Memory & Cognition (2021) 49:1617–1632
https://doi.org/10.3758/s13421-021-01189-8

Proactive and reactive metacontrol in task switching

Moon Sun Kang[1] · Yu-Chin Chiu[1]

Accepted: 10 May 2021 / Published online: 16 June 2021

Abstract

While cognitive control enables the selection of goal-relevant responses, metacontrol enables the selection of context-appropriate control operations. In task switching, metacontrol modulates task-switching efficiency by retrieving the associations between a contextual cue and a particular cognitive control demand. While the automatic retrieval of cognitive control is appealing due to its time and energy efficiency, the effects of different contextual cues have been shown in separate studies and appear to have different characteristics. Here, we devised a single task-switching paradigm to test whether we can observe both list-wide and item-specific metacontrol within subjects. In two experiments, we demonstrated reduced switch costs in lists associated with a high probability of switching as compared with lists with a low probability of switching (i.e., a list-wide switch probability [LWSP] effect). Similarly, we observed an analogous item-specific switch probability (ISSP) effect such that items associated with a high probability of switching incurred smaller switch costs as compared with items associated with a low probability of switching. We also confirmed that both list-wide and item-specific switch probability effects were not dependent on lower-level stimulus–response associations. However, the LWSP and the ISSP effects were uncorrelated, suggesting a lack of dependence. Together, these findings suggest that there are two distinct modes of metacontrol that are deployed in a context-sensitive manner in order to adapt to specific cognitive demands.

Keywords Cognitive control · Adaptive control · Metacontrol · Task-switching · Associative learning

Cognitive control refers to a psychological construct that engages in regulating cognitive and emotional processes in order to achieve goal-directed behaviors (Miller & Cohen, 2001). Cognitive control is required to select weaker, but appropriate responses while suppressing stronger, but inappropriate responses. The cognitive control operation can be modeled in a task-switching paradigm where participants are instructed to switch between two categorization rules, with each specifying a particular mapping between stimulus features and responses (Jersild, 1927; Monsell, 2003). For example, in one of our own cued task-switching paradigms, participants are instructed to switch between categorizing images of faces either according to the gender (male versus female) or the age (old versus young) of the face. A task cue (e.g., color of a frame surrounding the image) is used to indicate which categorization rule (gender or age) is relevant for the presented image on each trial. A repeat trial refers to the case where the same task rule is cued on the current trial compared with the previous trial. Whereas, a switch trial is the case where a different task rule is cued on the current trial compared with the previous trial. Generally, the response times are longer on switch trials than those on repeat trials. This difference has been referred to as switch costs, reflecting the additional time needed on switch trials to either reconfigure a difficult-to-access task set which has changed, or to suppress an easy-to-access previous task set (Allport et al., 1994; Rogers & Monsell, 1995). Cognitive control has traditionally been considered as a slow, top-down, endogenous, and resource-demanding process, lying on the opposite end of the continuum from a fast, bottom-up, exogenous, automatic process (Chiu, 2019; Cohen, 2017; Logan et al., 1975).

However, empirical evidence challenged this dichotomous categorization of control versus automatic processes by demonstrating that cognitive control can be deployed in a fast, bottom-up, and possibly automatic fashion (MacLeod & Dunbar, 1988; Meiran et al., 2015; see Bugg, 2012; Bugg & Crump, 2012, for reviews). For example, in a task-switching paradigm, "contextual cue-control state" (hereafter termed *context–control associations*) can be associated when a proper control state (e.g., heightened control state increasing "switch readiness" for better performance on switch trials) is

