The Case of the Cognitive (Opti)miser: Electrophysiological Correlates of Working Memory Maintenance Predict Demand Avoidance

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Abstract

■ People are often considered cognitive misers. When given a free choice between two tasks, people tend to choose tasks requiring less cognitive effort. Such demand avoidance (DA) is associated with cognitive control, but it is still not clear to what extent individual differences in cognitive control can account for variations in DA. We sought to elucidate the relation between cognitive control and cognitive effort preferences by investigating the extent to which sustained neural activity in a task requiring cognitive control is correlated with DA. We hypothesized that neural measures of efficient filtering will predict individual variations in demand preferences. To test this hypothesis, we had participants perform a delayed-match-to-sample paradigm with their ERPs recorded, as well as a separate behavioral demand-selection task. We focused on the ERP correlates of cognitive filtering efficiency (CFE)—the ability to ignore task-irrelevant distractors during working memory maintenance—as it manifests in a modulation of the contralateral delay activity, an ERP correlate of cognitive control. As predicted, we found a significant positive correlation between CFE and DA. Individuals with high CFE tended to be significantly more demand avoidant than their low-CFE counterparts. Low-CFE individuals, in comparison, did not form distinct cognitive effort preferences. Overall, our results suggest that cognitive control over the contents of visual working memory contribute to individual differences in the expression of cognitive effort preferences. This further implies that these observed preferences are the product of sensitivity to cognitive task demands. ■

INTRODUCTION

Decades of research in cognitive psychology have propounded that people can generally be considered "cognitive misers" (Fiske & Taylor, 2013; Kahneman, 2011). We tend to invoke quick heuristic means of thinking when evaluating the information around us, minimizing cognitive effort during demanding tasks rather than consistently and constantly expending cognitive resources on reasoning about these tasks fully (Stanovich, 2009; Ballé, 2002; Gilovich, Griffin & Kahneman, 2002). For instance, less demanding task alternatives are more frequently selected than more demanding ones (oftentimes operationalized by increasing or decreasing frequency of task switching, respectively: Kool, McGuire, Wang, & Botvinick, 2013; Kool, McGuire, Rosen, & Botvinick, 2010; Dreishbach & Haider, 2006; Monsell & Mizon, 2006; Dreisbach, Haider & Kluwe, 2002). Such demand avoidance (DA) is most pronounced when participants are aware of the cognitive demand associated with each alternative (Dunn, Gaspar, & Risko, 2019), but it can also be observed when participants are unaware of the demand-related difference between alternatives (Kool et al., 2010, 2013).

Although the conceptualization of cognitive effort as costly, and therefore as something to be avoided, is widespread (for a review, see Shenhav et al., 2017), such cognitive DA does not necessarily preclude engagement in cognitively demanding tasks. From filling out the *New York Times* Sunday crossword puzzle to flying jet planes, people clearly do engage in tasks that require substantial mental effort. This has recently become known as the "effort paradox," the phenomenon whereby people tend to minimize their cognitive efforts under certain circumstances, whereas under others, they ascribe value to effort and actively seek it (Inzlicht, Shenhav, & Olivola, 2018).

One potential factor contributing to the effort paradox may lie in interindividual variability in cognitive control. For example, individual differences in DA have been related to self-reported ratings along various dimensions of central executive function: intertemporal choice, self-control (Kool et al., 2013), working memory capacity, and task-switching costs (Shenhav et al., 2017; Kool et al., 2013). Further support for this conjecture comes from neuroimaging research showing that DA is associated with activity in regions supporting cognitive control, primarily lateral pFC (LPFC; McGuire & Botvinick, 2010). Utilizing the demand selection task (DST: Kool et al., 2010), a paradigm that quantifies people's preference for the less demanding of two task sets, McGuire and Botvinick showed that increased LPFC activation is associated with participants' self-reported experience of cognitive demand as well as their likelihood of consistently selecting the low-demand task set. Given the involvement

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of the LPFC in cognitive control (Ridderinkhof, Ullsperger, Crone, & Niewenhuis, 2004; Koechlin, Ody, & Kouneiher, 2003; for a review, see Badre & Nee, 2018), their results strongly suggest that cortical structures involved in cognitive control support behavioral DA.

Whereas McGuire and Botvinick (2010) did not detail any specific mechanism by which LPFC activity might influence DA, one insight regarding its functional role comes from studies showing that sustained LPFC activation, as well as lateral parietal activation (DeBaene & Brass, 2013; Corbetta & Shulman, 2002) is critical to the maintenance of information in visual working memory (VWM; Gazzaley & Nobre, 2012; Buschman, Siegel, Roy, & Miller, 2011; Curtis & D'esposito, 2003; Cohen et al., 1994, 1997). Because cognitive control entails selection of task-relevant information, that information has to be actively maintained in VWM, an act that in itself requires cognitive effort. Thus, it stands to reason that changes in one's cognitive effort biases should be related to variations in maintenance of information in working memory.

Support for the hypothesis that sustained LPFC activity explains cognitive effort preferences comes from electrophysiological studies of VWM. Negative-going ERPs recorded at posterior lateral and frontocentral electrode sites during maintenance have been found to correlate with the efficiency of information selection (Perez, Vogel, Luck, & Kappenman, 2012; Vogel, McCollough, & Machizawa, 2005). Recent work has focused on one ERP component in particular, the contralateral delay activity (CDA; for a review, see Luria, Balaban, Awh, & Vogel, 2016). The amplitude of the CDA waveform negativity increases with the number of items to be retained and asymptotes in accordance with the individual's VWM capacity (Perez et al., 2012; Vogel & Machizawa, 2004). Critically, CDA amplitude provides a direct measure of individual differences in cognitive control, operationalized as one's ability to attend to task-relevant information while disregarding task-irrelevant information (Vogel et al., 2005). When presented with task-irrelevant distractors, individuals with high VWM capacity (measured behaviorally) have a lower CDA as compared with their low-VWM-capacity counterparts (Vogel et al., 2005). This finding demonstrates that individuals who are less capable of controlling access to working memory tend to store a greater proportion of task-irrelevant information, thereby hampering their performance. Variations in CDA have recently been shown to be linked to individual differences in a broad array of mental faculties, including multiple measures of capacity, attention control, long-term episodic memory, and fluid intelligence, suggesting that CDA reflects "the operation of core cognitive processes that support a broad range of cognitive abilities" (Unsworth, Fukuda, Awh, & Vogel, 2015, p. 864).

