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Appealing to the cognitive miser: How effort avoidance modulates cognitive flexibility in forced-choice and voluntary task switching

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Abstract

Current cognitive control accounts view goal-directed behavior as striking a balance between two antagonistic control demands: Stability, on the one hand, reflects a rigid, focused state of control and flexibility, on the other, reflects a relaxed, distractible state, whereby goals can be rapidly updated to meet unexpected changes in demands. In the current study, we sought to test whether the avoidance of cognitive demand could motivate people to dynamically regulate control along the flexibility-stability continuum. In both forced-choice (Experiment 1) and a voluntary (Experiment 2) task-switching paradigms, we selectively associated either task-switches or task-repetitions with high cognitive demand (independent of task identity), and measured changes in performance in a following phase after the demand manipulation was removed. Contrasting performance with a control group, across both experiments, we found that selectively associating cognitive demand with task repetitions increased flexibility, but selectively associating cognitive demand with task switches failed to increase stability. The results of the current study provide novel evidence for avoidance-driven modulations of control regulation along the flexibility-stability continuum, while also highlighting some limitations in using task-switching paradigms to examine motivational influences on control adaptation.

Keywords: cognitive control, task switching, cognitive flexibility, mental effort

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Current cognitive control accounts view goal-directed behavior as striking a balance between two antagonistic control demands (see Braem & Egner, 2018; Brosowsky and Crump, 2018; Braver, 2012; Dreisbach, 2012; Dreisbach and Frober, 2019; Diamond, 2013; Egner, 2014; Goschke, 2003, 2013; Hommel, 2015). Cognitive stability, on the one hand, is a rigid, focused state, enabling goal-maintenance and the suppression of distraction. Cognitive flexibility, on the other hand, is a relaxed, more distractible state, where goals can be rapidly updated to meet unexpected changes in demands. Importantly, the efficacy of biasing control towards stability or flexibility is context dependent. In some contexts, like studying, you need to focus on a singular task over sustained periods and ignore many potential distractions. In other contexts, like cooking, however, you need to monitor and quickly switch between multiple tasks (e.g., cutting vegetables, boiling water, heating oil in a pan). Even being 'distractible' in this context could be beneficial if a distraction alerts you to an important change in the task environment (e.g., being distracted by the sound of burning).

Accordingly, adopting contextually inappropriate control strategies can have negative consequences. You might fail to notice the burning oil because you were overly focused on cutting vegetables, for instance, or you might fail to remember critical exam material because you were insufficiently focused when studying. Failures to adaptively regulate control can thus be disruptive for everyday functioning and–if persistent—characterize various clinical disorders (Chamberlain, et al., 2006; Geurts, Corbett, and Solomon, 2009; Meiran, Diamond, Toder, & Nemets, 2011; see Goshke, 2014 for a review). For example, extreme flexibility may result in overlay distractible behavior as observed in attention deficit hyperactive disorder (ADHD).

Extreme stability, by contrast, may result in overly rigid or perseverative behavior as observed in obsessive compulsive disorder (OCD) and autism. Thus, identifying the factors that enable adaptive control regulation in a context-sensitive manner is both of theoretical and clinical relevance. In the current study, we sought to test whether the avoidance of cognitive demand could motivate people to dynamically regulate control along the flexibility-stability continuum.

In the laboratory, cognitive flexibility is often measured using task-switching paradigms, where participants switch between two simple cognitive tasks (see Dreisbach, 2019; Monsell, 2003). Whereas task repetitions benefit from stability, task switches require flexibility. In forced-choice variants, switching efficiency, as measured by a 'switch cost' (slower and more error-prone responding on switch versus repeat trials), is used to index control, with large switch costs indicating a stable mode of control and small switch costs indicating a more flexible mode of control. In voluntary choice variants—where participants are free to choose which task they perform on every trial—the switch rate is taken as an index of voluntarily engaged control. Here, low switch rates indicate adoption of a more stable mode of control and high switch rates a more flexible mode of control (Dreisbach, et al., 2019). Much research has focused on how changes in task context can influence adaptive control. For instance, varying the proportion of forced task-switches (e.g., Demanet, Verbruggen, Liefooghe, and Vandierendonck, 2010; Mayr and Bell, 2006), including predictive contextual cues (e.g., Crump and Logan, 2010), and varying stimulus availability (Mittelstädt, Dignath, Schmidt-Ott, & Kiesel, 2018; Mittelstädt, Miller, & Kiesel, 2018; 2019) have all been shown to modulate control regulation.

However, more recently, research has also begun to examine motivational influences on adaptive control regulation, such as rewards (for reviews see Chiew & Braver, 2011; Dreisbach & Fischer, 2012; Dreisbach & Fröber, 2019; Goschke & Bolte, 2014; Hommel, 2015). Numerous studies have now demonstrated that the prospect of a performance-contingent reward biases control regulation towards stability (Chiew & Braver, 2013; 2014; Fröber & Dreisbach, 2014, 2016a; Jimura, Locke, & Braver, 2010; Locke & Braver, 2008; Padmala & Pessoa, 2011) at the cost of flexibility (Hefer & Dreisbach, 2017; Müller et al., 2007). Braem, Verguts, Roggerman, and Notebaert (2012), for instance, used a forced-choice task switching paradigm and rewarded 25% of trials. They found increased switch costs on trials immediately following a reward, suggesting that the reward shifted participants' control regulation to a more rigid, stable, mode of control on the following trial (see also, Shen & Chun, 2011; Kleinsorge & Rinkenauer, 2012). However, there have also been some cases where rewards have been used to promote cognitive flexibility. For instance, when rewards are not contingent on performance, control tends to be biased towards flexibility (Fröber & Dreisbach, 2014, 2016a; Notebaert & Braem, 2015). Similarly, increasing reward prospect from one trial to the next tends to bias control towards flexibility on the following trial (as compared to when reward remains high or remains low; Fröber et al., 2020; Fröber & Dreisbach, 2016b; Fröber et al., 2019; Kleinsorge & Rinkenauer, 2012; Shen & Chun, 2011).

Finally, and most relevant for the current study, selectively rewarding task switches has also been shown to bias control regulation towards flexibility. Braem (2017) used a mixed forced-choice and voluntary task switching paradigm. Within each block of trials, the first half contained only forced-choice trials and the second half only voluntary task-selection trials. During the forced choice trials, one group of participants was selectively rewarded on task-switch trials, whereas another group was selectively rewarded on task-repetition trials. They found that participants who were selectively rewarded on task-switch trials had a higher voluntary task switch rate than participants who were selectively rewarded on task-repetition trials. This result suggests that control regulation can be conditioned (e.g., Abrahamse, Braem, Notebaert, &

Verguts, 2016, Egner, 2014, Braem & Egner, 2018; Verbruggen, McLaren, & Chambers, 2014), in this case towards flexibility, and persists even after rewards have been removed.

