AMERICAN PSYCHOLOGICAL ASSOCIATION

Journal of Experimental Psychology:
Human Perception and Performance


ISSN: 0096-1523

2024, Vol. 50, No. 6, 587–604
https://doi.org/10.1037/xhp0001207

# Humans Do Not Avoid Reactively Implementing Cognitive Control

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The ability to exert cognitive control allows us to achieve goals in the face of distraction and competing actions. However, control is costly—people generally aim to minimize its demands. Because control takes many forms, it is important to understand whether such costs apply universally. Specifically, reactive control, which is recruited in response to stimulus or contextual features, is theorized to be deployed automatically, and not depend on attentional resources. Here, we investigated whether people avoided implementing reactive control in three experiments. In all, participants performed a Stroop task in which certain items were mostly incongruent (MI), that is, associated with a high likelihood of conflict (triggering a focused control setting). Other items were mostly congruent, that is, associated with a low likelihood of conflict (triggering a relaxed control setting). Experiment 1 demonstrated that these control settings transfer to a subsequent unbiased transfer phase. In Experiments 2–3, we used a demand selection task to investigate whether people would avoid choice options that yielded items that were previously MI. In all, participants continued to retrieve focused control settings for previously MI items, but they did not avoid them in the demand selection task. Critically, we only found demand avoidance when there was an objective difference in demand between options. These findings are consistent with the idea that implementing reactive control does not register as costly.

***Public Significance Statement***

While humans use attentional control to achieve their goals and to avoid distractions, it has been theorized that it is not always deployed because of its mental costs. However, not all forms of control are equal: It has been suggested that adjusting attention in response to a stimulus may be relatively cost-free. We provide a new test of this idea by integrating stimuli associated with different amounts of reactive control into a demand selection paradigm. We found that participants reactively focused their attention on items previously associated with higher demand and relaxed attention on items previously associated with lower demand. However, despite these differences in implemented control, participants did not avoid choice options associated with the previously high-demand options. This result indicates that reactively focusing attention is not costly. In addition to theoretical implications about the nature of control, these results indicate that setting up demands to rely on reactive control might substantially diminish subjective motivational and implementational constraints.

*Keywords:* item-specific proportion congruence, demand selection task, demand avoidance, reactive control

*Supplemental materials:* https://doi.org/10.1037/xhp0001207.supp



Our minds have the powerful ability to exert cognitive control, a set of functions that help us perform novel, nonroutine, and goal-directed actions rather than compelling, more habitual, alternatives (Miller & Cohen, 2001). Despite its usefulness, people aim to minimize demands for cognitive control (Kool et al., 2010; Schouppe et al., 2012; A. Westbrook & Braver, 2015). This tendency is captured in the notion that the exertion of cognitive control carries an intrinsic cost, so that people prefer tasks with the least effort, all else being equal (for a review, see Kool & Botvinick, 2018). Consequently, recent theories indicate that the exertion of cognitive control relies on a motivational tradeoff (Kurzban et al., 2013; Lieder & Griffiths, 2020; Shenhav et al., 2013, 2017), in which the cost of

This article was published Online First April 11, 2024.
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Bettina Bustos and Jackson S. Colvett contributed equally to this work.
Wouter Kool and Julie M. Bugg were supported by ONR/DoD (Grant N00014-23-1-2792). Julie M. Bugg was supported by the National Institutes of Health (Grant AG075590). Data for all experiments can be found at https://osf.io/xhe76/.
Bettina Bustos served as lead for data curation and formal analysis. Wouter Kool served as lead for resources and served in a supporting role for writing–original draft. Bettina Bustos, Jackson S. Colvett, Julie M. Bugg, and Wouter Kool contributed equally to conceptualization and writing–review and editing. Bettina Bustos and Jackson S. Colvett contributed equally to writing–original draft.
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control is weighed against its benefits (Kool & Botvinick, 2014; Shenhav et al., 2013). These theories assume that agents know the cost of control for a given task, and therefore, they do not explain how humans make decisions when faced with novel demands and task structures. In such situations, people need to estimate the cost of exerting cognitive control. How do they achieve this goal?

We approach this question from the theoretical perspective of event files theory (e.g., Hommel, 1998, 2022). When people respond to a stimulus, they encode the stimulus features, their response, and the surrounding context into episodic representations called "event files." Critically, they also store the control setting, the degree to which cognitive control was relatively focused or relaxed, into the episodic representation (Bugg & Crump 2012; Crump & Milliken, 2009; Dignath et al., 2019; Jiang et al., 2015 ). When features of this stimulus are encountered again, the event file is retrieved and the encoded control settings are implemented. Event file theory invites the interesting possibility that effort costs are also encoded in these episodic memory representations, such that the cost of exerting effort is stored in the event file alongside the control setting. Subsequent repetition of the encoded stimulus features would then retrieve the effort cost, guiding decision making (i.e., whether to exert control in the present). Here, we test this idea by capitalizing on the popular item-specific proportion congruence (ISPC) paradigm (Bugg et al., 2011), which demonstrates that people associate stimulus features with control demands. In an often-used version of this paradigm, participants perform a picture–word Stroop task, in which they name an animal picture (e.g., dog) while ignoring a superimposed word (e.g., CAT). These stimuli are split up into two distinct sets. Items from one set (e.g., dog and fish pictures) are mostly congruent (MC), such that they are mostly paired with congruent words (i.e., DOG and FISH, respectively). Items from the other set (e.g., cat and bird pictures) are mostly incongruent (MI), such that they are mostly paired with incongruent words (e.g., DOG, or FISH on a cat picture). Participants in this task learn the proportion congruence (i.e., control demands) of individual items, adapting their deployment of cognitive control to this statistical structure in a reactive fashion (after stimulus onset). Specifically, data from this paradigm suggest that when an MI item appears, participants retrieve a more focused control setting (e.g., suppressing distractor information) than when an MC item appears, resulting in a reduced Stroop effect for MI items (Figure 1; Bugg & Dey, 2018; Bugg & Hutchison, 2013; Bugg et al., 2011; see Bugg & Crump, 2012 for a review). Because the type of animal picture cannot be predicted in this paradigm, it means that control settings are retrieved through learned stimulus (item) associations. These reactive control settings are distinguishable from a proactive control setting that could be prepared before stimulus onset (e.g., Braver et al., 2007, 2021). Here, we ask whether these more focused, reactive control adjustments register as cognitively costly. Specifically, we ask whether the cost of those adjustments becomes associated with the item, leading to that item being avoided in a choice setting.

Considering this question through the lens of the dual mechanisms of control (DMCC; Braver et al., 2007, 2021) account, these control adjustments are known as reactive, or in response to the stimulus, since participants cannot predict the identity (and thus the control demand) of the upcoming stimulus. The reactive adjustments are learning-guided, meaning that participants rely on learned associations between stimulus identity (e.g., whether it is a dog or a cat) and demand (i.e., whether it is MC or MI) to determine how much control to retrieve and implement. The DMCC account contrasts this form of reactive control with proactive control, which is recruited in an anticipatory manner, in preparation for upcoming demand. A considerable body of research has provided evidence for this distinction between reactive and proactive control, both in their neural substrates (e.g., Braver et al., 2021; De Pisapia & Braver, 2006) as well as their behavioral profile (Bugg & Braver, 2016; Gonthier, Braver, & Bugg, 2016; Gonthier, Macnamara, et al., 2016; Richmond et al., 2015; Tang et al., 2022).

Aside from their temporal differences in control implementation, there is good reason to believe that reactive and proactive control do not share similar cost structures. In contrast with proactive control, which overlaps with traditional conceptualizations of control (Lowe & Mitterer, 1982; Norman & Shallice, 1986; Posner & Snyder, 1975; Schneider & Shiffrin, 1977; see also Braver, 2012; Kalanthroff et al., 2015), reactive control occurs quickly and flexibly outside of awareness (Bejjani et al., 2020) and is unaffected by high concurrent working memory demands (Spinelli et al., 2020; Suh & Bugg, 2021).

On the other hand, there are also reasons to believe that the exertion of increased reactive control carries a cost that could be encoded in the event file. Reactively responding to MI items may be associated with increased cognitive costs compared to MC items because incongruent trials simply require more focused attention. Consistent with this notion, Schouppe et al. (2014) showed that people prefer choice options that lead to MC trials compared to MI trials in a related, context-specific proportion congruence paradigm. However, there are two reasons to think this effect may reflect avoidance of proactive, rather than reactive control. First, participants could anticipate demand based on the appearance of the choice options, as the cue representing the choice options had been linked with proportion congruence in intermittent learning blocks. Second, participants were given an ample amount of time to prepare between choice and stimulus presentation (1,500 ms). In short, this task allowed participants to prepare control settings before stimulus onset. Therefore, it remains to be seen whether participants will avoid reactive control demands in the same way.

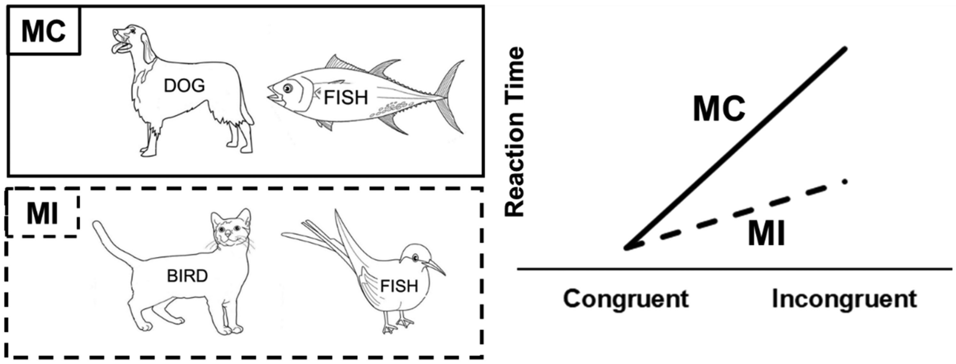
The ISPC paradigm provides a critical test case for teasing apart these hypotheses. In this task, more focused control settings are implemented even on "transfer" trials in which there is no difference in control demands (i.e., trials from both item sets are unbiased, 50% congruent), as long as these trials repeat predictive features of the MC and MI items that allow for retrieval of the previously associated control setting (Bugg & Dey, 2018; Bugg & Hutchison, 2013). If the brain encodes effort costs into the event file, previously learned control settings should affect choice behavior even when no difference in proportion congruence exists between previously MC and MI items and only the prior association can explain their preference.