Taken together, the findings of the abovementioned studies suggest that access to working memory, as measured by the CDA, is instrumental to cognitive control and, therefore, that it may be associated with cognitive effort preferences. To test this conjecture, this study investigates the putative relationship between access to working memory and cognitive effort by examining the extent to which variations in CDA-based measures of cognitive control are linked to individual differences in DA. We adopted two widely used paradigms for studying cognitive attentional control and DA: Vogel et al.'s (2005) bilateral cued delayed-match-to-sample paradigm and Kool et al.'s (2010) task-switching variant of the DST paradigm, respectively.

We utilized the bilateral cued delayed-match-to-sample paradigm as it enables us to assess individual differences in the electrophysiological correlates of the ability to exercise cognitive control over the contents of VWM. Specifically, this was operationalized by measuring cognitive filtering efficiency (CFE): the extent to which CDA amplitude changes in response to the presence of task-irrelevant distractors. Individuals with high CFE should successfully ignore the irrelevant distractors, meaning that the irrelevant distractors ought to induce no more CDA than the target stimuli presented alone. Conversely, failure in controlling distractors' intrusion into working memory would result in CDA amplitude generated in response to distractors as well as the targets, as though all were task relevant (see Figure 1 and Delayed-Match-to-Sample Task section for details).

In this study, we had all participants complete both the electrophysiological delayed-match-to-sample task discussed here and the behavioral DST. The coupling of these paradigms allowed us to examine the extent to which variations in electrophysiological measures of their CFE would relate to individual differences in their cognitive effort preferences. We measured the behavioral manifestation of cognitive effort preferences by employing the task-switching variant of the DST (see Figure 2 and Demand Selection Task section for details). This paradigm operationalizes DA as a preference for the less demanding of two task sets when participants are given a free choice between high- and low-demand alternatives on each trial. Thus, we can infer participants' cognitive effort preferences based on the relative probability with which they select the low-demand task set; the more often they select it from trial to trial, the more demand avoidant they are (i.e., the less effort they are willing to expend), and vice versa.[1]

Consistent with these patterns of previous results, we hypothesized that participants who employ more cognitive control over the contents of working memory in the delayed-match-to-sample task (as measured by CDA-based cognitive filtering) would also be more likely to develop a preference for one of the two task sets during the DST, whereas individuals with low CFE would be unlikely to develop preferences for either task set.

METHODS

Participants

Thirty-six participants (13 women) were recruited for participation through advertisements on Wright State

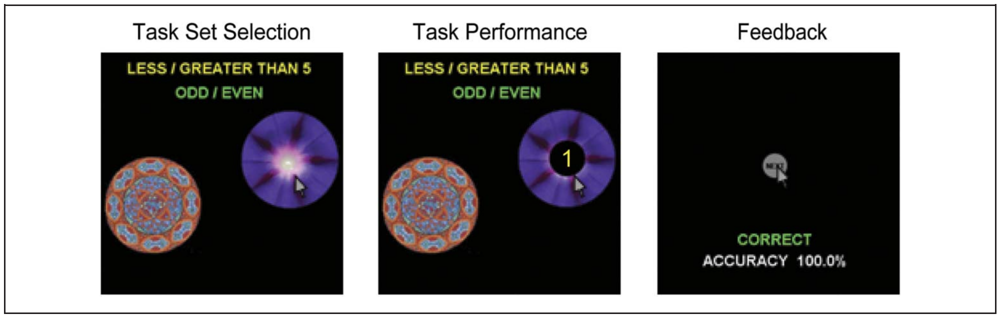

Figure 1. Schematic of a trial in the DST. Participants were instructed to select one of two task sets (denoted by patterned circles) on each trial by hovering their mouse over either one. Immediately, the selected task set would reveal a colored digit; participants were instructed to complete a parity or magnitude judgment task depending on the digit's color. After providing their response for the current trial, feedback was provided. Participants would then initiate the next trial by clicking a circle labeled "next" at the center of the screen.

University's WINGS Web site. Participants were paid $25 per hour for their participation in two experimental sessions, 2 hr each. Four participants were excluded from further analyses owing to an excessive number of ocular artifacts identified during EEG processing (see EEG Data Acquisition and Preprocessing section for details). Two additional participants' behavioral data showed chance performance, during the delayed-match-to-sample task, so they were excluded from further analyses.

All experimental protocols were approved both by Wright State University's institutional review board. The researchers assert that all experimental protocols adhere to guidelines for ensuring the anonymity and confidentiality of participants' data outlined in the Health Insurance Portability and Accountability Act and that all procedures were conducted with participants' fully informed consent as governed by the Declaration of Helsinki.

Experimental Design and Procedures

All participants went through two experiments, in two separate experimental sessions: the DST, in which only behavior was recorded, and the delayed-match-to-sample task, in which both behavior and EEGs were recorded. The order of the experiments was counterbalanced across participants.

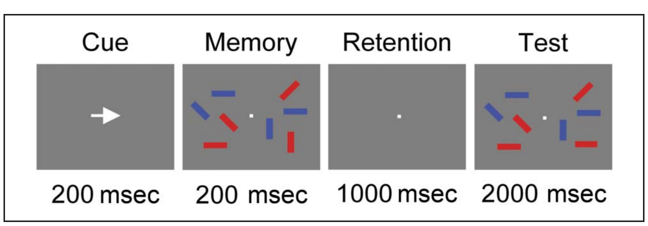

Figure 2. Schematic of a trial in the delayed-match-to-sample task (2Blue condition shown). Each trial began with a 200-msec precue (Cue), followed by 200-msec initial presentation of potential target and distractor items (Memory). Participants had to retain the potential targets for 1000 msec (Retention) and then determine whether any of the potential targets' orientations had changed (Test) when they reappeared for 2000 msec.

DST

On every trial, two differently patterned circles would appear on opposite sides of a fixation mark (see Figure 1). Participants were instructed to initiate each trial by hovering the mouse cursor over one of the two circles. Then, a colored (green or yellow) digit from 1 to 9 (excluding 5) would immediately appear at its center.

The digit's color on a given trial would determine which of two tasks the participants would need to complete: For green digits, they made parity judgments (by pressing the right mouse button for even values or the left for odd ones); for yellow digits, they made magnitude judgments (pressing the right mouse button for values greater than five or the left for less). In both cases, participants were told to respond as quickly and accurately as possible. Critically—and unbeknownst to them—the probability of a digit's color appearing on a given trial (and thus the probability of switching task instructions) depended on which of the two circles (task sets) had been selected. For each participant, one task set switched tasks between 90% of trials (high-demand task set), whereas the other switched on only 10% of trials (low-demand task set). Participants were also instructed to determine the difference between the two circles (besides their patterns) and that this could require spending several trials selecting each of them; they were also told that they should continue to select whichever of the two circles they preferred. Following these instructions, participants completed 30 representative trials as a training session, and those who failed to obtain at least 75% correct performance were asked to complete it again. Three participants required a second attempt at the training session; none fell short of the criterion after two such attempts.