One key assumption is that rewards motivate adaptive control regulation because they offset the intrinsic costs of engaging in control. It is a longstanding and pervasive idea in psychology that people are “cognitive misers”, adapting their behavior to minimize cognitive demands (e.g., Allport, 1954; Hull, 1943; Rosch, 1999; Solomon, 1948; Zipf, 1949). In cognitive psychology, cognitive demand or ‘effort’ has long been associated with controlled information processing (Posner & DiGirolamo, 1998; Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977) whereby people weigh the intrinsic cost of engaging in controlled, effortful, processing against the potential gains in performance (Monsell, 2003). Indeed, evidence suggests that people tend to avoid engaging in controlled processing when they can offload such processing to learning and memory processes that exploit environmental regularities (e.g., Brosowsky and Crump, 2018; 2020; Crump and Brosowsky, 2016). Recent work also suggests that people explicitly avoid engaging in control-demanding tasks. In so-called ‘demand selection tasks’ (Botvinick & Rosen, 2009; Dunn & Risko, 2016; Gold et al., 2015; Kool et al., 2010; McGuire & Botvinick, 2010), participants can select between two alternative courses of action that vary in terms of cognitive demand—here, operationalized as the likelihood of a task switch (see Monsell, 2003). This work has demonstrated that people tend to avoid selecting courses of action associated with increased executive control (i.e., tasks with a high likelihood of switches; Dunn et al., 2016; Kool et al., 2010; Gold et al., 2015).

Taken together, the aforementioned research demonstrates that people tend to avoid demanding tasks—an observation typically attributed to the aversive nature of mental effort (e.g., Shenhav et al., 2017). However, it remains an open question whether the avoidance of demand can motivate people to bias their control regulation towards more stable or flexible control states. Control regulation is typically framed as a cost-benefit analysis, whereby the anticipated costs of control are weighed against the potential benefits (e.g., Shenhav, Botvinick, & Cohen, 2013). To date, however, there is little work examining how or whether the avoidance of ‘costs’ influences the adaptive regulation of control (e.g., Mittelstädt, et al., 2018; 2019). Such work is necessary for developing a comprehensive framework of the cost-benefit analysis. Furthermore, finding novel evidence that demand avoidance is (or is not) a determinant of control regulation would be important for understanding maladaptive control regulation—which may result from an inability to appropriately monitor and anticipate cognitive demand. To address this gap, we examined whether cognitive demand avoidance can motivate adaptive control regulation.

Therefore, in the current study we examined whether selectively associating high cognitive demand with task switches versus repetitions would bias control regulation towards flexible versus stable control strategies, respectively. Inspired by Braem (2017), we reasoned that if demand avoidance were a determinant of control regulation then selectively associating high cognitive demand with task repetitions should cause participants to bias their control regulation towards flexibility (i.e., adopting a control regulation strategy that avoids demand). Similarly, selectively associating high cognitive demand with task switches should bias control towards stability. Although our experimental design follows a similar logic as Braem (2017), we extended it in two important ways. First, we included a third, control, group who received an equal number of high and low demand trials, unassociated with task switches and repetitions. Braem (2017) did not include such a control group. Without a baseline comparison, however, it is unknown whether their manipulation influenced both groups equally (i.e., increased flexibility in one group and decreased flexibility in the other) or only influenced one group (e.g., influenced flexibility in one group, but had no influence on the other group), as both possibilities could result in a difference between groups. Therefore, including the control group allows us to assess whether the avoidance of demand produces symmetrical effects along the stability-flexibility dimension. Second, we examined the influence of cognitive demand (rather than reward) on forced choice and voluntary task selection independently to determine whether our manipulation would influence task-switching efficiency and overt task selection behavior in a similar manner.

Experiment 1

In Experiment 1, we examined control regulation in the context of a forced-choice, cued task switching paradigm. On every trial an array of shapes was presented, and participants completed either a color or shape discrimination task, indicating which one out of two possible colors/shapes were presented in a higher quantity. Critically, cognitive demand was manipulated by varying the relative proportions of each shape or color, thereby increasing or decreasing the relative discriminability of the target stimulus (see Method). Participants were randomly assigned to one of three groups ("Flexible", "Stable" or "Control" group), each completing a learning and a transfer phase. In the learning phase, high cognitive demand was either associated with task repetitions (Flexible group), task switches (Stable group), or randomly assigned on every trial (Control group). In the transfer phase, all three groups received the same 'medium' demand trials (as determined by the titration phase; see Method). Thus, we expected that the learning phase would bias control regulation, which would then persist through the transfer phase (e.g., Braem 2017), as evidenced by smaller switch costs for the flexible group and larger switch costs for the stable group, as compared to our control group.

Method

Sample Size Justification

Sample sizes were determined by estimating the power to detect a range of effects using a Monte-Carlo simulation approach (e.g., Brosowsky et al., 2020; Crump et al., 2016). Using pilot data we collected using the current paradigm we estimated the distributions of ex-gaussian parameters representative of participant response times ($mu = 850$ ms [$sd = 243$ ms], $sigma = 224$ ms [$sd = 114$ ms], $tau = 265$ ms [$sd = 79ms$]). For each simulated participant, we sampled ex-gaussian parameters (truncated to +/- 1.5 standard deviations) and sampled 240 response times (120 switch/120 repeat trials) from the ex-gaussian distribution. To create a "switch cost" we subtracted half switch cost effect from the sampled response times on 'repeat' trials and added half the switch cost effect to the sampled response times on 'switch' trials. In particular, we were interested in estimating our ability to detect changes in the switch cost across two groups. The effect size, therefore, was the size of the difference in response time switch costs between groups (e.g., a 30-ms difference in switch costs). For each effect size and sample size we ran 1000 simulations analyzing the simulated data using a linear mixed-effect model with Group (High Switch Cost and Low Switch Cost) and Task (Repeat and Switch) as fixed effects and Subject as a random effect. From these simulations, we estimated that a minimum 38 participants per group were needed to detect a 30 ms difference in switch costs between groups with 80% power. We collected 50 participants per group to ensure we would meet this minimum threshold. With 50 participants we estimated we could detect a 30 ms difference in switch costs with 90% power (code and results available at osf.io/????).

Participants

Participants were 150 individuals (age = 40.35; 65 identified as female, and 83 identified as male) who completed a Human Intelligence Task (HIT) posted on the Amazon Mechanical Turk. Participants were paid $3.50 (U.S. dollars) for completing the HIT, which lasted approximately 25 minutes. Only Amazon workers who had completed more than 5000 HITs with 98% approval were able to complete the experiment.

Apparatus and Stimuli

The experiment was programmed in JavaScript and HTML/CSS. The experiment was presented in full-screen and stimuli were presented at the center of an off-white screen in near-black colored font. The response-key mappings were displayed throughout the experiment below the stimulus display.