We report four experiments that together test whether reactive control is costly, and whether its cost is encoded in event files (see Figure 2 for an overview). In each of these, participants first completed a "training" phase, where they responded to MC and MI picture–word Stroop items, learning stimulus–control associations through experience. While the majority of the ISPC literature has intermixed training and transfer items within the same block, transfer also has been observed when transfer items are presented on their own in a separate phase (Ileri-Tayar et al., 2022).

In Experiment 1, following training, participants completed a "transfer phase." In this phase, they responded to the same items,

**Figure 1**

*A Depiction of Four Possible Picture–Word Stroop Stimuli (Left) and an Idealized ISPC Effect (Right)*




*Note.* The dog and fish items are MC and the cat and bird items are MI in this example. Participants learn to associate the MI items with higher control demands than the MC items, and thereby retrieve a more focused control setting for MI items leading to a smaller Stroop effect (i.e., difference in RT, and sometimes error rate, between congruent and incongruent trials). RTs are generally similar for congruent MI and MC trials, such that the ISPC effect is driven by faster responding to MI-incongruent trials compared to MC-incongruent trials. ISPC = item-specific proportion congruence; MC = mostly congruent; MI = mostly incongruent; RT = reaction time.



allowing for previously learned control settings to be retrieved. However, all items in the phase were now unbiased, so that all items that were previously MI or previously MC were 50% congruent. This experiment allowed us to confirm that the retrieval of reactive control settings persists in a new phase where there is no difference in proportion congruence between items (cf., Ileri-Tayar et al., 2022). We found that people carried their previously learned control settings to an unbiased block of Stroop trials, which set the stage for the subsequent experiments in which the unbiased block included a choice component.

In Experiments 2, 3a, and 3b, the transfer phase consisted of a demand selection task (DST; Kool et al., 2010), to study whether the associations between stimulus features and control settings would bias subsequent choice. In the DST, participants choose between two options that require different amounts of cognitive control. Participants' behavior in the DST demonstrates a demand avoidance effect, such that they prefer the option with the least demands for cognitive control (see also A. Westbrook & Braver, 2015). Several versions of the DST have been used to demonstrate that people avoid a wide range of cognitive control demands, such as response conflict (Schouppe et al., 2014), task switching (Kool et al., 2010; Sayalı & Badre, 2021), working memory maintenance (Kool et al., 2010), increasingly complex task policies (Sayalı et al., 2023), and even the exertion of empathy (Cameron et al., 2019).

Each of the two choice options in the DST blocks of the current study yielded trials that were 50% congruent. However, one of the choice options mostly produced items that were previously MC, and the other items that were previously MI. We tested whether people preferred the choice option that produced previously MC items compared to the option that produced previously MI items. To foreshadow our results, we found that people transferred their previously learned control settings to previously MC and MI items in an unbiased DST block. However, participants showed no preference for the choice option with previously MC items, even when we carefully matched the context in which these control settings were learned (Experiments 3a and 3b). This pattern of results implies the intriguing possibility that the implementation of reactive control does not carry an intrinsic cost.

## Experiment 1

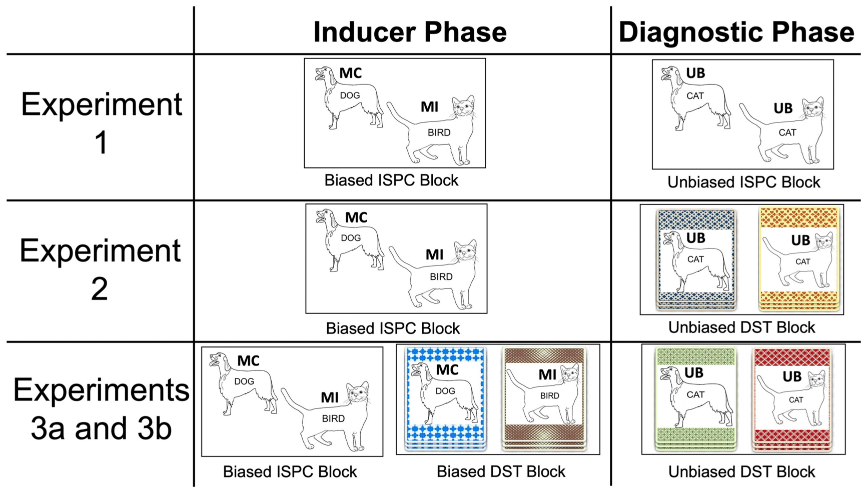
Experiment 1 examined whether the retrieval of reactive control settings persists even when a previously established difference in proportion congruence between items disappears. Specifically, participants first completed a training phase with MC and MI items, and then completed a transfer phase where they encountered the same items which were now all 50% congruent. This experiment served as a baseline study, as we would be unlikely to observe transfer in an unbiased DST block in the subsequent experiments if transfer is not first observed in an unbiased ISPC block in this experiment.

### Method

#### *Participants*

One-hundred and twenty-nine participants ($M_{age} = 19.44$, $SD = 1.13$; 100 female, 27 male, two preferred not to answer), from Washington University in St. Louis provided informed consent and earned class credit for participation. Twenty-one participants were removed for not meeting the accuracy threshold of 80%, resulting in a final sample of 108 participants ($M_{age} = 19.40$, $SD = 1.09$; 83 female, 23 male, two preferred not to answer). We conducted a power analysis using G*Power 3.1 (Faul et al., 2007) on the interaction of trial type and proportion congruence (i.e., an ISPC effect) for the transfer trials and found a minimum sample size of 30 to achieve .9 power, assuming an α of .05 and the effect size of $\eta_p^2 = .40$ (Bugg et al., 2011). However, this effect size was drawn from a study where diagnostic trials were integrated throughout the block rather than in a separate unbiased transfer phase. To be conservative, we collected data from more participants than the power analysis suggested, targeting a sample size that would be more comparable to the samples in the subsequent DST experiments.

**Figure 2**
*Experimental Design*




*Note.* In ISPC blocks, participants performed the Stroop task by responding to the identity of the animal picture on the screen, while ignoring the word. In DST blocks, participants chose between a choice option that mostly yielded MC items and a choice option that mostly yielded MI items and continued to perform the Stroop task following each choice. All four experiments began with a training phase in which ISPC was manipulated in the Stroop task using biased (MC and MI) items and this phase was followed by a transfer phase with unbiased (50% congruent) items. In Experiment 1, the transfer phase consisted of an unbiased ISPC block in which participants performed the Stroop task. In Experiments 2, 3a, and 3b, the transfer phase consisted of an unbiased DST block, in which participants made deck choices in addition to performing the Stroop task on unbiased items. Experiments 3a and 3b were identical to Experiment 2, except that there was an initial biased block of the DST prior to the transfer phase. In the biased DST block, MC and MI items retained the proportion congruence from the biased ISPC block. The biased DST block was then followed by the unbiased DST block. In Experiment 3a, these two blocks lasted 75 trials each. In Experiment 3b, they lasted 100 trials each. Thus, while the number of unbiased DST trials was reduced from 150 in Experiment 2 to 75 in Experiment 3a and 100 in Experiment 3b to accommodate the biased DST block, the total number of DST trials remained the same for Experiment 3a (150) and was larger for Experiment 3b (200). ISPC = item-specific proportion congruence; MC = mostly congruent; MI = mostly incongruent; UB = unbiased; DST = demand selection task. See the online article for the color version of this figure.

### *Stimuli*

The stimuli used in this study were a subset of a larger set of stimuli developed by Bugg et al. (2011). The picture–word Stroop stimuli were line drawings of two birds, two cats, two fish, and two dogs with animal words (BIRD, CAT, FISH, DOG) superimposed (see Bugg & Dey, 2018; Bugg et al., 2011). On congruent trials, the identity of the picture and the word matched (e.g., a picture of a cat with the word CAT superimposed), whereas on incongruent trials, the identity of the picture and the word conflicted (e.g., a picture of a cat with the word DOG superimposed). On incongruent trials, the word was equally likely to be any of the other three animals (e.g., for an incongruent cat, the word was equally likely to be "DOG," "BIRD," or "FISH"). We used jsPsych (de Leeuw, 2015) to develop these tasks for an online browser, so that participants could complete the task online using their own computer.

### *Procedure*

Before starting the main task, people were extensively instructed on (a) the correct stimulus–response mappings and (b) the picture–word Stroop task. The practice phase is explained in detail in the online supplemental materials. The dog, cat, bird, and fish images used in the practice phase were different from those used during the rest of the experiment.

The main experiment consisted of two phases. In the training phase, participants completed three 240-trial blocks of a standard ISPC paradigm where trials with two types of animal pictures (e.g., dog and fish) were 90% congruent and trials with the other two types of animal pictures (e.g., cat and bird) were 10% congruent. It was randomly selected for each participant which two animal types were MC. Participants were instructed to respond to the animal that appeared in the picture and ignore the animal names superimposed on the picture. Participants responded using the "A," "S," "D," and "F" keys on a standard QWERTY keyboard and learned their associated response-key mappings at the beginning of the experiment. The stimuli appeared centrally on the screen and remained on screen until response or until a 3,000 ms response deadline elapsed. After each trial, there was a 1,000 ms inter-trial interval where a fixation cross was presented centrally.

In the subsequent transfer phase, participants completed one unbiased block (192 trials) using the same animal–word Stroop items.

This task was identical to the training phase, except the proportion congruence for all items was 50%. In other words, all animal pictures were unbiased with the same 50% probability of yielding a congruent word. Accordingly, any difference in performance between previously MC and previously MI items in the transfer phase reflects participants retrieving and implementing the previously learned control settings. We did not inform participants that the final block was different from the previous blocks.

In summary, this experiment used a within-subjects 2 (proportion congruence: MC vs. MI) × 2 (trial type: congruent vs. incongruent) × 2 (phase: training vs. transfer) design. For both the training and transfer phases, an interaction between proportion congruence and trial type (i.e., an ISPC effect) serves as key evidence that different reactive control settings were retrieved and implemented for MC and MI items (or for previously MC and MI items, in the case of the transfer phase).

### *Transparency and Openness*

The participants in the current study were collected from two samples. Experiments 1 and 2 consisted of a sample of young adults recruited exclusively from Washington University in St. Louis in the United States. These experiments were conducted online using jsPsych. All experiments in this article were approved by the Washington University in St. Louis institutional review board. All analyses were performed in Python 3 (Van Rossum & Drake, 2009). Data and analysis files for all experiments are available at https://osf.io/xhe76/.