Delayed-Match-to-Sample Task

On every trial, two arrays of randomly oriented rectangular bars (one in each visual hemifield) were presented for 200 msec (memory arrays, shown in Figure 2), along with a white fixation dot (0.1° visual angle diameter) at the center of a 1920 × 1080 pixel monitor. On any single trial, both arrays would contain either two red bars (2Red condition), four red bars (4Red condition), or two red and two blue bars (Figure 2; 2Blue condition shown). At a viewing distance of 1.5 m, the bars subtended a 1° × 0.25° visual angle, with random orientations of 0°, 45°, 90°, or 135°. Bars were positioned within their respective arrays such that no two bars were centered within a 1.5° visual angle of one another to prevent overlap. The centroid of each array (within which the bars could be positioned) was at 3° eccentricity, subtending 2° horizontally and 4° vertically.

One of the two memory arrays was always precued (Figure 2; left precue shown) by an arrow, 200 msec before it appeared (Figure 2; cue interval). The two arrays disappeared for 1000 msec after the first presentation (Figure 2; retention interval) and then reappeared for 2000 msec (Figure 2; test array interval). On half of all trials in each condition, one of the red rectangles in the cued hemifield would change its orientation by 90° upon appearance of the test array. When such a change occurred, it was always in the cued hemifield (i.e., no invalid cues were employed). Participants were asked to report the change in orientation by pressing the "1" button on the keyboard when they perceived it, and the "2" button otherwise, as quickly and accurately as possible. Critically, participants were explicitly instructed to ignore any blue bars in the cued hemifield, because they would never change orientation.

Consistent with previous work (Unsworth & McMillan, 2014; Luck & Vogel, 2013; Fukuda, Awh, & Vogel, 2010; Fukuda, Vogel, Mayr, & Awh, 2010; Vogel et al., 2005), we also obtained behavioral measures of working memory capacity, which have been shown to be correlated with CDA amplitude over the retention interval (Luria et al., 2016). To derive the number of items maintained in working memory, each participant's capacity limit (K) was calculated according to Pashler's (1988) formula.

EEG Data Acquisition and Preprocessing

EEG data were acquired at 512 Hz using 71 Ag–AgCl active electrodes (Biosemi ActiveTwo), including 64 pin-type electrodes mounted on a fitted cap, labeled according to the extended 10–20 system. Seven external electrodes were secured over each participant's nose, left and right mastoids, canthi, and upper and lower orbitals. A vertical EOG channel was derived from the difference between the upper and lower orbital electrodes' potentials; and likewise, a horizontal EOG, from the left and right canthi. Raw data were referenced to the mean of the mastoid electrodes and then high-pass (0.01 Hz) and low-pass (60 Hz) filtered with a standard second-order Butterworth filter.

Segmented data were time-locked to memory array offset and then baseline corrected by the 200-msec interval preceding memory array onset (see Figure 2). Baseline-corrected and segmented EEG data were rejected as artifacts when the potential at any electrode exceeded ±80 μV. Segments were excluded from averaging if their horizontal or vertical EOG potential exceeded 32 μV. Because the memory and test arrays were presented at 3° eccentricity, with a 1° horizontal radius, this prevented inclusion of trials in which participants attempted to fixate the array in the cued hemifield.

EEG Analysis

In line with previous literature on the CDA (for a review, see Luria et al., 2016), we derived negative slow waveforms from artifact-free epochs at occipital (O1 and O2), parieto-occipital (PO3, PO4, PO8, and PO9), and parietal (P1, P2, P3, P4, P7, P8, P9, and P10) electrode sites contralateral and ipsilateral to the cued hemifield. The resulting ipsilateral slow waves were then subtracted from the corresponding contralateral ones to obtain CDA difference waveforms, averaged across electrodes. Mean amplitudes were calculated as the area under the waveforms for the period between 300 and 900 msec after the memory array offset, divided by their durations. We obtained single-point estimates of CFE by comparing the increase in CDA amplitude caused by the addition of red bars versus blue ones:

$$CFE = \frac{4\text{Red} - 2\text{Red}}{2\text{Red}} - \frac{2\text{Blue} - 2\text{Red}}{2\text{Red}} \tag{1}$$

where 4Red refers to the area under the CDA waveform for the 4Red condition, 2Red refers to the area under the CDA waveform for the 2Red condition, and 2Blue refers to the area under the CDA waveform for the 2Blue condition. According to Equation 1, higher CFE indices imply efficient distractor filtering, and lower scores imply unnecessary distractor maintenance (i.e., inefficient distractor filtering). More specifically, positive values of CFE indicate that the addition of red bars (increasing from 2 to 4) increases CDA amplitude by more than the addition of blue bars, negative values indicate that added blue bars increased CDA amplitude more than red ones, and a CFE of zero indicates an equal effect of both types of bars.

RESULTS

We first describe the results of each experimental paradigm separately and then describe the analyses relating the two paradigms as a test of our hypothesis that the neural correlates of attentional control—specifically CFE—are related to DA.

DST

We assessed cognitive DA at the individual level by taking the proportion of low-demand task set selections that each participant made over the course of the DST. All else being equal, participants ought to have had no reason to prefer one task set over the other, except for the demand manipulation (probability of switching tasks from trial to trial). Moreover, under the null hypothesis (that the demand manipulation had no effect), participants' preferences for one or the other task set ought to have formed with equal likelihoods. In other words, participant preferences would be randomly distributed between the two task sets. However, we observed a mean DA of 0.58 (*SEM* = 0.02) across participants; a one-sample t test of the proportion of low-demand selections against a population mean of 0.5 (theoretically indicative of chance preference) found that participants selected the low-demand task set with a higher likelihood than would be predicted by chance alone, $t(29) = 3.26$, $p = .003$, indicating that there was a general tendency toward DA in our sample.

As noted above, the only reason for participants to exhibit any consistent behavioral preference for either task set ought to have been the demand manipulation. Thus, any observed correlation between switch cost and DA beyond that expected by chance alone would demonstrate a difference between the cognitive demands imposed by each task set. To check the validity of our cognitive demand manipulation (i.e., the frequency of switching between tasks within each set), we therefore calculated an RT-based index of the cost of task switching and assessed the extent to which it was correlated with DA.