Throughout the experiment, participants completed color and shape discrimination tasks. For each task, 100 non-overlapping shapes were presented in random positions on a 400 x 400 px display. Instructions indicating which response corresponded with which key were always presented below the stimulus. In the color task, participants had to indicate whether there were more light blue (hexidecimal color code: #) or dark blue (hexidecimal color code: #) circles. Participants responded by pressing “Z” on the keyboard if there were more light blue than dark blue circles or “M” if there were more dark blue than light blue circles. In the shape task, participants had to indicate whether there were more black squares or black triangles. Participants responded by pressing “N” if there were more black squares or “M” if there were more black triangles. If participants responded correctly, the word “Correct” was displayed in green font for 500 ms before the next trial automatically began. If they responded incorrectly, the words

“Incorrect. Press the space bar to continue.” were displayed in red font. Pressing the space bar triggered the next trial.

Participants were randomly assigned to one of three groups (hereafter referred to as the “Flexible”, the “Stable”, and the “Control” groups) and completed three phases: a Titration phase, a Learning phase, and a Transfer phase. The first, Titration, phase contained two blocks of 96 trials, each consisting of only one of the two tasks, randomly assigned to the first or second block. These two blocks served to titrate the difficulty of each task independently. We used a 3-up-1-down adaptive staircase procedure to titrate the difficulty of each task. On each step, the relative proportion of shapes shifted by 2 out of 100 items. After three consecutive correct responses, the difficulty increased by one step. After an incorrect response, the difficulty decreased by one step. At the end of the 96 trials, the titrated proportion was assigned to the “Medium” demand for the remainder of the experiment. The Low and High demand trials were determined by selecting the proportion halfway between the Medium demand and 0/100 (Low) and halfway between Medium and 50/50 (High). For example, if a participant titrated to 66/100 as the medium demand, low was set at 83/100 and high was set at 58/100.

The second, Learning, phase, consisted of 241 trials, consisting of an equal number of color and shape trials, an equal number of low- and high-demand trials, and an equal number of task switches and task repetitions. We used custom functions to create trial lists ensuring these criteria were met. This required an extra trial at the beginning of the experiment. This trial was randomly assigned a difficulty but removed prior to all analyses. The association between difficulty and task-repetition differed across groups. For the Flexible group, every task-switch trial contained a low-demand target stimulus and every task-repeat trial contained a high-demand target stimulus. For the Stable group, every task-switch trial contained a high-demand target stimulus and every task-repeat trial contained a low-demand target stimulus. For the Control group, difficulty was randomly assigned on every trial with the constraint that there were an equal number low- and high-demand trials throughout the phase.

The third, and final, Transfer phase, consisted of 240 trials, an equal number of color and shape trials, and an equal number of task repeat and task switch trials. Critically, however, for all groups, all trials were medium demand.

Procedure

Participants were first given instructions and a general overview of the experiment. They were informed that they would have to complete one of two tasks on every trial and to respond as quickly and as accurately as possible. However, they were not informed about the difficulty manipulations. Verbatim instructions can be found in Appendix A. Participants then completed a titration block for each of the color and shape tasks in a random order, followed by the learning phase, then finally, the transfer phase. The learning and transfer phases were separated by an additional instruction screen, informing participants they were half-way finished the experimental trials and reiterating the instructions.

Results

Data analysis and manuscript preparation

This manuscript was prepared using R (R Core Team, 2019). A variety of notable R packages were used for data analysis (Bates et al., 2015; Fox & Weisberg, 2019; Kuznetsova et al., 2017; Singmann et al., 2019; Wickham et al., 2019; Wickham & Henry, 2019), data visualization (Fox & Weisberg, 2018; Kassambara, 2019; Lenth, 2018; Wickham, 2016; Wilke, 2019), and general manuscript preparation (Aust & Barth, 2018). All data, analysis, and manuscript preparation code can be found at osf.io/????/.

Participants with less than 60% accuracy in the transfer phase were excluded from all analyses. This removed 3 participants from the Flexible group, 2 participants from the Stable group, and 1 participant from the Control group. Prior to all analyses, the first trial for each block was removed and any trials with a response time greater than 3 seconds or less than 300 milliseconds were removed (removing 3.3% of observations). In addition, for response time analyses, all error trials were removed, all trials where the previous trial was an error were removed, and then finally, the van Selst and Jolicoer non-recursive outlier removal procedure was applied (Van Selst and Jolicoeur, 1994), removing 2.8% of observations.

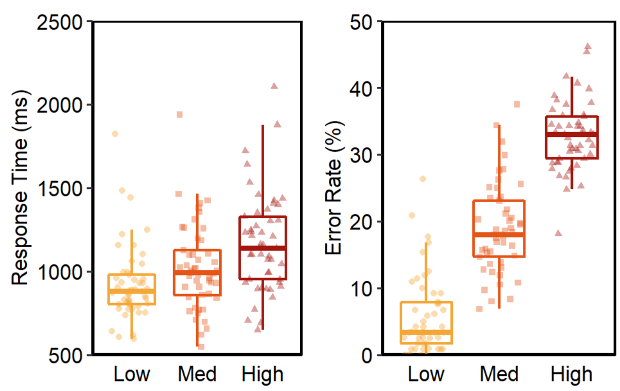

Figure 1. Results from the control group in Experiment 1. Response times and error rates are plotted as a function demand (low, medium, and high).

Titration and Difficulty Analyses

First, we sought to determine the success of our titration and cognitive demand manipulations. Collapsing across groups, we compared the resulting titration levels and found that the shape task ($M = 0.68$), on average, titrated to an easier difficulty than the color task ($M = 0.62$), $M_d = -0.05$, 95% CI [-0.06, -0.04], $t(143) = -9.46$, $p <$ .001.

Next, to validate whether the difficulty manipulations were successful, we examined performance across across the three levels of difficulty (Low, Medium, and High) for the control Group (see Figure 2; see Appendix A for full model results). As a reminder, the Control group completed Low, Medium, and High demand trials on both task-switches and task-repetitions. Therefore, the Control group performance provides the clearest estimate of our demand manipulation, independent of task-switching. To analyze the response times, we used a linear mixed-effect model with Demand as a fixed effect and Subject as a random effect. We found that participants in the control Group were significantly quicker responding on the Low trials ($M =$ 921.25 ms), as compared to both the Medium ($M = 1021.11$ ms), $\beta = 99.87$, 95% CI [87.59, 112.14], $t(17718.39) = 15.94$, $p <$ .001, and the High trials ($M = 1172.61$ ms), $\beta = 251.37$, 95% CI [236.17, 266.56], $t(17718.33) = 32.42$, $p <$ .001. Participants were also quicker to respond on Medium Trials as compared to High trials, $\beta = 151.5$, 95% CI [137.63, 165.38], $t(17718.42) = 21.4$, $p <$ .001.

We also compared error rates across each of the demand conditions and found that participants produced significantly fewer errors on Low trials ($M = 5.82$%), as compared to both Medium ($M = 18.95$%), $t(94.49) = -9.92$, $p <$ .001; and High trials ($M = 32.74$%), $t(93.63) = -23.44$, $p <$ .001. Similarly, participants produced significantly more errors on High versus Medium Trials, $t(89.02) = -11.11$, $p <$ .001.