## Results

Trials with reaction times (RTs) faster than 200 ms or slower than 3,000 ms were excluded from analysis, consistent with prior research with this task (e.g., Bugg & Dey, 2018; Bugg et al., 2011). These exclusions eliminated less than 1% of the trials. For this and the following experiments, only correct responses were included in the analysis of RT. Mean RTs and error rates are presented in Table 1. Results in error rate were consistent in pattern with results in RT and are reported in the online supplemental materials for conciseness. In this and all subsequent experiments, the α level for statistical tests was set to .05.

We analyzed performance in the training phase separately from the transfer phase. In this and in the following experiments, we additionally performed analyses separately for the first and second half of the transfer phase. We hypothesized that participants might initially retrieve and implement the reactive control setting associated with each item, but over time in the transfer phase, learn that the previously MC and MI items no longer differ, leading to a more similar control setting being retrieved for both item types. Analyzing the first and second half allowed us to test how people adapt to the changed control demands over time and measure to which degree participants transferred their control settings to the equivalent, unbiased control settings for the previously MC and MI items.

### *Training Phase*

There was a significant effect of trial type, $F(1, 107) = 258.53$, $p < .001$, $\eta_p^2 = .71$, such that responses to congruent trials ($M =$ 751 ms) were faster than responses to incongruent trials ($M =$ 811 ms). There was an effect of proportion congruence, $F(1, 107) = 18.85$, $p < .001$, $\eta_p^2 = .15$, indicating slower responses to MC items ($M = 805$ ms) compared to MI items ($M = 779$ ms). Most importantly, an interaction between trial type and proportion congruence revealed an ISPC effect, $F(1, 107) = 36.63$, $p < .001$, $\eta_p^2 = .26$ (see Figure 3). The Stroop effect was larger for MC items ($M = 110$ ms) than MI items ($M = 53$ ms).

It may be tempting to interpret this main effect of proportion congruence as evidence that MC items, overall, were associated with increased response demands. However, it is important to note that this analysis is biased by how average RTs for each factorial combination of trial type and proportion congruence are calculated. For example, for the MC items, only 10% of trials are incongruent, but they count as strongly as the 90% of congruent trials. Therefore, we compared average RT between proportion congruence conditions, ignoring trial type, and found that people were significantly slower on MI trials ($M = 800$ ms) compared to MC trials ($M = 761$ ms), $t(107) = 7.31$, $p < .001$, $d = 0.30$.

### *Transfer Phase—Stroop Performance*

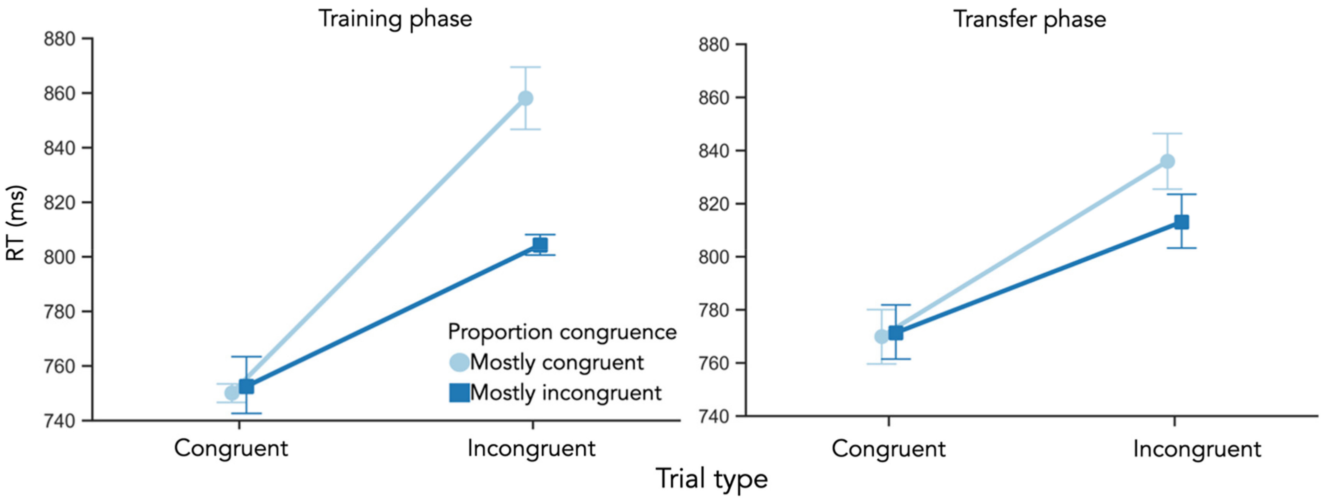
We also observed a Stroop effect in the transfer phase, indicated by a significant effect of trial type, $F(1, 107) = 114.37$, $p < .001$, $\eta_p^2 = .52$. Responses to congruent trials ($M = 770$ ms) were faster than responses to incongruent trials ($M = 824$ ms). We observed no effect of proportion congruence, $F(1, 107) = 2.15$, $p = .146$, $\eta_p^2 = .02$. As all item types were unbiased in this phase (as opposed to the training phase), this means that MI and MC trials yielded similar RTs. Most importantly, an interaction between trial type and

**Table 1**
*Mean RT (ms) and Error Rates in Experiment 1*

| Phase and block | ISPC | DV | Trial type: Congruent | Trial type: Incongruent | Stroop effect |
|---|---|---|---|---|---|
| Training ISPC | MC | RT | 750 (117) | 860 (159) | 110 (81) |
| | | Error rate | 4.41% (2.90) | 7.28% (6.27) | 2.87% (5.55) |
| | MI | RT | 753 (129) | 806 (140) | 53 (60) |
| | | Error rate | 4.14% (3.94) | 5.89% (3.69) | 1.75% (3.88) |
| Transfer ISPC | Previously MC | RT | 770 (160) | 836 (177) | 66 (76) |
| | | Error rate | 5.50% (5.08) | 7.54% (6.74) | 2.05% (4.94) |
| | Previously MI | RT | 771 (166) | 813 (170) | 42 (73) |
| | | Error rate | 5.36% (6.19) | 6.60% (5.76) | 1.24% (5.14) |

*Note.* Values in parentheses indicate *SD*. RT = reaction time; MC = mostly congruent; MI = mostly incongruent; DV = dependent variable; ISPC = item-specific proportion congruence.

**Figure 3**
*ISPC Effect in RT for Each Phase of Experiment 1*




*Note.* Error bars represent within-subject SEM. A significant ISPC effect was observed in the training phase (biased ISPC block) and transfer phase (unbiased ISPC block), indicating that the learned control settings in the training phase persisted in the transfer phase where all items were 50% congruent. ISPC = item-specific proportion congruence; RT = reaction time; SEM = standard error of the mean. See the online article for the color version of this figure.

proportion congruence indicated an ISPC effect, $F(1, 107) = 5.57$, $p = .020$, $\eta_p^2 = .05$ (see Figure 3). The Stroop effect was larger for previously MC items ($M = 66$ ms) than previously MI items ($M = 42$ ms).

Next, we used the same tests to measure Stroop performance in the first and second half of the transfer phase. In the first half, there was a significant Stroop effect, $F(1, 107) = 60.47$, $p < .001$, $\eta_p^2 = .36$, such that responses to congruent trials ($M = 762$ ms) were faster than responses to incongruent trials ($M = 816$ ms). We observed no effect of proportion congruence, $F(1, 107) = 0.65$, $p = .423$, $\eta_p^2 < .01$. Furthermore, an interaction between trial type and proportion congruence revealed an ISPC effect, $F(1, 107) = 9.82$, $p = .002$, $\eta_p^2 = .08$. Stroop effects were larger for previously MC items ($M = 77$ ms) than previously MI items ($M = 33$ ms).

In the second half, we also found a significant Stroop effect, $F(1, 107) = 55.52$, $p < .001$, $\eta_p^2 = .34$, such that responses to congruent trials ($M = 781$ ms) were faster than responses to incongruent trials ($M = 832$ ms). We observed no effect of proportion congruence, $F(1, 107) = 1.84$, $p = .177$, $\eta_p^2 = .02$. However, the lack of a significant interaction between proportion congruence and trial type indicated that the ISPC effect did not sustain throughout the second half of the block, $F(1, 107) = 0.87$, $p = .352$, $\eta_p^2 < .01$. Stroop effects were not significantly larger for previously MC items ($M = 58$ ms) than previously MI items ($M = 46$ ms).

## Discussion

Participants in our study implemented more control to MI items than to MC items, as evidence by reduced Stroop effects and increased RTs, during training. More importantly, we found that the item-specific control settings were retrieved and implemented in an unbiased transfer phase. As anticipated, the ISPC effect was strongest early in the transfer phase, as evidenced by the ISPC effect being significant in the first half of the transfer phase but not the second half.

Our transfer effect replicates and extends the finding from Ileri-Tayar et al. (2022), such that transfer was observed despite the transfer trials being presented in a separate unbiased block (rather than intermixed in a block with biased MC and MI training items; e.g., Bugg & Dey, 2018; Bugg et al., 2011). Having found that control settings transferred to an unbiased ISPC block in the transfer phase, we then turned to assess our key research question: will learning a stimulus–control association in the training phase drive demand avoidance to the previously MI items in an unbiased DST block?

# Experiment 2

Experiment 2 was designed to address two questions. First, we assessed whether previously learned control settings would transfer to a subsequent transfer phase in a different task environment. That is, the picture–word Stroop trials were embedded into a DST rather than being presented centrally on the screen as they were in the training phase. Second, we wanted to test whether the event files encoding the item-control association also incorporate associated control costs, driving a preference for choice options that yield previously MC items compared to options that yield previously MI items. The unbiased DST block is critical, because it ensures that any difference between previously MC and previously MI choice options is exclusively attributable to differences learned in the training phase. If reactive control costs are bound in an event file, then avoidance for the option that produces more previously MI items should be observed concurrently with an ISPC effect. If not, then there should be an ISPC effect for previously MC and MI items, but no avoidance for the option that produces primarily previously MI items.

## Method

### *Participants*

One-hundred and fifteen participants ($M_{age} = 20.07$, $SD = 1.22$; 57 female, 58 male), from Washington University in St. Louis provided informed consent and earned class credit for participation. Fourteen participants were removed for not meeting the accuracy threshold of 80%, resulting in a final sample of 101 participants ($M_{age} = 20.06$, $SD = 1.22$; 54 female, 47 male). Relevant previous DST literature found a demand selection effect using sample sizes of 43 and 24 (Experiments 1 and 2 of Kool et al., 2010). A power analysis using G*Power 3.1 (Faul et al., 2007) suggested a sample size of 22 participants to achieve power of .9 based on demand selection effects with an effect size of .38, from Kool et al. (2010). However, because the decks involved in this study were unbiased, we collected a larger sample size to ensure we had sufficient power to observe a demand avoidance effect if present in our novel design.