Figure 3A displays the negative correlation between DA and switch probability context, $r(28) = -.59, p < .001$, assessed by RT switch cost (RTs after task repetitions subtracted from RTs after task switches), suggesting that individual participants' cognitive effort preferences were most likely influenced by the demand manipulation.[2] A 2 (task set) × 2 (task switching) within-participants ANOVA conducted on RTs (Figure 3B) revealed a significant interaction between Task Switching and Task Set, $F(1, 29) = 13.07$, $p = .001$, such that the effects of trial-to-trial task switches depended on the task demands imposed (i.e., on the switch probability context), along with a significant main effect of Task Set, $F(1, 29) = 5.79, p = .023$, showing that RTs were generally slower in the high- than low-demand task set. Thus, the manipulation employed here did indeed impose differential task demands in the two switch probability contexts.

Finally, to rule out the possibility of speed–accuracy trade-offs, we examined the relationship between accuracy and RT. We did not find evidence to support this possibility, $r(28) = .19, p = .31$, suggesting that accuracy did not suffer significantly as a result of the demand manipulation overall.

Delayed-Match-to-Sample Task

We sought to characterize cognitive control over the contents of working memory by operationally measuring the unique contributions of task-irrelevant distractor processing to working memory capacity. Figure 4A shows the topographic distribution of the recorded electrical potentials across electrode sites, using spline interpolation for points between electrodes, in each of the three load conditions (2Red, 2Blue, and 4Red). The presence of contralateral negativity of potentials during the retention interval (i.e., when the CDA is measured) and the absence of such potentials before the memory array's onset suggest that this activity indeed reflects active maintenance of the stimulus items in working memory.

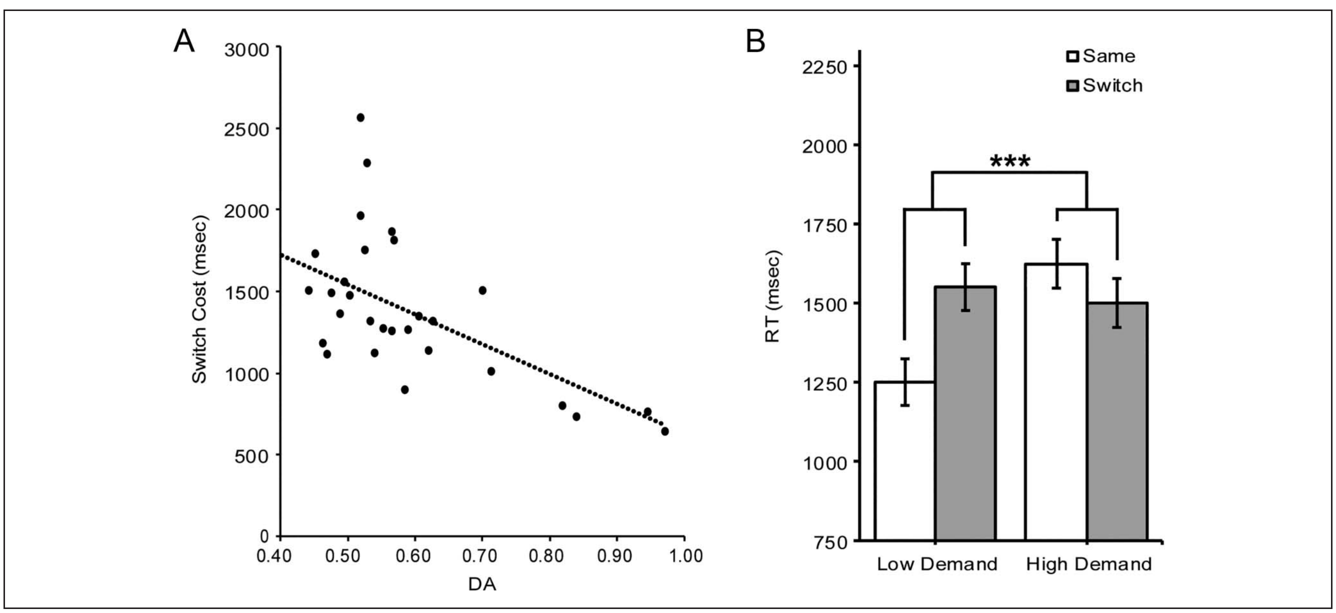

Figure 3. (A) Scatterplot depicting the negative correlation between RT switch cost and DA across participants. (B) Bar chart depicting RT in the high- and low-demand task sets, separately for trials where the task was either the same as the previous trial's or different. (*** indicates the significance of the interaction between task set and task switching at $\alpha = .001$.)

