 428(April), 748–751. <https://doi.org/10.1038/nature02447>
- Wang, X.-J. (2010). Neurophysiological and Computational Principles of Cortical Rhythms in Cognition. *Physiological Reviews*, 90(3), 1195–1268. <https://doi.org/10.1152/physrev.00035.2008>
- Wasmuht, D., Spaak, E., Buschman, T., Miller, E., & Stokes, M. (2017). Intrinsic neuronal dynamics predict distinct functional roles during working memory.
- Yarkoni, T., Poldrack, R. a., Nichols, T. E., Van Essen, D. C., & Wager, T. D. (2011). Large-scale automated synthesis of human functional neuroimaging data. *Nature Methods*, 8(8), 665–70. <https://doi.org/10.1038/nmeth.1635>