✉ Moon Sun Kang
kang396@purdue.edu

[1] Department of Psychological Sciences, Purdue University, 703 Third Street, West Lafayette, IN 47907-2081, USA

consistently required in a particular contextual cue (e.g., a block of trials, or a specific stimulus). When the context–control associations are formed, a proper control state has been shown to be retrieved by that particular paired contextual cue bottom-up as opposed to top-down (Chiu & Egner, 2019). The bottom-up retrieval of cognitive control represents a distinct form of adaptive, higher-level control (above the level of task-sets and responses), and it has been referred to as "metacontrol" (i.e., "the control of cognitive control"; Goschke, 2003; Hommel, 2015; Fröber & Dreisbach, 2020; Liu & Yeung, 2020). Metacontrol is analogous to developing skills or habits. Just as we consider habits as linking a particular stimulus with a specific response or sequences of responses (e.g., once I reach the top of stairs [stimulus], I turn right [response] to go to my office), we can consider metacontrol as linking a particular contextual cue with a higher-level control state (e.g., if I am in the library [contextual cue], I have better attentional focus [control state]). In the example of task-switching, while cognitive control is used to resolve task-sets or response conflicts at a trial-by-trial level, metacontrol is used to retrieve an appropriate control state at a contextual cue-by-cue level.

The empirical evidence of metacontrol has been extensively documented in the Stroop paradigm. Studies have shown that Stroop interference (i.e., performance difference between incongruent and congruent trials) can be modulated by various types of contextual cues, including temporal epoch, spatial location and specific item (e.g., Crump & Milliken, 2009; Jacoby et al., 2003; Logan & Zbrodoff, 1979). For instance, using the temporal epoch as a contextual cue, studies showed that Stroop interference is smaller for a *list* (i.e., trials occurring in the same block) where incongruent trials are more frequent (e.g., 75%) as compared with a list where incongruent trials are less frequent (e.g., 25%). The interpretation of this "list-wide proportion congruency" (LWPC) effect is that, by experiencing frequent conflicts in a mostly incongruent list, the control required to resolve conflict (e.g., selective attention to the color but not the word) becomes associated with that list and is retrieved much faster and applied more efficiently across all trials in that same list. Similar to the LWPC effect, others have shown an analogous item-specific proportion congruency (ISPC) effect. Namely, the Stroop interference effect is reduced for stimuli (or *items*) that frequently appeared on incongruent trials compared with stimuli that rarely appeared on incongruent trials (Bugg & Hutchison, 2013; Gonthier et al., 2016; Jacoby et al., 2003). Like the interpretation of the LWPC effect: The ISPC effect is due to the retrieval of an appropriate control state (e.g., increased selective attention to the color) according to an item's past control demand history.

Parallel to the LWPC and ISPC effects revealed in the Stroop paradigm, others have also demonstrated metacontrol in task-switching paradigms. For example, switch costs are reduced in a list where task switches are more frequent as compared with a list where task repetitions are more frequent (e.g., Dreisbach et al., 2002; Dreisbach & Haider, 2006; Liu & Yeung, 2020; Mayr et al., 2013; Monsell & Mizon, 2006; Schneider & Logan, 2006; Siqi-Liu & Egner, 2020). Such a list-wide switch probability (LWSP) effect is likely derived from a phenomenon where the high control state (e.g., readiness to switch) becomes associated with a specific list and is efficiently retrieved in the same list. This results in better performance (i.e., reduced switch costs) in a list with frequent switch trials compared with a list with frequent repeat trials. On the other hand, Chiu and Egner (2017) tested whether a particular control state can also become associated with a particular *item* (e.g., an image of a ball) and subsequently be retrieved to modulate performance when that same stimulus is encountered. Using a typical cued task-switching paradigm along with an item-specific switch probability manipulation, they found that items that frequently appeared on switch trials engendered smaller switch costs as compared with items that rarely appeared on switch trials (i.e., frequently appeared on repeat trials). Most importantly, these items were mixed in a list with a 50% switch probability. In other words, participants cannot anticipate which type of trial (e.g., switch/repeat trials) each trial will be. This item-specific switch probability (ISSP) effect is similar to the ISPC effect, demonstrating that items themselves can serve as a contextual cue to rapidly trigger the appropriate control state in a bottom-up manner (see also Leboe et al., 2008).