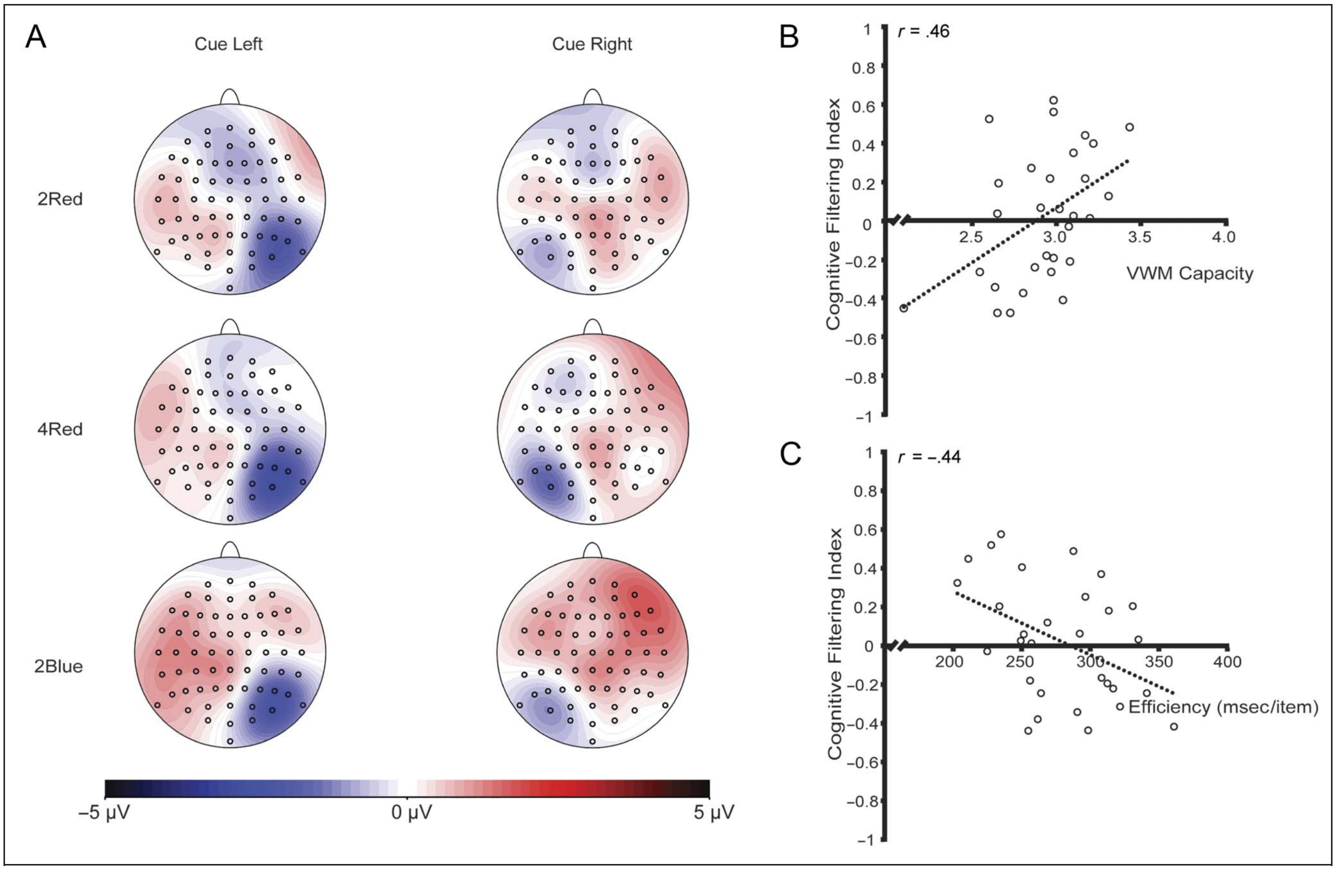

Figure 4. (A) Topography of the average CDA's amplitude from 300 to 900 msec (corresponding to the time interval used for deriving CFE from CDA amplitude) after the offset of the memory array across electrode sites in each condition (2Red, 4Red, and 2Blue). (B) Scatterplot depicting the positive correlation between behaviorally measured VWM capacity (measured according to Pashler's [1988] formula) and CFE. (C) Scatterplot depicting the positive correlation between behaviorally measured inverse efficiency (measured according to Townsend and Ashby's [1978] formula) per item and CFE.

To characterize cognitive control over the contents of working memory, we measured the unique contribution of task-irrelevant distractor processing during the retention interval to VWM capacity, using the CDA-based measures of CFE.[3] Previous research has shown that these neural measures correlate reliably with behavioral measures of WM capacity, which has been taken as evidence that those with higher behaviorally measured capacity do not necessarily maintain more items in working memory overall but instead more selectively restrict maintenance to task-relevant items while filtering out irrelevant ones (Luria et al., 2016; Oberauer & Hein, 2012; Lee et al., 2010; Luck et al., 2005; Vogel et al., 2005; Vogel & Machizawa, 2004). Therefore, to validate our measure of CDA-based CFE, we correlated it with behaviorally measured capacity (Figure 4B). We found that that the number of items maintained in working memory (measured behaviorally) is significantly correlated with the extent to which irrelevant items can be successfully ignored during VWM maintenance, $r(28) = .458, p = .011$. These results are in line with previous studies of CDA, in which CFE and capacity are generally found to be positively correlated (see Luria et al., 2016, for a review).

Similarly, we sought to validate the CFE measure employed here by characterizing whether participants who were better cognitive filterers would also tend to generate more efficient responses. We anticipated that participants who filter irrelevant items out of VWM successfully would have fewer comparisons to make between the maintained and displayed items relative to those who had maintained task-irrelevant distractors when evaluating the test display. To this end, we computed participants' inverse efficiency (Townsend & Ashby, 1978) per item and correlated it with CFE (see Figure 4); we found that participants who were higher on CFE were also significantly more likely to respond more efficiently (i.e., in less time per item), and vice versa, $r(28) = -.44, p = .015$.

Relating DA and the Neural Correlates of Cognitive Filtering

The two previous sections demonstrated that our DA and VWM paradigms were effective and faithfully replicated previous findings (Kool et al., 2010; Vogel et al., 2005, respectively). The behavioral switching manipulation employed in the DST did indeed induce differential switch costs in the low- versus high-demand task sets as a function of the difference between task switch probability contexts, suggesting that individual differences in

Table 1. Stepwise Linear Regression of DA on CFE and DA

Two-Step Multiple Regression of DA on K and CFE							
	Model Summary			*Predictor Summary*			
Model Predictors	*F*	*df*	*p*	*r*	r_s	*t*	p_{rs}
Filtering alone							
Filtering (CFE)				.43	.43	2.48	.019
Capacity alone							
Capacity (*K*)				.31	.31	1.73	.095
Capacity and filtering	3.317	2, 27	.05				
Capacity (*K*)				.31	.13	0.76	.46
Filtering (CFE)				.43	.32	1.84	.076

Pearson correlation coefficients and their associated *t* test of the correlation coefficient against 0 are given for the models of each predictor alone. The omnibus *F* test of the full model is provided for the model including both predictors, as well as *t* tests of their associated partial correlation coefficients (r_p). Omnibus *F* tests are not provided for single predictors, because these are equivalent to the *t* test of the correlation coefficient against zero. Critically, the regression model of DA on both CFE and VWM capacity shows that the covariance between DA and VWM capacity is largely accounted for by CFE, which remains trending toward significance as a predictor of DA despite the addition of VWM capacity to the model.

cognitive effort preference most likely stem from our demand manipulation. Meanwhile, we also found that the electrophysiological CFE measure was significantly related to working memory capacity during the delayed-match-to-sample task (see Delayed-Match-to-Sample Task section above), suggesting that the maintenance of items in working memory is directly related to the neural activity manifest in CDA-based measures of cognitive control. Having demonstrated the construct validity of our two paradigms, we next examined the extent to which individual differences in cognitive control and working memory (as measured by CFE) were related to participants' cognitive effort preferences (operationalized by DA), over and above the influence of overall VWM capacity (assessed behaviorally by *K*).

To demonstrate this relationship, we regressed DA (the preference for the low-demand task set) on VMW capacity and CDA-based CFE. We found a significant positive correlation, $r(28) = .43$, $p = .02$, between CFE and DA but only a marginally significant correlation between VWM capacity and DA, $r(28) = .31$, $p < .1$. Meanwhile, entering both VWM capacity and DA into the model together reduced the correlation between VWM capacity and DA, whereas CFE remained a marginally significant predictor of DA. Overall, the results of the regression (see Table 1) indicate that those who are more demand avoidant also tend to have higher CFE overall (Figure 5C) and that this relationship accounts for a marginally significant reduction in the covariance between VWM capacity and DA, $F(2, 27) = 3.32$, $p = .052$.