### Procedure

Participants first completed the same training phase as in Experiment 1 with the only difference being that there were two 240-trial blocks instead of three. In the following transfer phase, participants completed two unbiased, 75-trial DST blocks.[1]

On each trial of the DST (see Figure 4), participants chose between two "decks," symmetrically positioned to the left and right of the center of the screen. At the start of the trial, both decks appeared "dimmed," signaling that the participant first needed to hover their mouse cursor over a small circle (a home button) at the center of the screen, equidistant from the two decks. This movement undimmed the decks, signaling that they could now be selected. Participants selected one of the two decks by hovering the mouse cursor over the desired choice option. This action caused the unselected deck to dim again, providing visual feedback about which deck has been chosen, and in what location the upcoming Stroop stimulus would appear. By requiring participants to return to the home button at the start of each trial, the time cost for either staying or switching preferences was identical. Participants were given a response deadline of 5,000 ms to select a deck.

The decks always appeared along the perimeter of an imaginary circle separated by an angular distance of 45°, and their positions and appearance were randomly chosen for each block (Kool et al., 2010). There were three sets of decks, and one was randomly chosen for each participant independently.

Once a deck was selected, a picture–word Stroop stimulus was immediately presented on the selected deck while the unselected deck was dimmed. The picture–word Stroop stimulus remained on the screen until response or a 5,000 ms response deadline elapsed. A 1,000 ms blank interval followed each trial.

Both DST blocks of the transfer phase were unbiased. That is, each choice option had a 50% probability to yield an incongruent trial. However, one deck produced mostly (animal) items that were MC in the preceding ISPC blocks (i.e., 90% MC trials and 10% MI trials), whereas the other deck produced mostly items that were MI in the preceding ISPC blocks (i.e., 10% MC trials and 90% MI trials).

Before the main experiment, participants were extensively instructed on (a) the correct stimulus–response mappings using their nondominant hand, (b) the picture–word Stroop task, and (c) the DST, including movement of the mouse using their dominant hand. The practice phase is explained in detail in the online supplemental materials.

## Results

Trials with Stroop RTs faster than 200 ms or slower than 3,000 ms were excluded from all analyses (e.g., Bugg & Dey, 2018; Bugg et al., 2011). The exclusion of these trials led to the removal of 1% of the total trials for all participants. In the demand avoidance analysis, no trials were excluded. We first report Stroop performance in the training and transfer phases, and then report choice behavior for the unbiased DST block in the transfer phase. Mean RTs and error rates are presented in Table 2.

### Training Phase—Stroop Performance

There was a significant effect of trial type, $F(1, 100) = 124.84$, $p < .001$, $\eta_p^2 = .56$, indicating that responses to congruent trials ($M = 772$ ms) were faster than responses to incongruent trials ($M = 831$ ms). No effect of proportion congruence was observed, $F(1, 100) = 0.99$, $p = .322$, $\eta_p^2 = .01$. Again, a significant interaction between proportion congruence and trial type revealed an ISPC effect $F(1, 100) = 77.44$, $p < .001$, $\eta_p^2 = .44$ (Figure 5, left panel). The Stroop effect was larger for MC items ($M = 120$ ms) than MI items ($M = 12$ ms).

Next, we compared average RTs between proportion congruence conditions ignoring trial types. We made this comparison to assess overall differences in demands between these conditions (unbiased by the differing trial counts in the analysis of variance [ANOVA] reported above). We again found increased RTs for MI items ($M = 824$ ms) compared to MC items ($M = 780$ ms), $t(100) = 5.82$, $p < .001$, $d = 0.32$.

### Transfer Phase—Stroop Performance

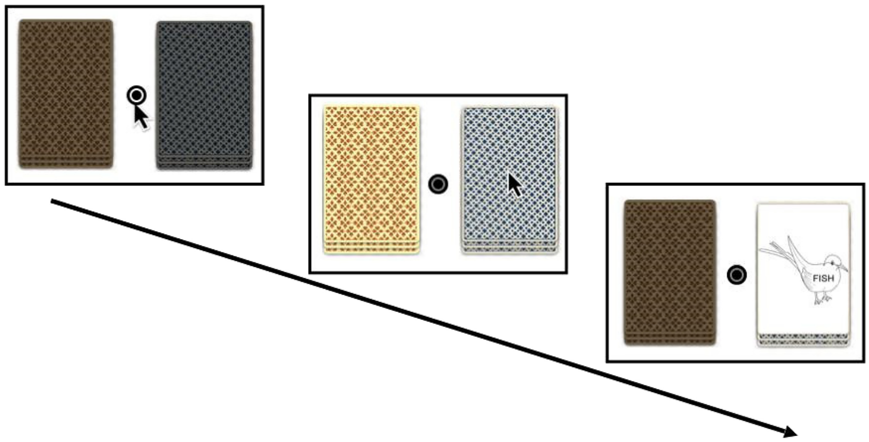
In addition to the exclusion criteria mentioned above, we also excluded one participant who did not have at least one observation of each trial type and proportion congruence combination (because this exclusion rendered it impossible to calculate their ISPC effect) for the performance analyses in this section.

Collapsing across both blocks of the DST phase, we found a significant effect of trial type, $F(1, 99) = 74.08$, $p < .001$, $\eta_p^2 = .43$, indicating that responses to congruent trials ($M = 721$ ms) were faster than responses to incongruent trials ($M = 805$ ms). We did not observe an effect of proportion congruence, $F(1, 99) = 1.38$, $p = .244$, $\eta_p^2 = .01$. However, a significant interaction between proportion congruence and trial type revealed an ISPC effect $F(1, 99) = 4.81$, $p = .031$, $\eta_p^2 = .05$, such that Stroop effects were larger for previously MC items ($M = 100$ ms) than previously MI items ($M = 76$ ms).

In the first DST block, a significant effect of trial type was observed, $F(1, 99) = 55.76$, $p < .001$, $\eta_p^2 = .36$ such that responses to congruent trials ($M = 738$ ms) were faster than responses to incongruent trials ($M = 828$ ms). No effect of proportion congruence was observed, $F(1, 99) = 2.43$, $p = .122$, $\eta_p^2 = .02$. However, a significant interaction between proportion congruence and trial type revealed an ISPC effect $F(1, 99) = 10.43$, $p = .002$, $\eta_p^2 = .10$ (Figure 5, center panel), such that Stroop effects were larger for previously MC items ($M = 120$ ms) than previously MI items ($M = 70$ ms).

[1] Because trials in the transfer phase of Experiment 2 involved a selection between decks, they took much longer than in Experiment 1. Therefore, we reduced the number of trials in the training phase compared with Experiment 1. This design choice allowed us to shorten the experiment without compromising the primary findings (robust ISPC training effect and transfer effects in unbiased blocks).

**Figure 4**
*A Depiction of the DST Phase in Experiments 2 and 3*




*Note.* The DST procedure was adapted from Kool et al. (2010). The DST decks appeared dimmed at the start of each trial, indicating a deck selection could not be made. Participants first needed to move their cursor over the home button (the black circle) at the center of the screen (see left panel), a point equidistant from the two choice options (i.e., decks of cards), Then both the decks appeared undimmed (see middle panel), which signaled that a deck could now be selected. Participants then chose a deck by moving the mouse to one of the two decks (in the middle panel, the right deck is selected) and responded to the picture–word Stroop stimulus that followed (as shown in the right panel). The decks differed in the animal items they were likely to produce. One deck produced mostly items (animals) that were MC in the preceding ISPC blocks, and the other deck produced mostly items (animals) that were MI in the preceding ISPC blocks. In unbiased DST blocks (Experiments 2, 3a, and 3b), all items (animals) were 50% congruent and only differed in that they were previously MC or MI (i.e., associated with relaxed vs. focused reactive control). When the DST block was biased (Experiments 3a and 3b), the items (animals) continued to differ in proportion congruence (i.e., be MC or MI), just as they did in the earlier ISPC block. DST = demand selection task; MC = mostly congruent; MI = mostly incongruent; ISPC = item-specific proportion congruence. See the online article for the color version of this figure.

In the second DST block, we also observed a significant effect of trial type, $F(1, 99) = 50.73$, $p < .001$, $\eta_p^2 = .34$, such that responses to congruent trials ($M = 703$ ms) were faster than responses to incongruent trials ($M = 784$ ms). As with the first block, we found no effect of proportion congruence, $F(1, 99) = 0.77$, $p = .382$, $\eta_p^2 = .01$. Unlike the first block, there was no interaction between proportion congruence and trial type, $F(1, 99) = 0.19$, $p = .666$, $\eta_p^2 < .01$ (Figure 5, right panel). This pattern of results suggests that individuals carried over the control settings that were learned during the training phase to the first unbiased DST block, but retrieval of these control settings did not persist throughout the entire transfer phase. However, a paired sample $t$ test did not reveal a significant difference in ISPC effects between blocks, $t(99) = 1.69$, $p = .094$, $d_z = .26$.