The modulation of performance by the LWSP or the ISSP manipulation could reflect improved control over the task-set updating process or improved control over the task-cue interpretation process. This is because the switch cost itself could reflect an endogenous, goal-shifting process as well as an exogenous, rule-enabling process (Logan & Bundesen, 2003). However, studies using two cues per task have demonstrated that switch costs were, at least, not fully driven by cue repetition/switch trials but also driven by task-set retrieval processes (i.e., task-set updates and reconfiguration; Crump & Logan, 2010; Monsell & Mizon, 2006). Moreover, using a voluntary task-switching paradigm, Chiu et al. (2020) has shown that participants chose to switch more often upon encountering items (without any task cue) that were associated with a high switch probability. Taken together, both LWSP and ISSP effects are behavioral signatures of metacontrol, demonstrating rapid retrievals of control that is highly adaptable to specific contexts (lists, items, etc.), and is time and energy efficient (Egner, 2014).

Despite the similarities in their behavioral patterns, the LWSP and ISSP effects are thought to reflect a distinct proactive versus reactive mode of metacontrol, respectively (Bugg & Crump, 2012, on the LWPC and ISPC effects). This distinction aligns well with the dual mechanisms of control (DMC) framework, which posits that there are two distinct modes of cognitive control, operating in different time scales (Braver, 2012) as different means to an end. According to the DMC framework, proactive mode of cognitive control recruits sustained attention to maintain goal-relevant information in anticipation and preparation for future cognitive demands (Cohen et al., 1997; De Pisapia & Braver, 2006). By contrast, the reactive mode of cognitive control recruits transient attention to meet cognitive demands just-in-time as a form of late correction (Braver et al., 2007, 2009). However, to claim that the LWSP effect reflects a proactive mode of metacontrol and is applied in an anticipatory manner, one needs to show a modulation of switch costs by list-wide switch probability on "diagnostic items" (i.e., stimuli that appeared on 50% switch and 50% repeat trials, or switch probability-unbiased items) as one would on inducer items (e.g., stimuli that appeared on 80% switch and 20% repeat trials, or switch probability-biased items) (Braem et al., 2019). The logic for this claim is the following: The metacontrol is achieved in inducer items through the repeated pairings of a particular inducer item and an appropriate control state (i.e., forming context–control associations). Diagnostic items, on the other hand, are not associated with any particular control demand because they occur on switch and repeat trials equally often, but simply appear in the same temporal context (i.e., list) as the inducer items. Recently, Siqi-Liu and Egner (2020) included diagnostic items in the high and low switch probability lists, and indeed observed reduced switch costs on the diagnostic items that appeared in a high switch probability list as compared with those that appeared in a low switch probability list. Thus, the LWSP effect likely reflects a proactive mode of metacontrol that allows the appropriate control state to be retrieved in an anticipatory manner regardless of what stimuli will appear on the next trial. By contrast, as the ISSP effect relies on recognizing the distinct identities of stimuli, which can only occur after the stimulus onset, it can only allow the appropriate control state to be retrieved "reactively" on a trial-by-trial or an item-by-item basis.

We devised and tested a single task-switching paradigm inducing list-based and item-based context–control associations, indexing proactive and reactive metacontrol, respectively. Our first goal was to demonstrate that both proactive and reactive metacontrol could occur within subjects. Given that metacontrol reflects context-sensitive adjustment of cognitive control, we should be able to observe both proactive and reactive modes of metacontrol within the same experimental session. Importantly, we include diagnostic items to ensure a clean assessment of proactive metacontrol. Although it is possible to instruct participants to adopt a task-set control strategy proactively (e.g., by instruction; Liu & Yeung, 2020), here we focus on experience-driven metacontrol as we are interested in whether proactive vs. reactive metacontrol can emerge naturally through experience within subjects. We expect that the list-based switch probability manipulation will induce proactive metacontrol, whereas the item-based switch probability manipulation will induce reactive metacontrol. Therefore, we should observe two indices, a list-wide switch probability (LWSP) effect on diagnostic items, and an item-specific switch probability (ISSP) effect in a list with a 50% switch probability, within subjects.