In sum, we found our titration method successfully produced 15-20% error rates, on average, and our demand manipulations successfully produced low (as evidenced by quicker response times and lower error rates) and high demand trials (as evidenced by slower response times and higher error rates).

Task Performance

First, we analyzed task performance using a linear mixed-effects model for response times and mixed ANOVA for error rates. For the response time analyses, we included Group (Flexible, Stable, and Control), Task Transition (Switch and Repeat), and Phase (Learning and Transfer) as fixed effects, and subject as a random effect. For the error rate analysis we included Task Transition and Phase as within-subjects factors and Group as the between-subjects factor. In both, the response time and the error rate analyses, we found significant three-way interactions (ps $< .001$), indicating that performance differed across the phases. To follow-up these interactions, we analyzed the learning and transfer phases separately. For the complete model results, see Appendix A.

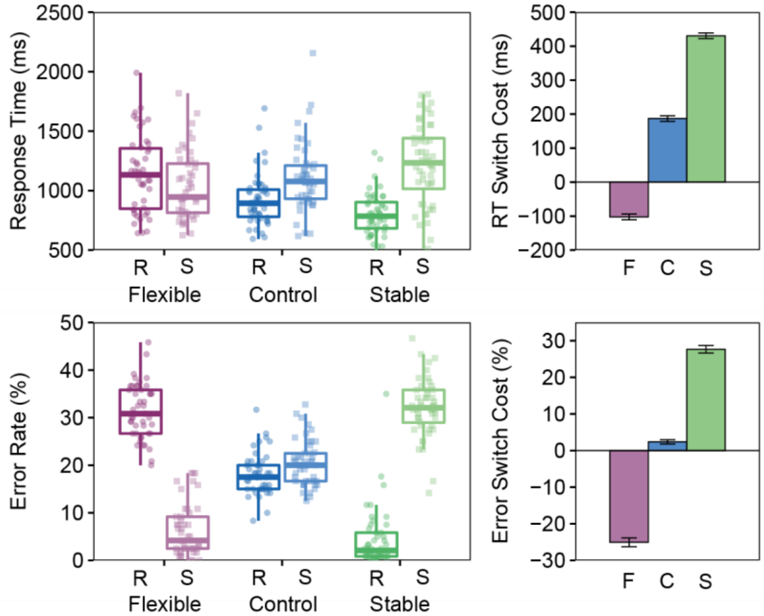

Figure 2. Results from the learning phase in Experiment 1. Participant mean response times and error rates are plotted as a function of group and trial type (S = task switch and R = task repeat). RT and error switch costs (as estimated by the generalized linear mixed models) are plotted as a function of group (F = flexible, C = control, and S = stable). Error bars represent standard error of the mean.

Learning Phase. To analyze response times (see Figure 3), we used a linear mixed-effects model with Group (Flexible, Stable, and Control) and Task (Switch and Repeat) as fixed effects and subject as a random effect. We were particularly interested in how switch costs (response times on switch trials minus repeat trials) varied across groups. To that end, we found that participant switch costs were significantly smaller for the Flexible group ($M = -102.33$ ms) as compared to the Control group ($M = 186.94$ ms), $\beta = -289.28$, 95% CI [-312.34, -266.22], $t(21352.77) = -24.59$, $p < .001$, as well as the the Stable group ($M = 430.54$ ms), $\beta = 532.87$, 95% CI [509.75, 556], $t(21352.85) = 45.16$, $p < .001$. Additionally, the switch cost for the Stable group was significantly larger than the Control group, $\beta = 243.6$, 95% CI [220.85, 266.34], $t(21352.22) = 20.99$, $p < .001$.

Next, we analyzed error rates using a mixed ANOVA with Group as the between-subjects factor and Task as the within-subjects factor. Here, we found a significant main effect of Task, $F(1{,}141) = 8.33$, $MSE = 23.82$, $p = .005$, $\hat{\eta}_p^2 = .056$, but no main effect of Group, $F(2{,}141) = 0.74$, $MSE = 37.86$, $p = .477$, $\hat{\eta}_p^2 = .010$, both qualified by an interaction between Group and Task, $F(2{,}141) = 677.81$, $MSE = 23.82$, $p < .001$, $\hat{\eta}_p^2 = .906$. Comparing switch costs across groups we found significantly lower error switch costs for the Flexible group ($M =$ 18.6%) as compared to the Control ($M = 8.6\%$), $t(65.66) = -19.09$, $p < .001$, and Stable groups ($M = 14.74\%$), $t(88.35) = -31.93$, $p < .001$. Switch costs were also significantly larger for the Stable group as compared to the Stable group, .

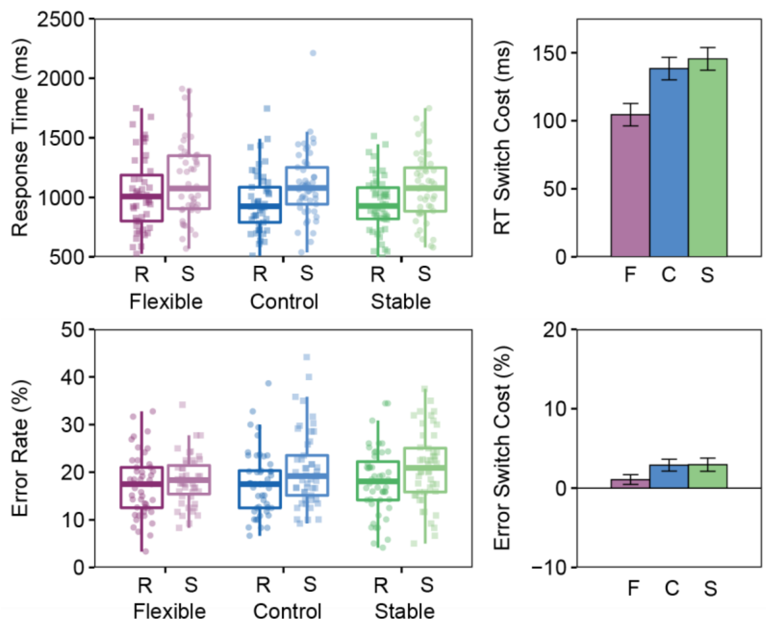

Figure 3. Results from the transfer phase in Experiment 1. Participant mean response times and error rates are plotted as a function of group and trial type (S = task switch and R = task repeat).

RT and error switch costs (as estimated by the generalized linear mixed models) are plotted as a function of group (F = flexible, C = control, and S = stable). Error bars represent standard error of the mean.