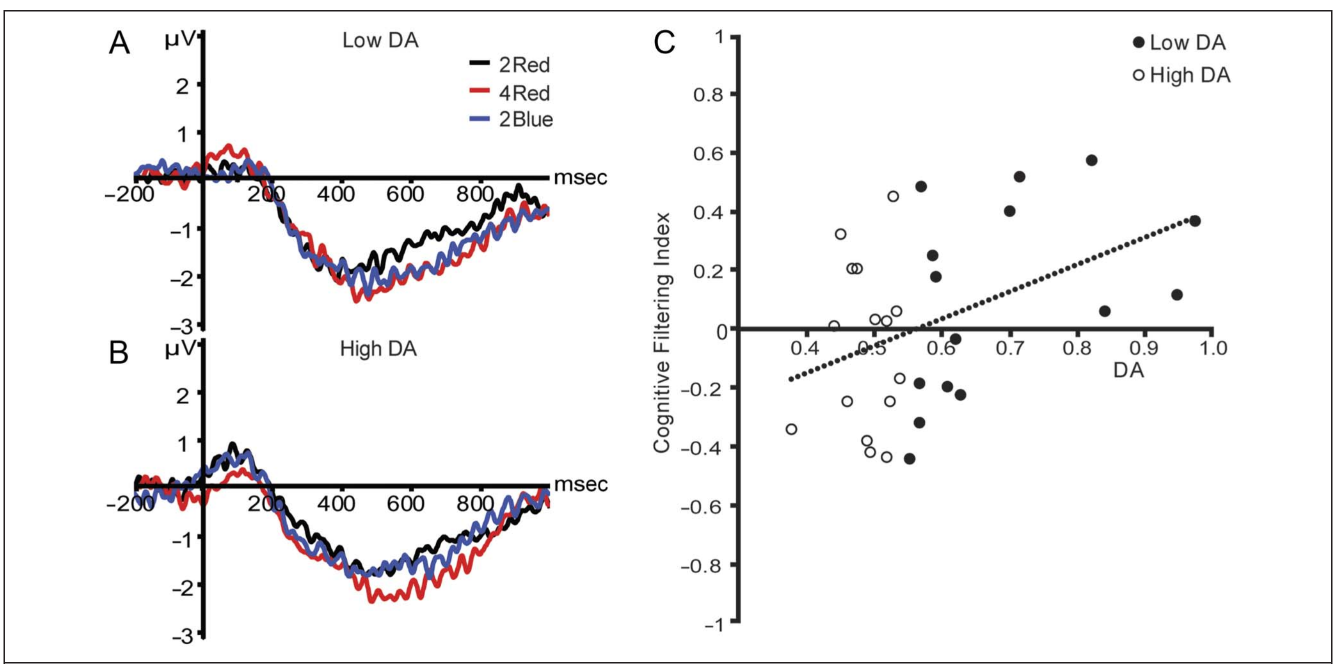

Figure 5. Each participant's DA was classified as either high or low, based on a median split of the sample. ERP waveforms for the two resulting subgroups are plotted separately for (A) low- and (B) high-DA participants. 0 msec corresponds to the offset of the memory array, such that the interval ending at 1000 msec corresponds to the duration of the retention interval. (C) Scatterplot of CFE versus DA across all participants. Data points are filled according to the median DA split.

To better visualize the effects of cognitive effort preferences (ostensibly the result of individual differences in cognitive control settings) on the CDA waveform itself, we split our sample into two groups based on a median split of the sample into low- and high-DA individuals (Figure 5A and B, respectively). As can be seen in Figure 5, this split reveals a clear distinction in CFE between the groups: Those with high DA on the DST tended to be more likely to filter out the blue distractors during the maintenance phase of the delayed-match-to-sample task than those with low DA.

In the high-DA group (Figure 5B), CDA amplitude in response to the 2Blue condition approximates that generated by the 2Red condition. Conversely, in the low-DA group (Figure 5A), the 2Blue condition effectively resembles the 4Red condition. This implies that high-DA individuals effectively ignore added distractors, restricting their working memory maintenance to task-relevant items, whereas those with low DA tend to engage in maintenance of displayed items irrespective of their task relevance.

To assess the specific contribution of the task-relevant and task-irrelevant items to DA, we regressed DA from the DST on the CDA amplitude generated in response to the 2Red, 4Red, and 2Blue conditions of the delayed-match-to-sample paradigm. We find that CDA amplitude in the 2Blue condition accounted for a marginally significant proportion of variability in DA when it was added to the model with the 2Red and 4Red conditions (see Table 2), suggesting that the effect of CFE on DA could potentially be because of individual differences in processing of the distractor items in VWM. Finally, we also correlated inverse efficiency per item on the delayed-match-to-sample paradigm with DA (see Figure 6) but found no significant relationship between the two, $r(28) = -.047$, $p = .80$.

Table 2. Multiple Regression of DA on All Bar Conditions (2Red, 4Red, and 2Blue)

Multiple Regression of DA on Bar Conditions							
Model	*F Change*	*df*	*p*	*r*	r_s	*t*	p_{rs}
2Red alone							
2Red				−.08	−.08	−0.43	.67
2Red and 4Red	0.02	1, 27	.90				
2Red				−.08	−.08	−0.43	.67
4Red				−.03	−.03	0.14	.89
All predictors	3.97	1, 26	.06				
2Red				−.08	.05	0.29	.77
4Red				−.03	.26	1.42	.17
2Blue				−.25	−.36	−1.99	.06

Zero-order correlations for each predictor (none of which correlates significantly with DA) alone as well as partial correlation coefficients with all three predictors included in the model together are provided. Omnibus *F* tests are not provided for single predictors, because these are equivalent to the *t* test of the correlation coefficient against zero The *t* statistics and associated *p* values for the partial correlation coefficients are also provided. Of note, though, none of the overall models is significant, although CDA amplitudes in the 2Blue condition marginally predict unique variance in DA.