This leads our main goal of investigating how the two modes of metacontrol relate to each other. One might hypothesize that the two modes of metacontrol are highly correlated with each other based on the idea that both rely on the same context-sensitive, associative learning mechanism. By contrast, if the two modes of metacontrol constitute independent mechanisms—similar to how the two modes of cognitive control was described in the DMC framework (Braver, 2012; Braver et al., 2007)—they should not be positively correlated. The latter was once documented with the Stroop paradigm when correlating the LWPC and the ISPC effects (i.e., Gonthier et al., 2016). In the current study, to extend this finding to the task-switching domain, we investigate how the list-based and item-specific switch probability effects relate to each other.

We conducted Experiment 1 first and then Experiment 2 as a replication study. In Experiment 1, we used only "response incompatible" stimuli. The rationale is to capitalize on the fact that these stimuli elicit two different responses according to the two categorization rules, and therefore minimize contributions from lower-level stimulus–response associations (Schmidt & Besner, 2008). Note that even though the LWSP/ISSP effect bears much resemblance to the LWPC/ISPC effects, the LWPC/ISPC effects demonstrated in the Stroop paradigm sometimes suffer from this confound (but see Bugg & Hutchison, 2013; Bugg et al., 2011). While Experiment 2 was near identical to Experiment 1, we added response compatible stimuli (i.e., producing the same responses according to the two categorization rules). Since response compatible items can bypass the context–control learning favoring stimulus–response association (e.g., Schmidt & Besner, 2008), our goal here is to ensure that the LWSP and ISSP effects are *not* dependent on lower-level stimulus–response learning by examining if the LWSP and ISSP effects are similar or different between response compatible and response incompatible items. Regarding the results, we observed the LWSP effect as well as the ISSP effect in both experiments. We found that the LWSP and ISSP effects were observed similarly regardless of the items' response compatibility. Despite these robust effects of context–control learning, the two effects did not correlate with each other.

Experiment 1

Method

Participants

A total of 77 undergraduate students (M_{age} = 19.22 years, SD_{age} = 1.39 years, 39 males, 38 females) provided informed consent to participate in this study approved by the Purdue University Institutional Review Board. Participants were given two credits for an hour of participation. The sample size was set to be at least 64, which was determined by using G*Power 3.0 with the following parameters: Type I error = 0.05, power = 0.9, and $\eta_p^2 = 0.06$ (interaction effect; Chiu & Egner, 2017). We counted the number of participants in the sample at the end of each week and stopped data collection when that number was greater than or equal to 64. Data from 75 participants were included in the final analysis after excluding two participants due to their mean accuracy being outside of the group mean ± 2 standard deviations.

Stimuli

We used forty color images of objects (Moreno-Martínez & Montoro, 2012) in a cued task-switching paradigm that requires participants to switch between categorizing objects as living versus nonliving and as larger versus smaller than a shoebox. As a result of these categorization rules, the stimulus-set included four categories (i.e., living and larger than a shoebox, living and smaller than a shoebox, nonliving and larger than a shoebox, nonliving and smaller than a shoebox) of 10 unique images in each category. For each participant, a total of 12 images (six from two of the categories, randomly selected) were used in the experiment. The two categories selected for each participant depended on the participant's assigned category-to-response mapping, but were both response incompatible (i.e., producing different responses according to the two categorization rules). We only used response incompatible stimuli to maximize learning for each item (i.e., more trials per item). A different set of four images from each of the four categories was used for practice exclusively. The images were displayed at a size of 400 pixels in width and 300 pixels in height.

Design and procedure

Participants categorized an object stimulus according to a rule indicated by the color of a frame surrounding the stimulus. The blue frame cued the animacy task where a stimulus should be categorized as living or as nonliving and the red frame cued the size task where a stimulus should be categorized as smaller or as larger than a shoebox (see Fig. 1a). Each trial started with a fixation for 500 ms, followed by an object stimulus with a colored frame for 1,200 ms, and ended with a feedback screen for 500 ms. Participants were required to make a response within 1,200 ms. The participants were shown the text 'correct' for a correct response, 'incorrect' for an incorrect response, and 'no response' for no response or response made after the stimulus offset. Two keys on a standard QWERTY keyboard ('V' & 'N') were used for indicating categorization responses. Participants started with practice trials to familiarize themselves with the assigned stimulus–response mapping which was counterbalanced across participants.