Transfer Phase. Turning to the response times in the Transfer phase (see Figure 4), we found significantly smaller switch costs in the Flexible group ($M = 104.49$ ms) as compared to the Control group ($M = 138.32$ ms), $\beta = -33.83$, 95% CI [-56.69, -10.98], $t(21396.03) = -2.9$, $p = 0.004$, as well as the the Stable group ($M = 145.47$ ms), $\beta = 40.98$, 95% CI [18.07, 63.9], $t(21395.75) = 3.51$, $p < .001$. However, the switch costs did not significantly differ between the Stable and Control groups, $\beta = 7.15$, 95% CI [-15.74, 30.04], $t(21396.16) = 0.61$, $p = 0.54$. Finally, we examined error rates using a mixed ANOVA and found a significant main effect of Task, $F(1{,}141) = 31.30$, $MSE = 13.95$, $p < .001$, $\hat{\eta}_p^2 = .182$, but no main effect of Group, $F(2{,}141) = 0.79$, $MSE = 80.50$, $p = .457$, $\hat{\eta}_p^2 = .011$ and no interaction between Group and Task, $F(2{,}141) = 1.49$, $MSE = 13.95$, $p = .228$, $\hat{\eta}_p^2 = .021$.

Discussion

In Experiment 1, we manipulated the cognitive demand associated with task-switch versus repetition trials across three groups of participants to determine whether the avoidance of cognitive demand would motivate participants to engage in more flexible or stable control strategies. First, results from the learning phase demonstrate that our demand manipulations were successful: Participants in the Flexible group showed reversed switch costs and participants in the Stable group showed inflated switch costs compared to our control group. We then compared performance in the transfer phase, where all three groups received medium-demand trials. Here, we find smaller switch costs for the Flexible group as compared to the Control and Stable groups. Thus, selectively associating high cognitive demand with task-repetitions appears to have biased control regulation towards flexibility, improving switching efficiency for this group in the transfer phase. This suggests that the avoidance of cognitive demand can indeed motivate participants to shift their control strategy towards flexibility. However, we did not find any evidence for differences in switch costs between the Stable and Control groups, suggesting that selectively associating high cognitive demand with task-switches did not influence their switching efficiency relative to the control group. That is, despite the increase in demand associated with task switching during the learning phase, these participants did not show any changes in control regulation as compared to the control group.

Experiment 2

In Experiment 2, we examined whether cognitive demand avoidance would motivate control regulation in the context of a voluntary task-switching paradigm. In a forced-choice context, the experimenter determines whether any given trial, or set of trials, requires flexibility. Thus, some have argued that voluntary task-switching paradigms, where participants are free to choose the task on each trial, provides a more direct measure of control because flexibility (or stability) is truly optional (Arrington & Logan, 2004). Research using the demand selection task has already shown that participants tend to select lists of trials with low switch rates versus high switch rates, suggesting that participants were sensitive to the demand-context associations and adjusted behavior to avoid high demand (e.g., Gold et al., 2015; Kool et al., 2010). Thus, we might expect that when repeat trials are associated with high demand, participants will increase their voluntary switch rates and when switch trials are associated with high demand, participants will decrease their voluntary switch rates.

Our task, however, differs in some important ways from the prior. In the demand selection task, participants choose between two task contexts, each associated with a high or low demand, which is incidentally manipulated using the frequency of task-switches (e.g., Demanet, Verbruggen, Liefooghe, and Vandierendonck, 2010; Mayr and Bell, 2006; Mittelstädt et al., 2018). In the voluntary task-switching paradigm, by contrast, we are not interested in which task participants choose on any given trial. Instead, we are interested in whether participants choose to switch more or less frequently between the two tasks, indicative of a more flexible or stable control strategy. This is a subtle, but important distinction. Selecting a low-demand over high-demand does not necessarily require a shift in control strategy but switching more frequently does. Therefore, although the prior work suggests people will avoid demand, it cannot speak to whether demand avoidance can motivate changes in adaptive control regulation along the flexibility-stability continuum.

One final point worth discussing is the tendency for participants to choose to repeat tasks more often than switch (e.g., Arrington & Logan, 2005; Arrington, Weaver, & Pauker, 2010; Mittelstädt, et al, 2018). That is, despite participants being instructed to choose each task equally as often in a random order (Arrington & Logan, 2005), participants typically show a repetition bias, producing repetitions more often than expected by chance. The repetition bias in task-switching stands in contrast to the well-established finding that when asked to generate random sequences, people tend to alternate more often than repeat (Nickerson, 2002; Rapoport & Budescu, 1997). To account for the repition bias, Arrington and Logan (2005) suggested that task selection is driven by two competing heuristics: The availability heuristic, where tasks are selected on the basis of the most active task set (Baddely, 1996) and the representiveness heuristic, where tasks are selected on the basis of a mental representation of a random sequence (Rapopart & Budescu, 1997). Critically, the assumption is that participants are biased towards using the availability heuristic because it is less effortful than the representativeness heuristic (e.g., Mittelstädt et al., 2018; Vandierendonck et al., 2012; Yeung, 2010).

Returning to the current study, we can make some additional predictions regarding the learning phase. Specifically, if the repetition bias is driven solely by effort-avoidance, we should expect to see the bias abolished when task-repetitions are made more effortful; in fact, we might even expect to observe a switch-bias. Similarly, we might expect to inflate the repetition bias by making task-switches even more demanding relative to task-repetitions. As in Experiment 1, however, the primary question of interest is not whether participants adapt during the learning phase, but whether we observe differences in performance when the demand-manipulation is removed during the transfer phase. Such effects would be indicative of adaptive control regulation driven by demand-avoidance.

Method

Participants

Participants were 150 individuals (mean age = 40.58; 72 identified as female, and 75 identified as male) who completed a Human Intelligence Task (HIT) posted on Amazon Mechanical Turk. Participants were paid $3.50 (U.S. dollars) for completing the HIT, which lasted approximately 25 minutes. Only Amazon workers who had completed more than 5000 HITs with 98% approval were able to complete the experiment.

Apparatus and stimuli

The apparatus and stimuli were nearly identical to those used in Experiment 1. However, on every trial, participants were first presented the task-selection display (“Shape or Color?”) and responded by pressing “Z” for shape or “X” for color. After task selection, a blank screen was displayed for 750 ms, followed by the target stimulus. In the shape task, participants had to indicate whether there were more black squares or black triangles. Participants responded by pressing “N” if there were more black squares or “M” if there were more black triangles. If participants responded correctly the word “Correct” was displayed in green font for 500 ms before the next trial automatically began. If they responded incorrectly, the words “Incorrect. Press the space bar to continue.” were displayed in red font. Pressing the space bar triggered the next trial.

Procedure

Participants were first given instructions and a general overview of the experiment. As in Experiment 1, they were informed that they would have to complete one of two tasks on every trial and to respond as quickly and as accurately as possible, and were unaware of the task demand manipulations. Unlike Experiment 1, participants were given additional instructions about selecting the task on every trial. Specifically, they were instructed to try to select each of the tasks about equally as often, in a random order (Arrington & Logan, 2005; Verbatim instructions can be found in Appendix A). Participants then completed a titration block for each of the color and shape tasks in a random order, followed by the learning phase, then finally, the transfer phase. The learning and transfer phases were separated by an additional instruction screen, informing participants they were half-way finished the experimental trials and reiterating the general instructions.