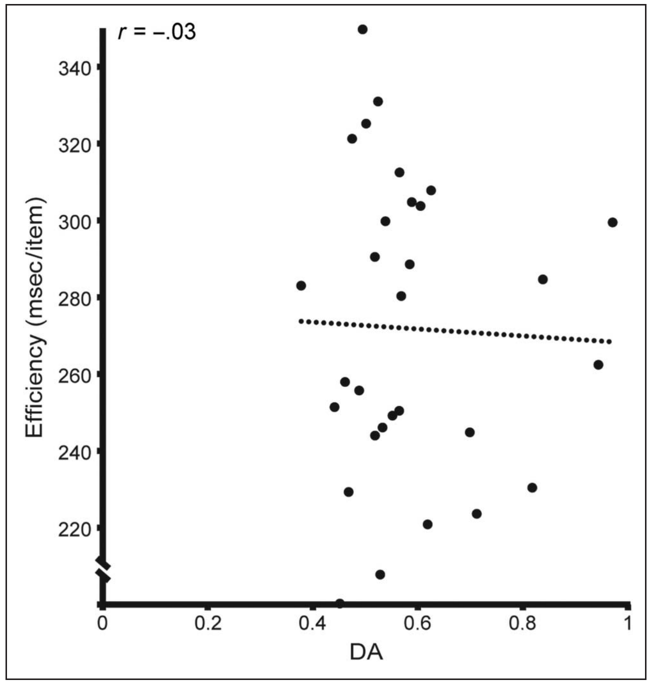

Figure 6. Scatterplot of the null correlation between behaviorally measured inverse efficiency (measured according to Townsend and Ashby's [1978] formula) per item and DA.

DISCUSSION

This study was conducted to examine the hypothesis that ongoing neural activity underlying cognitive control is tightly linked to individual differences in cognitive effort preferences. To that end, we utilized two common paradigms for studying cognitive control and DA—Vogel et al.'s (2005) bilateral cued delayed-match-to-sample paradigm and Kool et al.'s (2010) task-switching variant of the DST paradigm. Respectively, these two paradigms allowed us to assess the relationship between individual differences in CDA-based measures of cognitive control over the contents of VWM (specifically, CFE) and cognitive effort preferences manifested behaviorally as DA. We found a significant positive correlation between these two measures, wherein high-CFE individuals demonstrated a preference for the low-demand task set, whereas low-CFE individuals showed no consistent preference for either one. Overall, this suggests that sustained neural activity underlying cognitive control over the contents of VWM accounts for a significant proportion of variability in demand-based task set preferences.

In general, behavioral task preferences are guided by central executive processes, such as cognitive control, in determining the allocation of cognitive resources to the task at hand (Inzlicht et al., 2018; Burgess, Gray, Conway, & Braver, 2011). When people determine how much cognitive effort they prefer to put forth as they engage in task performance, they are effectively weighing the cognitive cost of performance against its potential for reward (Umemoto, Inzlicht, & Holroyd, 2019; Botvinick & Braver, 2015).[4] This process, of evaluating the cost of performance relative to its potential rewards, requires allocating limited cognitive resources. It is these capacity limitations on central executive processing that render effort aversive (Shenhav et al., 2017), resulting in behavioral DA. Because central executive processing requires the recruitment of working memory resources (Unsworth et al., 2015; Duncan, 2010), specifying how people direct these working memory resources can provide a window on how they form cognitive effort preferences. Therefore, the underlying rationale of the present work was that the efficiency of maintaining and manipulating multiple items in working memory should be closely related to demand-based task preferences.

We focused on the efficiency rather than the capacity of working memory maintenance as it provides putative means for uncovering how processing resources are allocated to items based on their task relevance (Baddeley, 2010; Engle, 2010; Engle & Kane, 2004). As task-irrelevant items gain access to VWM, their maintenance depletes the overall pool of resources, leaving only the balance available for the processing of relevant items. Thus, the ability to overcome the presence of irrelevant items is at the core of efficient cognitive control. To assess VWM efficiency, we utilized a well-established neural correlate of VWM, the CDA, capitalizing on its ability to index both capacity and efficiency of working memory maintenance (Luria et al., 2016). Previous research has shown that CFE (i.e., CDA modulation by relevant and irrelevant items) is related to individual variations in VWM capacity (Vogel et al., 2005). Moreover, variations in CDA in general have been linked to individual differences in a myriad of cognitive abilities (e.g., capacity, attention control, long-term episodic memory, and fluid intelligence) and attentional control in particular (Unsworth et al., 2015).

The current work suggests that CDA-derived CFE is also predictive of individual cognitive effort preferences in the form of DA. There is substantial functional overlap between cortical areas subserving cognitive effort preference formation, specifically LPFC (McGuire & Botvinick, 2010), and those implicated in cognitive control and VWM maintenance (Badre & Nee, 2018; Luria et al., 2016). Previous research has demonstrated that increased DA is positively correlated with IQ and general neuropsychological ability (Gold et al., 2015), whereas a similarly broad range of cognitive abilities are also correlated with the CDA's amplitude, including multiple measures of VWM capacity and attentional control (Unsworth et al., 2015). On the basis of these converging lines of evidence, we propose that the neural activity reflecting the manipulation of informational content during maintenance is indicative of subsequent deployment (or rather the withholding) of cognitive resources, as manifested in DA.

The electrophysiological measure of CFE is especially well suited to studying the formation of cognitive effort preferences, particularly as they are captured by the DST paradigm. The CFE provides a "clean," continuous measure of usage of VWM resources independent of the allocation of spatial attention—first, by factoring out the involvement of low-level featural differences (Cowan, 2010) between the items displayed in the unattended versus attended visual hemifield, and second, because it is a measure of sustained activity during maintenance, it is divorced from the actual visual stimulus information. These advantages are especially important in the context of the DST, as one could otherwise argue that our current account of task set preferences in this paradigm simply reflects periodic changes in the deployment of visuospatial attention. Thus, the CFE relation to DA in the DST cannot be explained as simply an artifact of visuospatial attention.