In the main experiment, participants completed three task-switching lists of 320 trials, each associated with a high, medium, or low list-wide switch probability. The three lists were administered in an ascending (i.e., low, medium, high) or a descending order, which was counterbalanced across participants. Note that we did not include all possible orders (i.e., the medium list never appeared as the first or the last list). This choice was made to avoid the complexity of having all possible orders. Furthermore, as the practice trials used a different set of stimuli, and none of those stimuli were biased, we did not think that the practice trials would differ from the following list in terms of difficulty. The participants were not informed about the list-wide switch probability at the beginning of each list. In the low switch probability list, half of the items were associated with a 20% chance of switching (two items, 64 repeat trials and 16 switch trials per item), and half were associated with a 50% chance of switching (two items, 40 repeat trials and 40 switch trials per item). Together, these items resulted in a mean switch probability of 35% at the list level. Similarly, in the high switch probability list, half of the items were associated with a 50% chance of switching (two items, 40 repeat trials and 40 switch trials per item), and half were associated with an 80% chance of switching (two items, 16 repeat trials and 64 switch trials per item), resulting in a mean switch probability of 65% at the list level. Note that in the high and the low switch probability lists, the items associated with a biased switch probability (i.e., 20% or 80%) are referred to as inducer items. Whereas, the items associated with a 50% chance of switching are referred to as diagnostic items and are used to assess the existence of "proactive" metacontrol.

Embedded in the medium switch probability list was an item-specific switch probability design with a mean switch probability of 50% at the list level. That is, half of the items were associated with a 20% chance of switching (two items, 64 repeat trials and 16 switch trials per item) and half of the items were associated with an 80% chance of switching (two items, 16 repeat trials and 64 switch trials per item). In the medium switch probability list with 50% switch probability at the list level, the items associated with a biased switch probability (i.e., 20% or 80%) are used to assess the existence of "reactive" metacontrol. Participants were also not informed about these item-level switch probabilities in the entire experiment. While the number of switch/repeat trials in each list varied according to the list-wide switch probability, trials were randomized to ensure that the incidence of each stimulus appearing in each task was roughly the same (i.e., no more than two trials in difference). Therefore, each item was not biased to be responded with one particular response more frequently than the other response. Note that there were four