Results

Data Analysis

All data analysis procedures were identical to those outlined in Experiment 1.

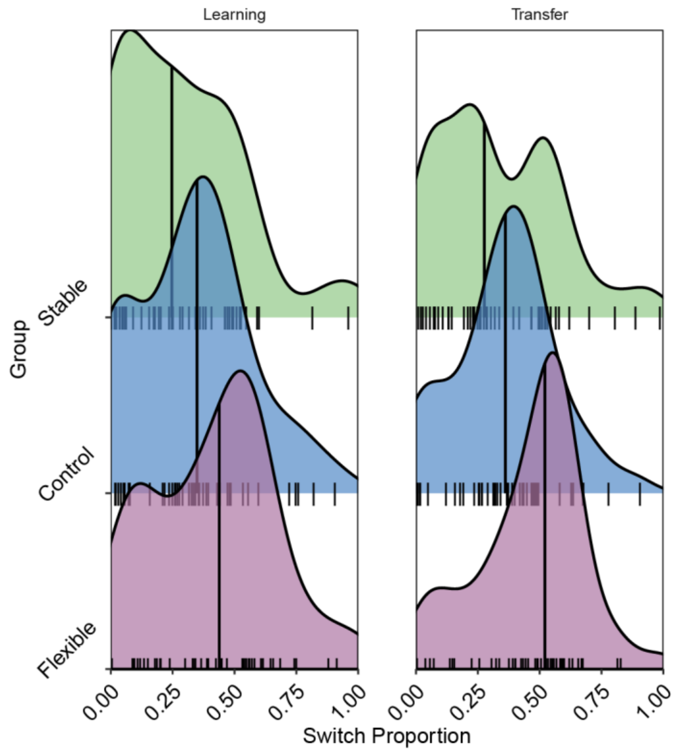

Figure 4. Results from Experiment 1. Switch proportions are plotted by Group (Flexible, Control, and Stable) and Phase (Learning and Transfer).

Difficulty and titration analyses

Collapsing across groups, we compared the resulting titration levels and found that the shape task ($M = 0.65$), on average, titrated to an easier difficulty than the color task ($M = 0.61$), $M_d = -0.05$, 95% CI $[-0.06, -0.04]$, $t(144) = -9.89$, $p < .001$.

As in Experiment 1, to validate whether the demand manipulations were successful, we examined performance across across the three levels of difficulty (Low, Medium, and High) for the control Group. To analyze the response times, we used a linear mixed-effect model with Difficulty as a fixed effect and Subject as a random effect. We found that participants in the control Group were significantly quicker responding on the Low trials ($M = 957.68$ ms), as compared to both the Medium ($M = 1077.14$ ms), $\beta = 119.46$, 95% CI [106.33, 132.59], $t(17186.6) = 17.83$, $p < .001$, and the High trials ($M = 1251.6$ ms), $\beta = 293.92$, 95% CI [277.47, 310.38], $t(17186.73) = 35.01$, $p < .001$. Participants were also quicker to respond on Medium Trials as compared to High trials, $\beta = 174.46$, 95% CI [159.37, 189.56], $t(17186.29) = 22.65$, $p < .001$.

We also compared error rates across each of the demand conditions and found that participants produced significantly fewer errors on Low trials ($M = 3.43\%$), as compared to both Medium ($M = 16.54\%$), $t(56.58) = -10.34$, $p < .001$; and High trials ($M = 30.36\%$), $t(60.96) = -24.58$, $p < .001$. Similarly, participants produced significantly more errors on High versus Medium Trials, $t(87.56) = -8.86$, $p < .001$.

To summarise, the results of the titration and demand manipulations in Experiment 2, replicated the results of Experiment 1: we found our titration method successfully produced 15-20% error rates, on average, and our demand manipulations successfully produced low (as evidenced by quicker response times and lower error rates) and high demand trials (as evidenced by slower response times and higher error rates).

Task Selection

We submitted the task selection responses, as a proportion of task switches, to a mixed ANOVA with Group (Flexible, Stable, and Control) as the between subjects factor and Phase (Learning and Transfer) as the within-subjects factor (see Figure 5). First, we found no significant interaction between Group and Phase, $F(2{,}143) = 0.14$, $MSE = 0.02$, $p = .873$, $\hat{\eta}_p^2 = .002$. There was a main effect of Group, $F(2{,}143) = 5.07$, $MSE = 0.09$, $p = .007$, $\hat{\eta}_p^2 = .066$; Participants in the Flexible group ($M = 0.44$) produced significantly more task switches than participants in the Control group ($M = 0.34$), $t(92.48) = 2.19$, $p = .031$, and the Stable group ($M = 0.31$), $t(97.98) = 3.09$, $p = .003$. However, there was no significant difference in switch rates between the Stable and Control groups, $t(94.65) = 0.87$, $p = .386$.

There was also a signifcant main effect of Phase, $F(1{,}143) = 8.90$, $MSE = 0.02$, $p = .003$, $\hat{\eta}_p^2 = .059$. Participants across all groups showed an increase in switch rates from the Learning phase ($M = 0.34$) to the Transfer phase ($M = 0.39$).

Task Performance

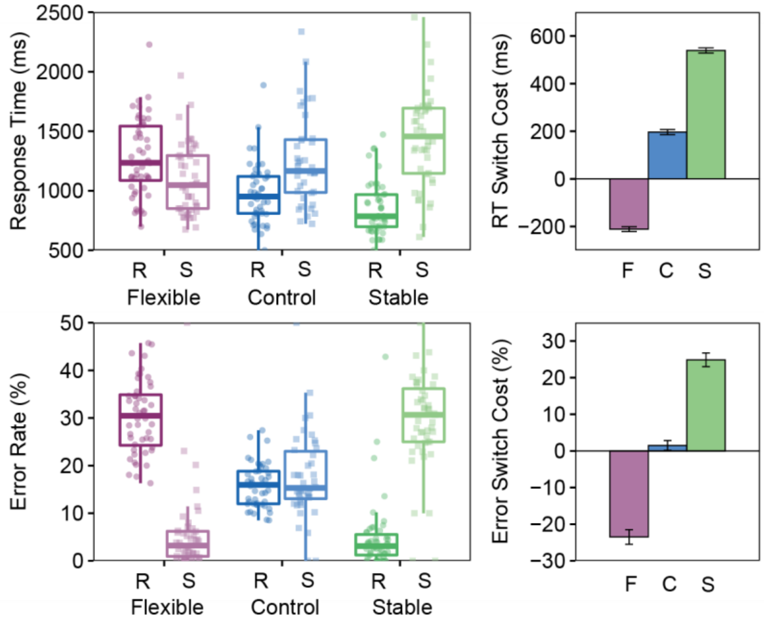

Figure 5. Results from the learning phase in Experiment 2. Participant mean response times and error rates are plotted as a function of group and trial type (S = task switch and R = task repeat). RT and error switch costs (as estimated by the generalized linear mixed models) are plotted as a function of group (F = flexible, C = control, and S = stable). Error bars represent standard error of the mean.