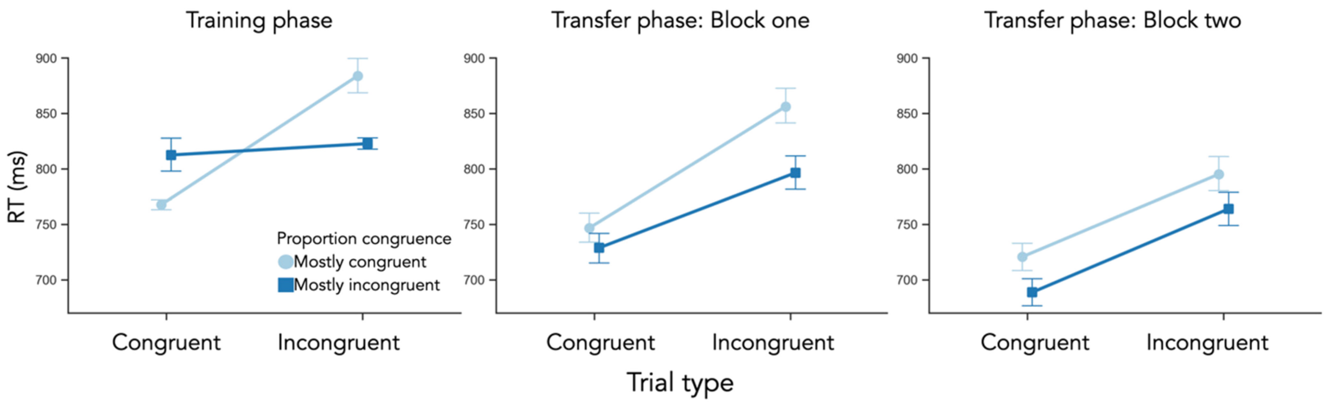
**Table 2**
*Mean RT (ms) and Error Rates in Experiment 2*

| Phase and block | ISPC | DV | Trial type: Congruent | Trial type: Incongruent | Stroop effect |
|---|---|---|---|---|---|
| Training ISPC | MC | RT | 768 (122) | 888 (169) | 120 (95) |
| | | Error rate | 4.88% (3.69) | 7.14% (7.08) | 2.26% (6.59) |
| | MI | RT | 814 (164) | 826 (156) | 12 (75) |
| | | Error rate | 6.22% (5.49) | 5.23% (4.12) | −0.70% (5.13) |
| Transfer DST 1 | Previously MC | RT | 746 (136) | 866 (202) | 120 (152) |
| | | Error rate | 4.59% (7.51) | 6.15% (6.99) | 1.56% (9.89) |
| | Previously MI | RT | 752 (172) | 822 (225) | 70 (145) |
| | | Error rate | 4.97% (6.78) | 5.29% (7.81) | 0.32% (9.0) |
| Transfer DST 2 | Previously MC | RT | 725 (118) | 808 (171.) | 83 (120) |
| | | Error rate | 6.85% (10.16) | 6.71% (8.78) | −0.14% (13.27) |
| | Previously MI | RT | 715 (165) | 791 (231) | 75 (162) |
| | | Error rate | 4.24% (5.37) | 7.07% (8.26) | 2.83% (7.20) |

*Note.* Values in parentheses indicate *SD*. Note that items in the Transfer DST Blocks 1 and 2 were 50% congruent in each location. RT = reaction time; MC = mostly congruent; MI = mostly incongruent; DV = dependent variable; ISPC = item-specific proportion congruence; DST = demand selection task.

**Figure 5**

*ISPC Effects in RT for Each Phase of Experiment 2*




*Note.* Error bars represent within-subject SEM. A significant ISPC effect was observed in the training phase and the first block of the transfer phase (unbiased DST). This indicates that the learned control settings in the training phase initially persisted in the completely unbiased transfer phase during the DST task. ISPC = item-specific proportion congruence; RT = reaction time; SEM = standard error of the mean; DST = demand selection task. See the online article for the color version of this figure.

### *Transfer Phase—Choice Behavior*

To examine choice behavior in the DST blocks, we compared the percentage of low-demand choices for each participant to chance. For this set of analyses, there were no exclusion criteria beyond those mentioned in the Participants section reported above.

We performed a one-tailed Wilcoxon signed-rank test against chance to examine choice rates in each block of the transfer phase, predicting that people would avoid the deck that yields previously MI items.

Across all 101 participants, the mean proportion of trials on which the low-demand deck was selected across both DST blocks was 0.51 ($SD = 0.17$), 51 subjects (50%) selected the low-demand deck more often than the high-demand deck, and a Wilcoxon signed-rank test revealed that choice rates did not significantly differ from chance ($w = 11{,}043.5$, $p = .171$).

To examine whether choice rates differed between blocks we conducted a further analysis examining each block separately (Figure 6 depicts the evolution of the choice rate across both blocks). Participants selected the low-demand deck on 0.52 of trials ($SD = 0.19$) in the first DST block and on 0.49 of trials ($SD = 0.22$) in the second DST block. As evidenced by a Wilcoxon signed rank test, neither of the choice rates differed significantly from chance ($w = 2{,}748.5$, $p = .280$ in the first DST block, $w = 2{,}791$, $p = .233$ in the second DST block).

As a more stringent test of our hypotheses, we then restricted analyses to participants who showed a positive ISPC effect in the training phase (following Ileri-Tayar et al., 2022) to assess performance only for participants who initially learned the stimulus–control associations. However, this approach did not yield qualitatively different results in this and the following studies and therefore we restrict reporting of these analyses to the online supplementary materials.

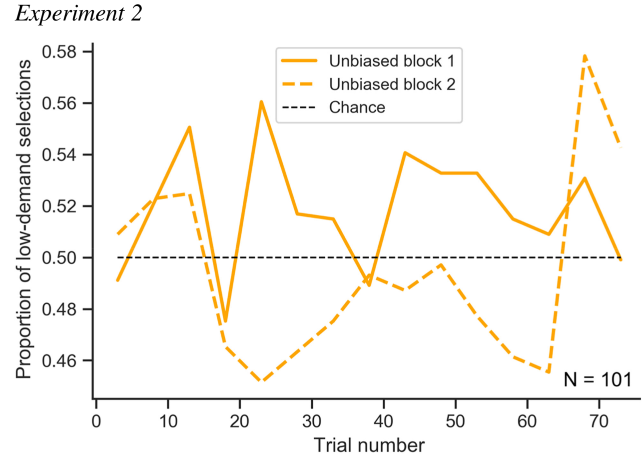
## Discussion

The results of Experiment 2 suggest that reactively implementing a control setting does not also retrieve its effort cost. We found a significant ISPC effect in the DST transfer phase, indicating that participants retrieved a more focused control setting for previously MI items. Observing transfer was notable, since the task environment where the stimulus–control associations were learned (i.e., trials presented centrally on screen) was dissimilar to the task environment where the control settings were retrieved (i.e., trials were presented in multiple locations and with the additional load of choosing between decks). This result suggests that retrieval of the control settings upon the reoccurrence of the predictive stimulus feature occurs in a stable manner, even when the task context is not identical.

Despite this, there was no evidence that participants avoided the choice option that yielded items that were previously MI. In other

**Figure 6**

*Proportion of Low-Demand Selections as a Function of Trial Number in the Transfer Phase (Unbiased DST Blocks) in Experiment 2*




*Note.* When averaged across trials, this proportion was not significantly different from chance for either unbiased DST block by itself, $p > .233$, or when choices were combined across blocks, $p = .171$. DST = demand selection task. See the online article for the color version of this figure.

words, they did not avoid the option that imposed more reactive control demands. From the perspective of event files theory, this finding suggests that the retrieval of control settings was not paired with the cost associated with implementing those control settings. Alternatively, it is possible that participants initially learned a difference in demand between the stimuli, but quickly learned there was no difference in demand between decks in the unbiased DST block. However, the significant ISPC effect throughout the first DST block indicated an objective difference between decks in terms of behavioral performance. Despite this behavioral difference, there was no preference for the choice option that minimized control demands, even in the first block alone.

## Experiment 3a

The results of Experiment 2 indicate that participants did not treat previously MI items as more costly, even when those items triggered the retrieval of a relatively focused control setting. This finding suggests that reactive control may not be costly, or that its cost is not encoded into the event file. However, a few alternative explanations remain.

First, it is possible that the control demands imposed by the ISPC manipulation do not register as costly in a DST, even in the presence of a true difference in conflict likelihood between the choice options. Therefore, in Experiments 3a and 3b, we included a biased DST block between the training ISPC blocks and the unbiased DST block. The inclusion of a biased DST block allows us to test whether people avoid a choice option that yields mostly MI trials compared to one that yields mostly MC trials (cf., Schouppe et al., 2014). If the choice option that yields mostly MI trials is avoided in a biased DST block, it is unlikely that the absence of demand avoidance in the transfer phase of Experiment 2 reflected insensitivity to differences in item-specific control demands (i.e., demands that were induced via the proportion congruence manipulation targeting reactive control) in a DST.

Second, it is possible that the difference in task context between the ISPC and DST blocks interfered with retrieval of the effort cost of control in the unbiased DST block (even though control settings showed robust transfer). That is, a difference in task context may have made the event files for trials in the training phase less available for retrieval in the transfer phase (Dignath et al., 2019; Spapé & Hommel, 2008). We reasoned that the inclusion of the biased DST block before the unbiased DST block in Experiments 3a and 3b may facilitate retrieval of the costly nature of control in the unbiased DST block, since the blocks are similar (i.e., both involve selecting between choice options and then completing a picture–word Stroop trial). That is, giving participants the opportunity to further learn stimulus–control associations for MC and MI items in a DST context may aid retrieval of effort costs in a subsequent unbiased DST block. However, if reactive control costs are not encoded in the event file, we should still observe a lack of a choice preference in the transfer phase in Experiments 3a and 3b.

### Method

#### Participants

In Experiment 3a, 102 participants ($M_{\text{age}} = 37.71$, $SD = 10.63$; 42 female, 60 male) were recruited on Amazon Mechanical Turk and provided informed consent. Sixteen participants who did not reach 80% accuracy across the entire experiment were removed, resulting in a final sample of 86 participants ($M_{\text{age}} = 38.55$, $SD = 10.68$; 38 female, 48 male).

#### Design, Stimuli, and Procedure

The design, stimuli, and procedure of Experiment 3a were identical to Experiment 2, except for the following differences. After a block of biased ISPC trials (720 trials), the training phase continued with a biased DST block. In this biased DST block (75 trials), MC and MI items retained the proportion congruence from the biased ISPC block: choices from one deck would produce mostly MC items (that were 90% congruent) and choices from the alternate deck would produce mostly MI items (that were 10% congruent).

The biased DST block was then followed by a final DST block that was unbiased (75 trials), similar to Experiment 2. As before, one deck yielded 90% previously MC items and the other yielded 90% previously MI items. However, items in this phase were 50% congruent regardless of the choice option. The visual appearance of the decks was also changed (e.g., deck color and pattern) between DST blocks to eliminate the possibility of transfer based solely on deck appearance associations.

We reduced the number of unbiased DST trials from 150 in Experiment 2 to 75 in Experiment 3a to accommodate the biased DST block (of 75 trials), keeping the total number of DST trials the same across Experiments 2 and 3a (150). In addition, we found that the ISPC effect in the unbiased DST phase of Experiment 2 dissipated in the second block of 75 trials. Thus, this change to the procedure only removed an unbiased DST block during which we expected not to observe any performance difference between decks.

### Results

As in the previous experiments, RTs faster than 200 ms or slower than 3,000 ms were excluded (e.g., Bugg & Dey, 2018; Bugg et al., 2011). This exclusion eliminated less than 1% of the trials. Mean RTs and error rates are presented in Table 3.