The present findings suggest that successfully manipulating maintained items (i.e., by filtering distractors, indexed by CFE), and not simply maintaining them, is critical for the formation of cognitive effort preferences as captured by the DST. In the particular variant of the DST replicated here (from Kool et al., 2010), the high- and low-demand task sets were spatially defined by their respective patterned circles (Figure 1). As a result, segregating the trial sequence-level information and maintaining it over time are critical to individuals' ability to distinguish the two task sets' relative levels of cognitive demand. Because, in this study, we applied the demand manipulation at the trial sequence level, participants had to compare sequences of trials—rather than simply maintain them—between switch probability contexts, in forming their cognitive effort preferences. Indeed, implicit sequence learning has been shown to correlate specifically with the manipulation and maintenance of information in VWM, rather than maintenance per se (for a review, see Janacsek & Nemeth, 2013). This might explain our finding that CFE, but not VWM capacity (as indexed by CDA amplitude) on its own, relates to cognitive effort preference formation. CDA amplitude has been found to correlate with performance on a variety of tasks, but only when filtering out irrelevant or incongruent distractors (Luria et al., 2016; Unsworth et al., 2015). Notably, this converges with our finding that, among our three experimental conditions, only the 2Blue bar condition (i.e., when irrelevant distractors were present) predicted DA. Because, in the DST, individuals must differentiate between the cognitive demands imposed by the two task sets before they could leverage such information to set their cognitive effort preferences, we conclude that CFE is instrumental in explaining individual differences in detecting such cognitive demand differences. Further research is needed to determine whether our results are limited to circumstances wherein demand is manipulated at the trial sequence level; for instance, VWM capacity might correlate with DA in the context of either explicit or single-trial-level demand manipulations.

The present results are also commensurate with recent research in our laboratories (Juvina et al., 2018) showing that DA is the result of a two-stage process. Individuals must first detect and learn the cognitive demands imposed by high- and low-demand task sets, before they can form meaningful cognitive effort preferences for either set (Juvina et al., 2018). For individuals to have consistently displayed demand avoidant behavior, they would have had to be able to distinguish between the levels of demand imposed by each task set, implying that their cognitive effort preferences were formed based on sensitivity to the demand manipulation. Given that CFE correlates positively with DA, it seems likely that CFE constitutes a potential neural marker of individuals' detection of cognitive demands, rather than one of their preference for either low or high demand (selection). Individuals with greater cognitive control over the contents of VWM (as measured by CFE) are more likely to distinguish between levels of cognitive demand in forming effort preferences, whereas those low in cognitive control fail to distinguish between levels of demand and therefore fail to form any consistent preferences. Finally, the latency of the CFE (measured during the delay period between memory and test arrays, within 400 msec of stimulus onset) implies that such a filtering process most likely occurs before response selection, which indeed can only be undertaken after the appearance of the test array. So, although the current study's results do not themselves causally link CFE and DA, our study provides indirect evidence that cognitive control processes precede the choice of a less demanding task set (i.e., DA). Parenthetically, the notion that CFE constitutes a putative measure of cognitive control that predicts the demands induced by task switching can also be considered to reflect changes in meta-control, that is, in how flexible cognitive control processes are in response to varying task demands (Hommel, 2015). Although this is certainly possible, more research is required to determine the impact of meta-control on demand preferences, cognitive effort, and their underlying neural substrates.

Overall, the findings of the current study implicate cognitive filtering as a mechanism of cognitive control instrumental to cognitive effort preference formation. DA—the preference for minimizing the cognitive effort required to meet task demands—has been taken as evidence that people are generally cognitive misers (Kool et al., 2010, 2013). However, development of cognitive effort preferences indicative of DA should not preclude individuals' exertion in forming such preferences. Individuals have been shown to value effort and even actively seek it (Inzlicht et al., 2018). Indeed, whereas some individuals develop preferences for low-demand alternatives in the DST, others fail to show any demand-based preferences (Kool et al., 2010, 2013). Our findings support an account of behavioral DA, which implies that those who manifest cognitive effort preferences are actually devoting cognitive resources more efficiently, with the goal of learning to distinguish the demand induced by each task set, as compared with those who form no preferences (and who thus seem comparatively low on DA). The latter group may simply fail to devote sufficient cognitive resources to learn the nature of the demand manipulation or at least devote them inefficiently. Meanwhile, those in the former group, who develop significant cognitive effort preferences, likely deploy sufficient cognitive resources more efficiently and should be considered "cognitive optimizers" rather than "cognitive misers."

Finally, it should be noted that these cognitive optimizers display reduced CDA amplitudes compared to other participants in response to task-irrelevant distractors, rather than increased amplitude in response to target stimuli (see Table 2). Operationally, this implies that optimizers expend less of their limited cognitive resources on distractor processing, leaving their remaining VWM capacity available for target processing. This suggests that their ability to efficiently maintain targets in working memory does not result from their overall capacity for processing potential targets. We conjecture that, given the positive correlation between CFE and DA, those who engage in less filtering during the DST might actually experience less cognitive demand explicitly (i.e., they are potentially less aware of the demand that they are encountering, since they do not detect it). Furthermore, we conjecture that such reduced filtering would occur despite increased actual exposure to high cognitive demand, since high and low demand selections among low-filtering individuals would fail to account for the difference in cognitive demands between variants. Future research will establish the distinction between detecting cognitive demands and actually avoiding them. Importantly, such research could prove useful in helping individuals optimize their deployment of VWM resources (and potentially other resources as well) to improve performance in a variety of contexts.

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Notes

1. It should be noted, though, that in previous studies employing the task-switching variant of the DST, most samples

contain a subset of participants who fail to develop preferences for either task set (Dunn et al., 2019; Kool et al., 2010, 2013; McGuire & Botvinick, 2010), whereas few, if any, participants show a preference for the high-demand task set. This has been taken as an evidence of demand avoidance, in that it indicates a preference for low- over high-demand alternatives. However, this conclusion ignores the cognitive effort required in developing a preference for either alternative. That is, participants need not only to perform the prescribed tasks on every trial but also to distinguish between the levels of cognitive demand that the high- and low-demand alternatives surreptitiously impose. It therefore remains an open question whether those who fail to develop a preference are exerting greater or lesser cognitive control over their decisions than those who prefer the low-demand alternative.

2. The switch cost measure we use here is confounded by the proportion of trials participants completed in each variant (Kool et al., 2010); those who preferred the low-demand task set, for instance, would encounter fewer task switches than those who preferred the high-demand variant, and thus between-subject variability in switch cost reflects differences in task-switching experience. In fact, Kool et al. (2010) measured RT-based switch costs using a separate task for only this reason. Within the DST, though, this correlation represents the cognitive demands of the trials that participants actually completed, thus closely reflecting the switch probability context. In particular, because our participants had ad libitum access to both task variants, it stands to reason that their preferences for either variant should only stem from the amount of switching in which they happened to engage (see Kiesel et al., 2010, and Monsell, 2003, for reviews of switch cost).

3. Working memory capacity, as measured behaviorally according to Pashler's (1988) formula, confounds maintenance of task-relevant and task-irrelevant items, whereas we sought to separate cognitive control over the contents of VWM from its capacity (see Unsworth & Spillers, 2010, for a discussion of this distinction)

4. A separate body of literature considers such preferences as reflecting participants' cognitive control states (meta-control; for a review, see Hommel, 2015).

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