Learning Phase. To analyze response times, we used a linear mixed-effect model with Task (Switch and Repeat) and Group (Flexible, Stable, and Control) as fixed effects, and subject as a random effect (see Figure 6; for full model results, see Appendix B). We found RT switch costs to be significantly smaller for the Flexible group ($M = -211.07$ ms), as compared to the Control ($M = 197.68$ ms), $\beta = -408.75$, 95% CI [-437.44, -380.06], $t(23268.24) = -27.92$, $p < .001$, and Stable groups ($M = -211.07$ ms), $\beta = 750.02$, 95% CI [720.91, 779.13], $t(23271.32) = 50.5$, $p < .001$. Similarly, switch costs were significantly larger for the

Stable group compared to the Control group, $\beta = 341.27$, 95% CI [311.03, 371.5], $t(23270.05) = 22.12$, $p < .001$.

Turning to error rates, using a mixed-ANOVA with Group and Task as factors (removing 10 participants with missing cells), we found a significant interaction between Group and Task, $F(2{,}133) = 192.21$, $MSE = 71.52$, $p < .001$, $\hat{\eta}_p^2 = .743$, but no significant main effect of Task, $F(1{,}133) = 0.89$, $MSE = 71.52$, $p = .348$, $\hat{\eta}_p^2 = .007$, or Group, $F(2{,}133) = 0.65$, $MSE = 103.57$, $p = .524$, $\hat{\eta}_p^2 = .010$. Comparing error switch costs across groups, we found significantly lower switch costs for the Flexible group ($M = -23.48\%$) as compared to the Control ($M = 1.5\%$), $t(78.59) = -10.47$, $p < .001$, and Stable groups ($M = 24.88\%$), $t(91.63) = -17.77$, $p < .001$. Similarly, switch costs were significantly larger for the Stable group as compared to the Stable group, .

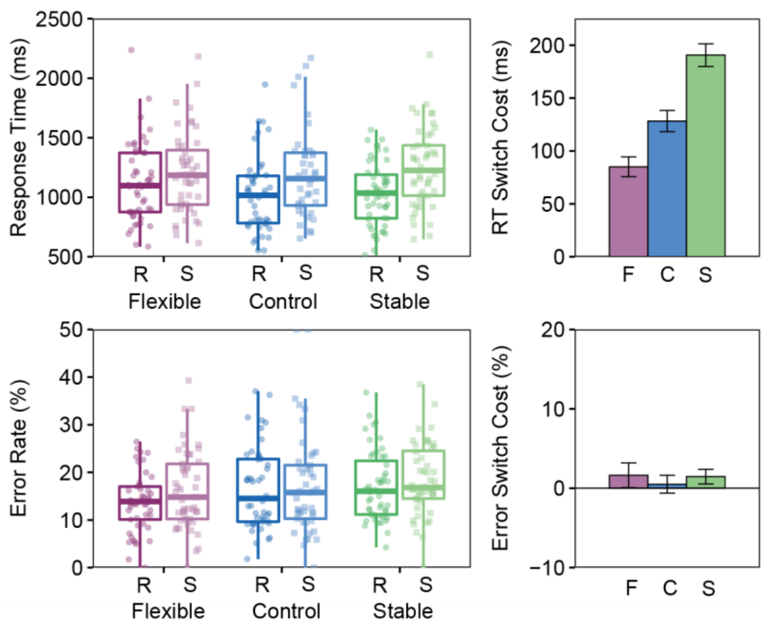

Figure 6. Results from the transfer phase in Experiment 2. Participant mean response times and error rates are plotted as a function of group and trial type (S = task switch and R = task repeat).

RT and error switch costs (as estimated by the generalized linear mixed models) are plotted as a function of group (F = flexible, C = control, and S = stable). Error bars represent standard error of the mean.

Transfer Phase. Analyzing response times using a linear mixed-effect model with Group and Task as fixed effects and Subject as a random effect, we found significantly smaller RT switch costs in the Flexible group ($M = 84.91$ ms) as compared to the Control group ($M = 129.18$ ms), $\beta = -44.27$, 95% CI $[-71.15, -17.39]$, $t(22873.36) = -3.23$, $p = 0.001$, as well as the the Stable group ($M = 190.53$ ms), $\beta = 105.62$, 95% CI [77.82, 133.43], $t(22896.98) = 7.45$, $p < .001$. Moreover, we found significantly larger switch costs in the Stable group compared to the Control group, $\beta = 61.35$, 95% CI [32.64, 90.07], $t(22897.88) = 4.19$, $p < .001$.

Analyzing error rates using a mixed-ANOVA with Group and Task as factors (removing 4 participants with missing cells), we found no significant main effects of Task, `e2$er.t.task` or Group, $F(2{,}139) = 1.15$, $MSE = 114.62$, $p = .321$, $\hat{\eta}_p^2 = .016$; And no significant interaction between Group and Task, $F(2{,}139) = 0.24$, $MSE = 36.13$, $p = .790$, $\hat{\eta}_p^2 = .003$.

Discussion

In Experiment 2, we again manipulated the cognitive demand associated with task-switches versus repetition trials to determine whether the avoidance of cognitive demand would motivate participants to engage in more flexible versus stable control strategies. Unlike Experiment 1, however, we used a voluntary task-switching paradigm to determine whether the demand manipulation would influence voluntary switch rates. First, performance in the learning phase again demonstrates the success of our demand manipulations on response time and error rates: Participants in the Flexible group produced reverse switch costs and participants in the Stable group produced inflated switch costs (as compared to the Control group). Our primary measure of interest was the overt task selection behavior, however. Here, whereas the Flexible group produced higher ta switch rates than both Stable and Control groups across learning and transfer phases, there was no evidence that the Stable group produced fewer task switches than the Control group. Turning to task-switching efficiency, we observed differences across all three groups in the transfer phase, with the Stable group producing the largest switch cost, followed by the Control group, and then the Flexible group. This result is consistent with prior work showing switch costs are sensitive to the frequency of switch rates (e.g., Demanet, Verbruggen, Liefooghe, and Vandierendonck, 2010; Mayr and Bell, 2006; Mittelstädt et al., 2018).

Taken together, these results mirror the effects from Experiment 1: Whereas we found evidence that selectively associating high demand with task-repetitions could bias control regulation towards flexibility, we found only weak evidence that selectively associating high demand with task-switches could bias control regulation towards stability. In this case, we found no difference in task selection switch rates (our primary measure of interest) but did find differences in switching efficiency which are consistent with a more stable mode of control.