#### Training Phase—Stroop Performance

When analyzing Stroop RTs from the choice task (the biased DST block and unbiased DST block), we removed participants who did not have at least one observation of each trial type and proportion congruence combination (mirroring Experiment 2). This exclusion led to the removal of 17 participants.

**Biased ISPC Blocks.** There was a significant effect of trial type, $F(1, 85) = 138.80$, $p < .001$, $\eta_p^2 = .62$, such that responses were slower for incongruent trials ($M = 833$ ms) than congruent trials ($M = 772$ ms). There was a significant effect of proportion congruence, $F(1, 85) = 11.10$, $p = .001$, $\eta_p^2 = .12$, indicating that participants responded more slowly to MC items ($M = 828$ ms) than MI items ($M = 798$ ms). Most importantly, a significant interaction of proportion congruence and trial type revealed an ISPC effect, $F(1, 85) = 19.05$, $p < .001$, $\eta_p^2 = .18$ (Figure 7, left panel), such that Stroop effects were larger for MC items ($M = 112$ ms) than MI items ($M = 61$ ms).

As before, a follow-up comparison between proportion congruence conditions ignoring trial types revealed that average RTs for MI items ($M = 822$ ms) were higher than for MC items ($M = 783$ ms), $t(85) = 4.90$, $p < 0.001$, $d = 0.22$. This result again

**Table 3**
*Mean RT (ms) and Error Rates in Experiment 3a*

| Phase and block | ISPC | DV | Trial type: Congruent | Trial type: Incongruent | Stroop effect |
|---|---|---|---|---|---|
| Training ISPC | MC | RT | 772 (167) | 884 (231) | 112 (103) |
| | | Error rate | 3.19% (3.15) | 5.37% (6.17) | 2.18% (4.86) |
| | MI | RT | 768 (175) | 828 (193) | 61 (66) |
| | | Error rate | 2.92% (4.50) | 3.55% (3.16) | 0.62% (4.20) |
| Training biased DST | MC | RT | 750 (155) | 919 (227) | 169 (231) |
| | | Error rate | 3.07% (4.71) | 7.80% (16.59) | 4.74% (16.84) |
| | MI | RT | 816 (257) | 844 (202) | 29 (199) |
| | | Error rate | 1.84% (7.70) | 2.69% (3.43) | 0.85% (7.88) |
| Transfer unbiased DST | Previously MC | RT | 745 (170) | 862 (223) | 117 (155) |
| | | Error rate | 2.78% (5.12) | 3.84% (5.09) | 1.06% (6.30) |
| | Previously MI | RT | 752 (194) | 820 (196) | 68 (119) |
| | | Error rate | 2.99% (5.12) | 3.26% (4.86) | 0.28% (7.20) |

*Note.* Values in parentheses indicate *SD*. Note that items in the transfer unbiased DST Block were 50% congruent in each location. RT = reaction time; MC = mostly congruent; MI = mostly incongruent; DV = dependent variable; ISPC = item-specific proportion congruence; DST = demand selection task.

demonstrates that the main effect of proportion congruence in the ANOVA was driven by unbalanced trial counts between conditions.

**Biased DST Block.** We observed a significant effect of trial type, $F(1, 68) = 28.26$, $p < .001$, $\eta_p^2 = .29$, such that responses were slower for incongruent trials ($M = 865$ ms) compared to congruent trials ($M = 757$ ms). There was no effect of proportion congruence, $F(1, 68) = 0.04$, $p = .838$, $\eta_p^2 < .01$. Stroop effects were larger for MC items ($M = 169$ ms) than MI items ($M = 29$ ms), $F(1, 68) = 14.91$, $p < .001$, $\eta_p^2 = .18$, indicating an ISPC effect (Figure 7, center panel).

We again ran a follow-up comparison between proportion congruence conditions ignoring trial types and once again found that average RTs for MI items ($M = 857$ ms) were higher than for MC items ($M = 775$ ms), $t(85) = 4.69$, $p < .001$, $d = 0.44$.

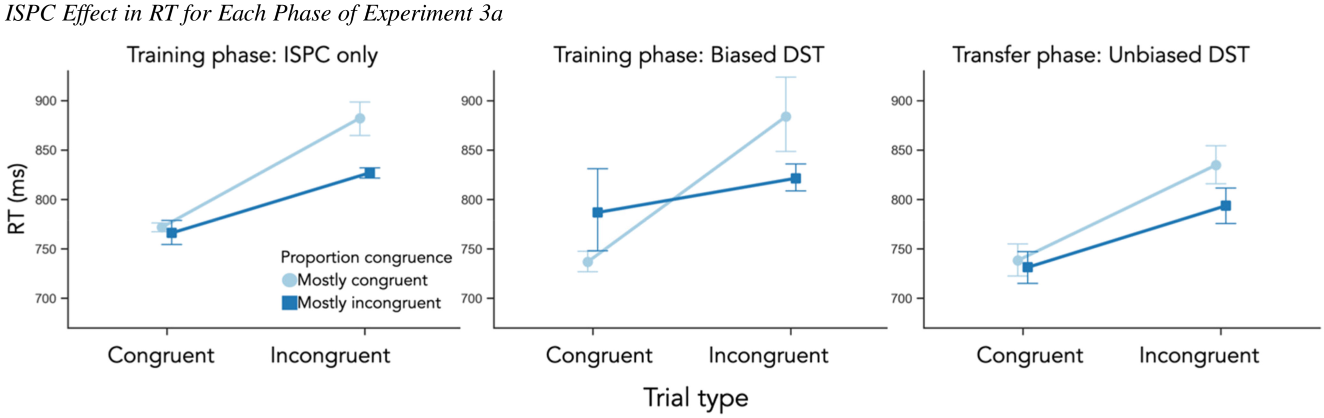
### *Transfer Phase—Stroop Performance*

**Unbiased DST Block.** There was a significant effect of trial type, $F(1, 68) = 50.78$, $p < .001$, $\eta_p^2 = .43$, such that responses to incongruent trials ($M = 825$ ms) were slower than responses to congruent trials ($M = 734$ ms). There was no effect of proportion congruence, $F(1, 68) = 1.33$, $p = .253$, $\eta_p^2 = .02$. Indicating transfer of the ISPC effect, we found an interaction between proportion congruence and trial type, $F(1, 68) = 5.72$, $p = .020$, $\eta_p^2 = .08$ (Figure 7, right panel). The Stroop effect was larger for previously MC items ($M = 117$ ms) than previously MI items ($M = 68$ ms).

### *Choice Performance*

As with Experiment 2, we performed a one-tailed Wilcoxon signed-rank test to examine choice rates for both the biased and unbiased DST blocks. We analyzed these data separately for the first 50 trials of the unbiased DST phase. Again, for the analyses below there were no exclusion criteria beyond those mentioned in the Participants section reported above. Figure 8 plots the evolution of demand selection rates across trials for both the biased and unbiased DST block.

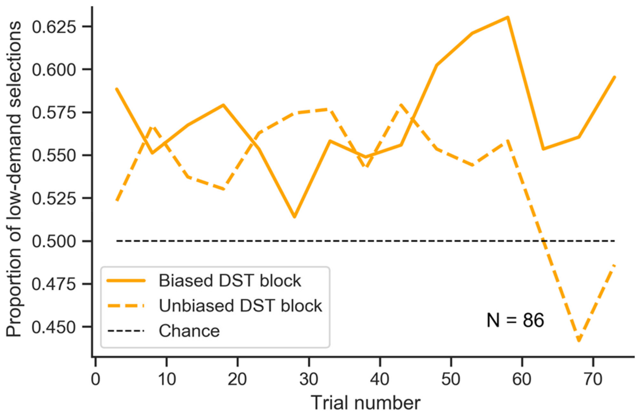
**Figure 7**
*ISPC Effect in RT for Each Phase of Experiment 3a*




*Note.* Error bars represent within-subject SEM. A significant ISPC effect was observed in both training phases (ISPC only and biased DST) and the transfer phase (unbiased DST), indicating that the learned control settings in the training phase persisted in the completely unbiased transfer phase. RT = reaction time; SEM = standard error of the mean; ISPC = item-specific proportion congruence; DST = demand selection task. See the online article for the color version of this figure.

**Figure 8**

*Proportion of Low-Demand Selections as a Function of Trial Number in the Training Phase (Biased DST Block) and Transfer Phase (Unbiased DST Block) in Experiment 3a*




*Note.* When averaged across trials, demand avoidance in the biased DST block differed significantly from chance, $p = .006$, but it did not differ significantly from chance in the unbiased DST block, $p = .119$. An exploratory analysis examining only the first 50 trials of the unbiased DST block suggested that demand avoidance significantly differed from chance, $p = .017$. DST = demand selection task. See the online article for the color version of this figure.

**Biased DST Block.** Participants selected the low demand choice option on 0.57 of trials ($SD = 0.24$), which differed significantly from chance, $w = 2{,}453.5$, $p = .006$.

**Unbiased DST Block.** The mean proportion of trials on which the low-demand deck was selected was 0.54 ($SD = 0.27$), which did not differ significantly from chance, $w = 2{,}144.5$, $p = .119$. However, visual inspection of the temporal evolution of demand avoidance in this transfer phase (Figure 8) suggested a demand avoidance effect that was present early in the unbiased DST block (approximately the first 50 trials), but eventually dissipated. With that in mind, we focused our analysis on just the first 50 trials of the unbiased DST block. Indeed, average low-demand choice during this part of the block was 0.56 ($SD = 0.26$), which significantly differed from chance, $p = .017$.

## Discussion

In addition to again finding that the ISPC effect transferred to an unbiased transfer phase, Experiment 3a revealed that participants avoided MI items in a biased DST block that preceded this phase. Our initial analyses suggested that this avoidance did not carry over to the unbiased DST block in the transfer phase. However, a post hoc exploratory analysis suggested that demand avoidance arose early in the unbiased DST block, but then faded. Of course, selecting a range of promising demand avoidance scores based on visual inspection, and then running a statistical test on that same data constitutes a form of "double dipping" (Vul et al., 2009). It is not a valid method of inference because the data that are tested are selected to be biased. Therefore, we preregistered this analysis, and sought to replicate this pattern in a new experiment.

# Experiment 3b

Experiment 3b was a preregistered replication of Experiment 3a, see https://osf.io/962ch.