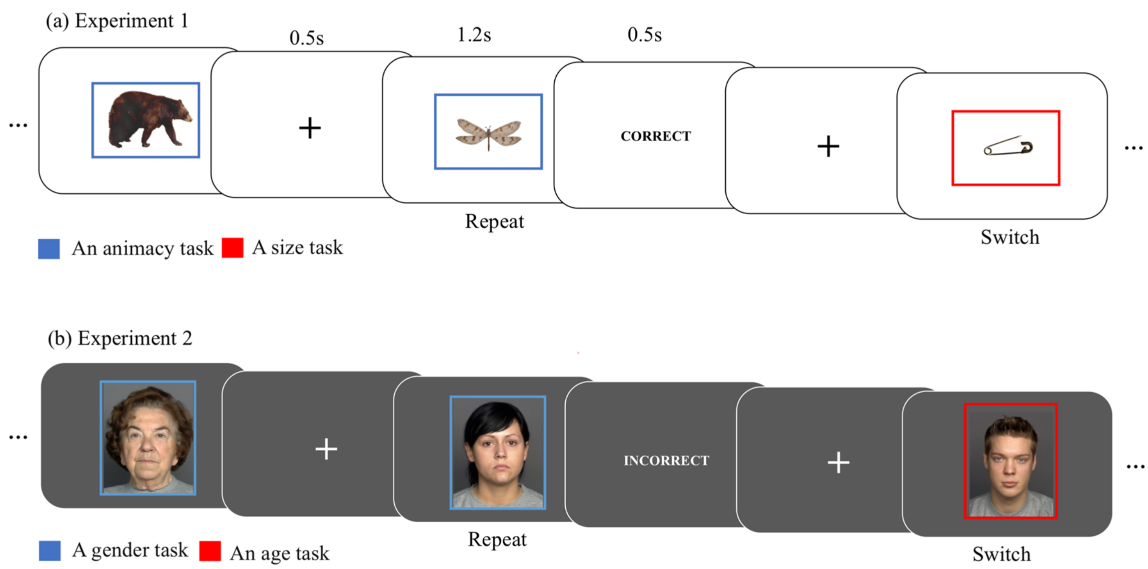

Fig. 1 A cued task-switching procedure for Experiment 1 (**a**) and 2 (**b**). Participants performed one of two categorization tasks cued by the frame color (blue or red) on each trial. (Color figure online)

unique items in each list and a particular item that appeared in one list never appeared in the other lists.

Data analysis

To examine whether the task-switching performance was modulated by context–control learning, we analyzed both response time (RT) and accuracy (ACC). To address our research question of whether participants exhibited proactive metacontrol over the task-switching processes, data of *diagnostic items* (50% switch probability) from the low and the high switch probability lists were subject to a 2 (list-wide switch probability: low, high) × 2 (transition: switch, repeat) repeated-measures analysis of variance (rmANOVA). Additionally, to compare the size of list-wise switch probability manipulation on diagnostic versus inducer items, data of diagnostic and inducer items were subject to a 2 (item type: diagnostic, inducer) × 2 (list-wide switch probability: low, high) × 2 (transition: switch, repeat) rmANOVA analysis. To assess reactive metacontrol, data of switch probability-biased items from the medium switch probability list were subject to a 2 (item-specific switch probability: low, high) × 2 (transition: switch, repeat) rmANOVA. Note that data from the medium switch probability list was not included in the ANOVAs assessing proactive metacontrol. Likewise, data from the high/low switch probability lists was not included in the ANOVAs assessing reactive metacontrol. Analyses on RT excluded trials with incorrect responses and RT values beyond ± 3 standard deviations of each participant's entire RT mean. We reported means of response times and accuracy with their standard deviations. For the effect-size measures, we reported η_p^2 and Cohen's d for the key LWSP and ISSP effects.

Results

Proactive metacontrol

Response times As expected, participants had longer response times on switch trials compared with repeat trials, $F(1, 74) = 288.80$, $p < .001$, $\eta_p^2 = .80$. The mean RT did not differ between the high and the low switch probability lists, $F(1, 74) = 2.51$, $p = .117$, $\eta_p^2 = .03$. Importantly, we replicated the LWSP effect as there was a significant Transition × List-Wide Switch Probability interaction, $F(1, 74) = 8.44$, $p = .005$, $\eta_p^2 = .10$. The interaction was due to smaller switch costs (i.e., RT of switch vs. repeat trials) incurred by the diagnostic items in the high switch probability list ($M = 62.4$, $SD = 42.8$) than those in the low switch probability list ($M = 80.7$, $SD = 48.1$), resulting in a LWSP effect of 18.3 ms ($SD = 54.5$), Cohen's $d = .34$ (see Fig. 2a and Table 1).

The same pattern of results was found *when we also excluded trials following incorrect trials*. That is, there was a significant main effect of transition, $F(1, 74) = 302.58$, $p < .001$, $\eta_p^2 = .80$, a nonsignificant main effect of list, $F(1, 74) = 2.59$, $p = 112$, $\eta_p^2 = .03$, and most importantly a significant List-Wide Switch Probability × Transition interaction, $F(1, 74) = 7.56$, $p = .008$, $\eta_p^2 = .09$. The interaction was again due to smaller switch costs for the diagnostic items in the high switch probability list ($M = 64.4$, $SD = 44.6$) than those in the low switch probability list ($M = 83.8$, $SD = 51$), resulting in a LWSP effect of 19.4 ms ($SD = 61.1$), Cohen's $d = .32$.