General Discussion

To date, most research examining motivational influences on control regulation has focused on rewards, manipulating the receipt or prospect of a reward and measuring the transient aftereffects (Chiew & Braver, 2013; 2014; Fröber & Dreisbach, 2014, 2016a; 2016b; Fröber et al., 2020; Fröber & Dreisbach, 2016b; Fröber et al., 2019; Shen & Chun, 2011). Braem (2017) demonstrated that selectively rewarding task-switches, as compared to task-repetitions, could motivate participants to adopt more flexible control strategies, even after the rewards were no longer present. Typically, the influence of reward on cognitive control is explained as a cost-benefit tradeoff, whereby the intrinsic costs of engaging in control are offset by increasing the potential reward (e.g., Shenhav et al., 2013). This view suggests that the costs of control regulation may be as important as the potential rewards for determining control states. However, no prior study has examined the extent to which the avoidance of behavioral costs can motivate adaptive control regulation. In the current study, we tested whether the selective association of high cognitive demand with task switches versus repetitions can influence control regulation along the stability-flexibility continuum. In both experiments, we find clear evidence that selectively associating task repetitions with high demand can bias control towards a more flexible control state (as evidenced by lower switch costs and higher voluntary switch rates). However, we found little evidence that selectively associating task switches with high demand biased participants to adopt a more stable control state; In Experiment 1, for instance, we found no differences in switch costs and in Experiment 2, we found no differences in voluntary switch rates, but did find larger switch costs. Taken together, these results provide the first evidence that the avoidance of cognitive demand can motivate people to bias their control regulation along the flexibility-stability continuum and suggests that demand-avoidance is an important determinant of adaptive control regulation.

One plausible explanation for the asymmetry in our results–successfully biasing control towards flexibility, but not stability–is that task-switching paradigms, like the ones used here, already biases control towards stability. Assuming task-switching is inherently more demanding than repeating (cf. Gold et al., 2015; Kool et al., 2010), participants may naturally be biased towards a more stable control state. That is, stability is the default control state in a typical task-switching paradigm and, therefore, making switching more demanding, cannot motivate participants to engage more strongly in a strategy they are already engaging in. Interestingly, this limitation might be specific to motivational influences, since, for example it is possible to increase switch costs by manipulating the proportion of task-switches (e.g., Demanet, Verbruggen, Liefooghe, and Vandierendonck, 2010; Mayr and Bell, 2006; Mittelstädt et al., 2018). Braem (2017) did not include a control group to compare the reward-modulated switch rates, and it is hence unclear whether the same asymmetry would appear when selectively rewarding task switches versus repetitions. One should therefore be cautious when interpreting modulations of control regulation in task-switching paradigms. Our results suggest that standard task switching protocols (with 50% switches) may inadvertently induce a stability-biased control strategy.

Also noteworthy is the surprisingly small effect our demand manipulation had on task selection behavior in Experiment 2. Recall that in the learning phase, task switches or task repetitions were selectively associated with high-demand target stimuli. Yet, participants in all groups still produced a repetition bias (producing <50% task switches) and only differed from one another by 10 to 15%. This is quite surprising considering that if participants in the Stable group had chosen to switch tasks on every trial, they would have reduced their error rate by upwards of 20%! Similarly, if participants in the Flexible group had chosen to repeat the same task on every trial, they would also had reduced their error rate by ~20%. That is, participant incurred a huge performance cost by not fully capitalizing on the demand associations. This, in part, might be explained by our instruction to try to perform each task equally often in a random order; the standard instruction used in voluntary task-switching paradigms (e.g.,). Participants, therefore, might have attempted to adhere to this instruction despite their awareness that adopting different strategies would have produced fewer errors. Alternatively, they may have not been aware of our demand manipulations and unable to fully capitalize on it. Still, the lack of error-driven learning on task selection behavior here is somewhat puzzling. Although prior work has shown the importance of instructional manipulations on voluntary switch rates (e.g., Liefooghe, Demanet, & Vandierendonck, 2010), future research is necessary to understand how these manipulations interact with avoidance-driven control regulation.

The influence of rewards on control regulation has also been shown to vary depending on how rewards are presented. For instance, prior work has demonstrated the theoretical importance of distinguishing between performance-contingent and non-contingent rewards (Fröber & Dreisbach, 2014, 2016a) as well as the prospect and reception of rewards (Notebaert & Braem, 2016). Here, we examined the reception of performance non-contingent demands. However, prior research examining cognitive effort has demonstrated the importance of effort anticipation for driving behavioral change (Dunn, Inzlicht, and Risko, 2019), and in daily life, task-demands often vary in accordance with our peformance (i.e., levelling up difficulty when a performance criterion is met). Thus, we might expect that such distinctions will also be important for understanding the motivational influence of demand-avoidance and provides a potentially fruitful avenue for future research.

More generally, the effect of demand-avoidance on forced and voluntary task-switching makes an important contribution to the question of how cognitive control is itself managed (Dreisbach et al., 2019; Hommel, 2015). Adaptive goal-directed behavior requires identifying the current situational demands and adjusting control to meet those demands in a context-appropriate manner. From an applied, clinical, perspective, identifying and understanding the determinants of control regulation are important because cognitive disorders are often characterized by a dysregulation along the flexibility-stability continuum (e.g., Goshke, 2014). Failing to appropriately adapt to cognitive demand—an inability to monitor or anticipate demand, lack of avoidance, or extreme avoidance—may result in persistent control regulation failures as characterized by various clinical disorders. From a theoretical perspective, control regulation is often characterized as a cost-benefit tradeoff, whereby the potential rewards of engaging in control are weighed against the costs of engaging in control (e.g., Shenhav, Botvinick, & Cohen, 2013). The results of the current study are consistent with this view, providing novel evidence that changes to the inherent costs of control result in adaptations in control regulation. Finally, the motivational influence of rewards is thought to offset the inherent cost of control as demonstrated by various experimental manipulations (Braem, 2017; Braem et al., 2012; Chiew & Braver, 2013; 2014; Fröber & Dreisbach, 2014, 2016a; 2016b; Fröber et al., 2020; Fröber & Dreisbach, 2016b; Fröber et al., 2019; Shen & Chun, 2011). However, the asymmetry of our results suggests that typical task-switching paradigms (50% switch rates) may naturally elicit stable control states and have unintended consequences on the size and direction of experimental manipulations. For instance, performance-contingent rewards may appear to only induce stable control states because this is the state the task already elicited, which is now being reinforced. Therefore, our results suggest that some care needs to be taken when interpreting these experimental manipulations of control within the context of a task-switching paradigm.

Conclusions

The results of the current study provide novel evidence for avoidance-driven modulations of control regulation along the flexibility-stability continuum (Dreisbach et. al., 2019). In both forced-choice and voluntary task-switching, we found that selectively associating cognitive demand with task repetitions increased flexibility, but selectively associating cognitive demand with task switches failed to increase stability. These findings are consistent with cost-benefit frameworks of control regulation (e.g., Shenhav, Botvinick, & Cohen, 2013) demonstrating that changes in the inherent cost of control can motivate control adaptation.

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