## Method

### Participants

We recruited 157 participants ($M_{age} = 38.83$, $SD = 10.60$; 78 female, 74 male, five preferred not to answer) on Amazon Mechanical Turk. All participants provided informed consent. Sixteen participants who did not reach 80% accuracy across the entire experiment were removed, resulting in a final sample of 141 participants ($M_{age} = 39.04$, $SD = 10.71$; 72 female, 64 male, five preferred not to answer).

### Design, Stimuli, and Procedure

The design, stimuli, and procedure were identical to Experiment 3a, except there were now 100 trials in each DST block (instead of 75). We increased the number of trials of the biased DST block to boost potential stimulus-control learning and increased the number of trials for the unbiased block accordingly. Also, participants were asked four additional questions regarding their awareness of any differences between the two decks, how they chose between the decks, and whether they noticed anything different about the animal pictures.

## Results

### Training Phase—Stroop Performance

Preregistered exclusions eliminated less than 1% of the trials. Mean RTs and error rates are presented in Table 4. For the Stroop RTs from both the biased DST block and unbiased DST block, we again removed participants who did not have at least one observation of each trial type and proportion congruence combination. This exclusion led to the removal of 17 participants.

**Biased ISPC Blocks.** There was an effect of trial type, $F(1, 140) = 209.91$ $p < .001$, $\eta_p^2 = .60$, such that responses to incongruent trials ($M = 850$ ms) were slower than responses to congruent trials ($M = 783$ ms). There was a significant effect of proportion congruence, $F(1, 140) = 5.88$, $p = .017$, $\eta_p^2 = .04$, indicating that participants responded more slowly to MC items ($M = 841$ ms) than MI items ($M = 824$ ms). As in Experiment 3a, there was a significant interaction of proportion congruence and trial type, $F(1, 140) = 53.90$, $p < .001$, $\eta_p^2 = .28$, such that Stroop effects were larger for MC items ($M = 120$ ms) than MI items ($M = 43$ ms).

We then ran a follow-up comparison between proportion congruence conditions ignoring trial type and found that that average RTs for MI items ($M = 841$ ms) were higher than for MC items ($M = 793$ ms), $t(140) = 6.83$, $p < .001$, $d = 0.28$). This result once again demonstrates, unlike what is suggested by the ANOVA above, MI items yielded increased RTs.

**Biased DST Block.** We found a significant effect of trial type, $F(1, 123) = 106.76, p < .001, \eta_p^2 = .47$, such that responses were slower for incongruent trials (883 ms) than congruent trials (756 ms). There was no effect of proportion congruence, $F(1, 123) = 3.01$, $p = .085$, $\eta_p^2 = .02$. As in Experiment 3a, there was a significant ISPC effect. We observed an interaction between proportion congruence and trial type, $F(1, 123) = 25.80$, $p < .001$, $\eta_p^2 = .17$, such that Stroop effects were larger for MC items ($M = 179$ ms) than MI items ($M = 66$ ms).

**Table 4**
*Mean RT (ms) and Error Rates in Experiment 3b*

| Phase and block | ISPC | DV | Trial type | | Stroop effect |
|---|---|---|---|---|---|
| | | | Congruent | Incongruent | |
| Training ISPC | MC | RT | 781 (149) | 901 (218) | 120 (110) |
| | | Error rate | 2.48% (2.16) | 3.80% (5.86) | 1.33% (5.42) |
| | MI | RT | 802 (195) | 845 (181) | 43 (68) |
| | | Error rate | 2.55% (3.83) | 3.39% (3.52) | 0.83% (4.22) |
| Training biased DST | MC | RT | 759 (157) | 938 (273) | 179 (216) |
| | | Error rate | 2.64% (3.67) | 4.32% (10.94) | 1.68% (10.94) |
| | MI | RT | 792 (209) | 858 (195) | 66 (137) |
| | | Error rate | 1.83% (6.57) | 3.28% (4.62) | 1.45% (8.27) |
| Transfer unbiased DST | Previously MC | RT | 767 (179) | 867 (183) | 100 (114) |
| | | Error rate | 3.30% (4.86) | 3.38% (4.67) | 0.08% (5.70) |
| | Previously MI | RT | 766 (175) | 819 (181) | 53 (94) |
| | | Error rate | 3.11% (4.50) | 3.26% (5.73) | 0.16% (6.43) |

*Note.* Values in parentheses indicate *SD*. Items in the transfer unbiased DST Block were 50% congruent in each deck. RT = reaction time; MC = mostly congruent; MI = mostly incongruent; DV = dependent variable; ISPC = item-specific proportion congruence; DST = demand selection task.



A follow-up comparison between proportion congruence conditions ignoring trial type once again found that average RTs for MI items ($M = 876$ ms) were higher than for MC items ($M = 774$ ms), $t(140) = 6.57$, $p < .001$, $d = 0.52$).

### *Transfer Phase—Stroop Performance*

**Unbiased DST Block.** There was an effect of trial type, $F(1, 123) = 106.76$, $p < .001$, $\eta_p^2 = .47$, such that responses to incongruent trials ($M = 832$ ms) were slower than responses to congruent trials ($M = 751$ ms). There was an effect of proportion congruence, $F(1, 123) = 4.23$, $p = .042$, $\eta_p^2 = .03$, indicating that responses were slower for previously MC items ($M = 802$ ms) than previously MI items ($M = 768$ ms). As in Experiment 3a, we observed an interaction between proportion congruence and trial type, $F(1, 123) = 16.49$, $p < .001$, $\eta_p^2 = .12$. We found that the ISPC effect transferred to trials in the unbiased DST block, such that the Stroop effect was larger for previously MC items ($M = 97$ ms) than previously MI items ($M = 63$ ms) (Figure 9).

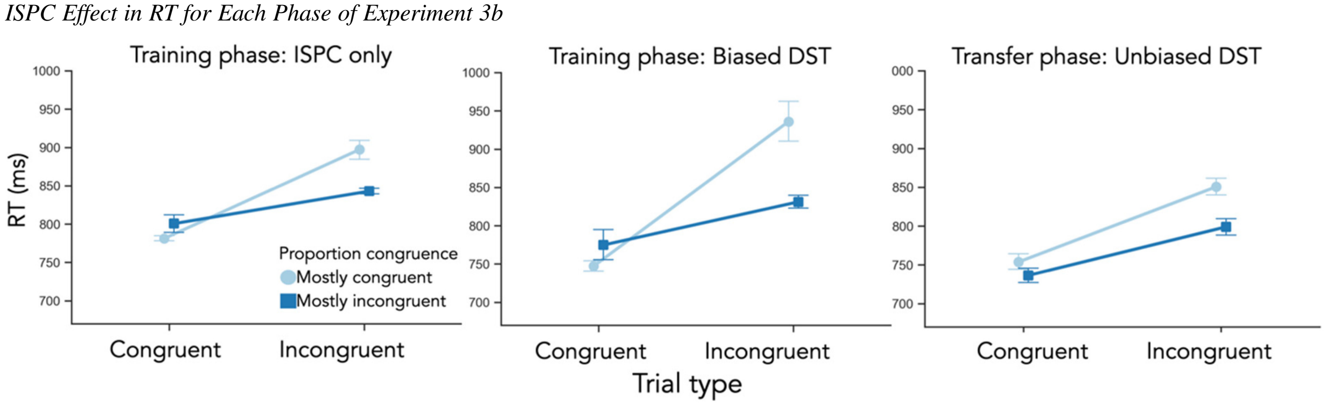
### *Choice Performance*

For the analyses below, there were no exclusion criteria beyond those mentioned in the Participants section reported above. Figure 10 plots the evolution of demand selection rates across trials for both the biased and unbiased DST block.

**Biased DST Block.** Participants selected the low demand option on 0.59 of trials ($SD = 0.25$), which differed significantly from chance, $p < .001$.

**Unbiased DST Block.** Across the entire block, participants selected the low-demand option on 0.51 of trials ($SD = 0.27$), which did not differ significantly from chance ($p = .441$). Contrasting the results of the exploratory analysis in Experiment 3a, we did not observe evidence for demand avoidance in the first 50 trials of the unbiased DST block. The low-demand choice rate

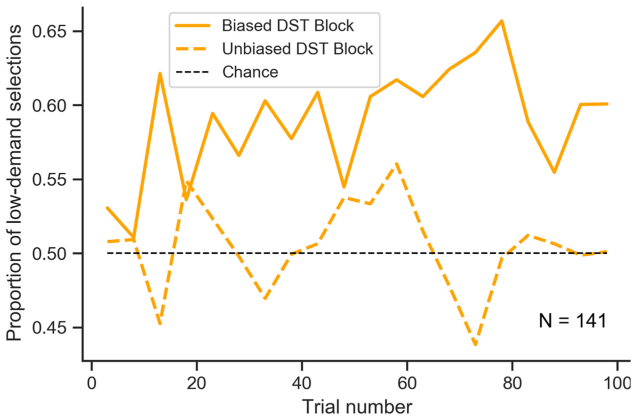
**Figure 9**
*ISPC Effect in RT for Each Phase of Experiment 3b*




*Note.* Error bars represent within-subject SEM. A significant ISPC effect was observed in both training phases (ISPC only and biased DST) and the transfer phase (unbiased DST), indicating that the learned control settings in the training phase persisted in the completely unbiased transfer phase. ISPC = item-specific proportion congruence; RT = reaction time; SEM = standard error of the mean; DST = demand selection task. See the online article for the color version of this figure.

**Figure 10**

*Proportion of Low-Demand Selections as a Function of Trial Number in the Training Phase (Solid Line, Biased DST Block) and Transfer Phase (Dashed Line, Unbiased DST Block) in Experiment 3b*




*Note.* When averaged across trials, demand avoidance in the biased DST block differed significantly from chance, $p < .001$, but it did not differ significantly from chance in the unbiased DST block, $p = .441$, nor was it apparent in the first 50 trials, $p = .321$. DST = demand selection task. See the online article for the color version of this figure.

was 0.51 ($SD = 0.25$), which did not significantly differ from chance, $p = .321$ (see Figure 10).

### Discussion

Together, Experiments 3a and 3b provided four key insights. First, we replicated Experiments 1 and 2, demonstrating a transfer of item-specific control settings to the unbiased transfer phase. Second, we demonstrated that participants avoided MI items in a DST block where MC and MI items retained their proportion congruences. The fact that we observed an ISPC effect in both the ISPC blocks and biased DST block of the training phase demonstrates that participants learned item-control associations. Third, we observed demand avoidance for the choice option that produced mostly MI items in the biased DST block. This result is important, as it demonstrates that the DST is sensitive to control demands that are induced reactively.

Fourth, and most importantly, we again found that participants did not avoid previously MI items in an unbiased DST block, even though participants retrieved and implemented focused control settings for those previously MI items. In other words, while previously MI items were treated with a more focused control setting, participants did not avoid the choice option that produced them more often. Indeed, hints of an early demand avoidance effect in Experiment 3a were ruled out in the subsequent preregistered replication.

The difference in choice behavior between the biased and unbiased DST phases is intriguing. In both phases, the presence of an ISPC effect indicates that participants retrieved control settings consistent with the learned stimulus–control associations, such that (previously) MI items retrieved more focused control settings. However, this effect only resulted in demand avoidance in the biased DST block. Simply retrieving the control setting when exposed to previously MC and MI items did not induce demand avoidance. That is, participants were sensitive to demand differences when an objective difference existed (i.e., when there was more conflict from one context than the other context), but not when only the learned control settings were retrieved. This result suggests that reactively implementing a focused control setting is, by itself, not demanding.

## General Discussion

We presented evidence that reactively implementing more focused control settings does not register as costly. We first established that learned item-specific control settings transfer to a subsequent phase of ISPC trials with unbiased items (Experiment 1), and to blocks of a DST in which choice options yield unbiased items (Experiments 2, 3a, and 3b). Despite this transfer of control settings, we found that these control settings did not drive demand-related choices. In the unbiased DST phase, participants did not prefer choice options that yielded items that triggered less attentional focus (i.e., previously MC items). However, we found that participants preferred choice options in biased DST phases that yielded trials that were actually MC (Experiments 3a and 3b). Even though control settings for MI items were more focused in both biased and unbiased DST blocks, participants only avoided them in the biased DST blocks. These results demonstrate that the implementation of a focused control setting does not, by itself, register as cognitively costly. In addition, they suggest that the estimation of cognitive costs is not based on the amount of control exerted, but rather on another, more subjective, evaluation process.

### Biased Control Settings Transfer to Unbiased Trials

Our results replicate recent findings that previously learned control settings continue to bias information processing after the biased demand structure disappears, even when the task context changed drastically (Ileri-Tayar et al., 2022; cf., Bejjani et al., 2020). Why did people continue to implement outdated control settings in the transfer phase? Ileri-Tayar et al. (2022) posited that the presence of the predictive cue (in the current study, the animal picture) automatically triggers retrieval of the associated control setting. In addition, updating the control settings requires trial-and-error correction through reinforcement learning (Chiu & Egner, 2019). Consistent with this hypothesis, we found that the ISPC effect was weaker in the second half of the unbiased block compared to the first. Another possibility is that updating the internal representation of the task structure carries a cognitive cost: Collins (2017) showed that structure learning reduced reward learning and increased response times. A similar cost may have slowed the updating of task structure in our task.

### Demand Avoidance Is Not Driven by Implemented Control

Our participants did not avoid choice options that yielded mostly previously MI items, even though they still demanded more focused control. This finding suggests that the costly nature of cognitive control is not bound in the event file along with visual features, motor features, and control settings (e.g., Dignath et al., 2019; Hommel, 1998, 2022; Jiang et al., 2015). Otherwise, the retrieval of this cost would have influenced choice in the unbiased DST phase.

In contrast, the lack of demand avoidance in the unbiased DST blocks of Experiments 2, 3a, and 3b suggests that the mere implementation of reactive control is not effortful. Even if the original cost was not encoded in the event file, the more focused scope of attention triggered by the previously MI items could have been registered as effortful. However, participants were indifferent between the two options in the unbiased phase. This result is consistent with an emerging literature that suggests that, unlike other forms of cognitive control, reactive control is automatic. Reactive control adjustments typically occur outside of awareness (Bejjani et al., 2020; Crump et al., 2008; Diede & Bugg, 2017, 2019) and are unaffected by high concurrent working memory demands (Spinelli et al., 2020; Suh & Bugg, 2021). Our results add to this literature and suggest a promising avenue for research aiming to increase the use of cognitive control in everyday life. If such demands for control can be set up so that they rely on reactive control, it would substantially diminish motivational and implementational constraints.

In both the biased and unbiased DST blocks, participants exerted more control for items from the MI option, but they only avoided them in the biased phase. This divergence between block types suggests that demand avoidance may not rely on the actual amount of implemented control. Instead, the results cohere with work that suggests that demand avoidance is driven by a more subjective assessment of costs. For example, Dunn et al. (2016) measured demand avoidance in a task that dissociated effort perception from objective behavioral markers such as RT and error rate. They found that participants avoided a task that they perceived as more effortful, even when contrasted with a task that yielded identical behavioral performance that was perceived as less effortful (Dunn et al., 2016). Our results complement these findings, showing that tasks that demand different levels of control can be perceived as equally effortful. Avoidance behavior in the biased DST phases of our tasks may have been driven by participants using the proportion of congruent trials (i.e., conflict) as a proxy cue for demand (Dunn & Risko, 2019; Dunn et al., 2019).

Models of effort-based decision making (Kool & Botvinick, 2014), and metacontrol at large (e.g., Lieder & Griffiths, 2017; Lieder & Iwama, 2021; Shenhav et al., 2013, 2017), suggest that control costs are estimated based on the actual amount of exerted control. By using these estimates during effort-based decision making, the brain can then choose lines of action that minimize the amount of control exerted. Our results suggest that these models should incorporate subjective assessments of control costs. So, models of metacontrol should rely on heuristics, effort-reducing short cuts, in estimating effort costs. Such an approach would also carry a computational benefit because the brain would avoid the counterproductive issue of using effort-demanding calculations to reduce effort downstream (Boureau et al., 2015).

## Limitations, Future Research, and Conclusions

Our experiments focused solely on reactive control demands. However, the DMCC also proposes that humans are able to deploy proactive control. Prior work suggests that humans find proactive control costly. For example, demand avoidance occurs when choice options are a priori associated with demand (Schouppe et al., 2014), and whenever participants can probabilistically anticipate the level of conflict of a choice option (such as in the biased DST block in Experiments 3a and 3b). Even though we cannot draw conclusions about proactive control from our own studies, they do invite a set of interesting questions. Is the costly nature of proactive control encoded in the event file? Do people avoid proactive demands for cognitive control, even in an unbiased DST phase? Or are assessments of proactive control demands similarly subjective and based on heuristic effort cues? These questions are ready to be tackled by future research.

While a choice between two options in a DST is a seemingly simple choice, it is worth considering that a multitude of factors might drive participants' preference for one choice option over the others. Several of these (e.g., location, deck color, and design) were counterbalanced to avoid a confound with demand avoidance (Kool et al., 2010). Yet, because we observed no significant demand selection effects in the unbiased DST blocks, it is possible that factors different from the cognitive effort imposed by the MC and MI items drove down demand avoidance. For example, in the face of weaker evidence of a difference between decks, participants may exploit an option they were comfortable with rather than exploring both choice options.[2] However, it should be noted all participants were encouraged to explore at the start of each block, and our task design ensured that they could not rapidly continue to choose the same option.

We decided to use the DST because it assesses choice preferences without explicitly signaling to participants how choice options differ. This feature of the task carries several advantages. Most importantly, it allows researchers to measure preferences in the absence of demand characteristics and to investigate how those preferences develop over time. However, there are also some downsides to this paradigm. As has been noted before, the DST requires people to first detect differences between options before they can avoid them (Juvina et al., 2018; Mækelæ et al., 2023), which may have influenced our assessment of reactive control costs in the unbiased phases. Importantly, our participants avoided reactive control costs in the biased DSTs, but they did not show this preference in the unbiased ones (even though we found transfer of the ISPC effects).

For example, participants may have simply not detected the differences in demand between options. While it is possible that participants were not aware of the difference, we observed reliable ISPC effects in the unbiased DST phases of each of our four experiments. That is, participants' attentional control systems treated the two decks differently. This result casts doubt on the idea that differences in demand were not detectable. Future research may investigate how reactive control costs are treated when differences between choice options are explicitly signaled. For example, using the Cognitive Effort Discounting paradigm from J. A. Westbrook and Braver (2013), one can investigate whether demand avoidance of reactive control emerges when people are informed of the costs and benefits of each option.

Another explanation for the difference between the biased and unbiased DST blocks is that people may have used a more explicit and proactive strategy in the biased phases. However, there are several reasons to believe that the biased DST assessed reactive control. First, we gave participants relatively few trials to learn a new association between deck and demands, whereas reactive control associations already existed at the start of these decks. Second, we gave participants no time to prepare control proactively after deck selection, because the Stroop stimulus was immediately presented. Evidence for proactive control is typically only observed when the cue to stimulus interval is lengthy (at least 2,000 ms; Bugg & Smallwood, 2016). More generally, several studies have shown that it is difficult to get participants to strategically use proactive control in the Stroop task (e.g., Bugg & Diede, 2018; Bugg et al., 2015; Suh et al., 2022; see also Liu & Yeung, 2020, for a similar finding in task switching), and its use tends to be limited to contexts in which reactive control is not an available option (Bugg, 2014), unlike in the biased DST blocks. Third,

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

Stroop performance in the biased DST blocks shows more signatures of reactive control compared to proactive control. Specifically, proactive control is marked by a congruency cost, or reduced facilitation from the word on congruent trials in MI conditions, resulting in slower RTs on congruent trials (Gonthier, Braver, & Bugg, 2016; Gonthier, Macnamara, et al., 2016). While the ISPC effect observed in the biased DST phase in Experiment 3a might show slightly more action on the congruent trials than is typical, consistent with a congruency cost, Experiment 3b firmly rules this possibility out. The ISPC effect in this experiment shows that this effect is stably driven by the incongruent trials, a key signature of reactive control.

In this article, we have reported four studies that together suggest that the implementation of reactive control does not register as costly. Even though actual differences in control demands persisted after the true bias was neutralized (i.e., an increased amount of reactive control implementation on previously MI compared to previously MC items), participants' choices did not track control demands. This pattern of results is consistent with the idea that reactive control may be automatic and not costly to implement. These results have important implications for adaptive control research (e.g., Braem et al., 2019), event file theory (e.g., Hommel, 2022), and models of metacontrol (e.g., Kool & Botvinick, 2014; Lieder & Griffiths, 2017; Lieder & Iwama, 2021; Shenhav et al., 2013, 2017).

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Received May 24, 2023
Revision received February 7, 2024
Accepted February 8, 2024 ■