To further examine whether the magnitude of the LWSP effect was different between inducer and diagnostic items, we performed a 2 (*item type*: inducer, diagnostic) × 2 (List-Wide Switch probability: low, high) × 2 (transition: switch, repeat) rmANOVA. As expected, the analysis revealed a significant

Table 1 Descriptive statistics in Experiment 1, mean (standard deviation)

Switch probability	Transition	RT (ms)	RT* (ms)	ACC (%)
Low switch probability list	Repeat	644.6 (54.6)	641.1 (56.2)	88.2 (6.2)
	Switch	725.3 (67.7)	724.8 (67.0)	75.2 (12.5)
High switch probability list	Repeat	665.6 (53.1)	662.4 (54.2)	84.5 (7.6)
	Switch	728.0 (67.8)	726.8 (68.2)	75.7 (11.7)
Low switch probability items	Repeat	660.1 (51.1)	658.5 (51.9)	87.6 (6.4)
	Switch	732.7 (67.1)	732.8 (69.6)	77.9 (13.4)
High switch probability items	Repeat	664.8 (60.6)	661.2 (62.6)	88.0 (8.5)
	Switch	726.2 (63.6)	722.5 (62.4)	79.4 (10.6)

RT* = mean response times with a dataset excluding trials following incorrect trials

main effect of transition, $F(1, 74) = 341.53$, $p < .001$, $\eta_p^2 = .82$, and a significant List-Wide Switch Probability × Transition interaction, $F(1, 74) = 11.48$, $p = .001$, $\eta_p^2 = .13$. Interestingly, the critical three-way interaction of Item Type × List-Wide Switch Probability × Transition was not significant, $F(1, 74) < 0.01$, $p = .975$, $\eta_p^2 < .01$. The LWSP effects were similar between diagnostic ($M = 18.3$, $SD = 54.5$) and inducer ($M = 18.5$, $SD = 53.7$) items. No other effects were significant—that is, main effect of item type, $F(1, 74) = 0.10$, $p = .747$, $\eta_p^2 < .01$; main effect of list-wide switch probability, $F(1, 74) = 2.85$, $p = .096$, $\eta_p^2 = .04$; Item Type × List-Wide Switch Probability, $F(1, 74) = 0.15$, $p = .698$, $\eta_p^2 < .01$; Item Type × Transition: $F(1, 74) = 2.18$, $p = .144$, $\eta_p^2 = .03$.

Accuracy As expected, participants had lower accuracy on switch trials than on repeat trials, $F(1, 74) = 190.29$, $p < .001$, $\eta_p^2 = .72$. There was no difference in the accuracy between the high and the low switch probability lists, $F(1, 74) = 1.79$, $p = .185$, $\eta_p^2 = .02$. Importantly, the LWSP effect was also observed in accuracy as List-Wide Switch Probability × Transition interaction was significant, $F(1, 74) = 10.86$, $p = .002$, $\eta_p^2 = .13$. The interaction was due to smaller switch costs incurred by the diagnostic items in the high switch probability list ($M = 8.7$, $SD = 8.3$) than those in the low switch probability list ($M = 13.1$, $SD = 9.5$), resulting in a LWSP effect of 4.4% ($SD = 11.4$), Cohen's $d = .38$. Like RT, an additional rmANOVA including an *item type* (i.e., inducer, diagnostic items) variable revealed a nonsignificant three-way interaction effect of Item Type × List-Wide Switch Probability × Transition, $F(1, 74) = 0.03$, $p = .861$, $\eta_p^2 < .01$, suggesting that the LWSP effects were not different between the diagnostic ($M = 4.4$, $SD = 11.4$) and the inducer items ($M = 4.1$, $SD = 14.0$).

Reactive metacontrol

Response times As expected, participants took longer to respond on switch trials than on repeat trials, $F(1, 74) = 252.42$, $p < .001$, $\eta_p^2 = .77$. Participants responded with a similar speed on trials with high switch probability items and on trials with low switch probability items, $F(1, 74) = 0.10$, $p = .753$, $\eta_p^2 < .01$. Importantly, we replicated the ISSP effect as there was a significant Item-Specific Switch Probability × Transition interaction, $F(1, 74) = 4.51$, $p = .037$, $\eta_p^2 = .06$. The interaction was due to smaller switch costs for high switch

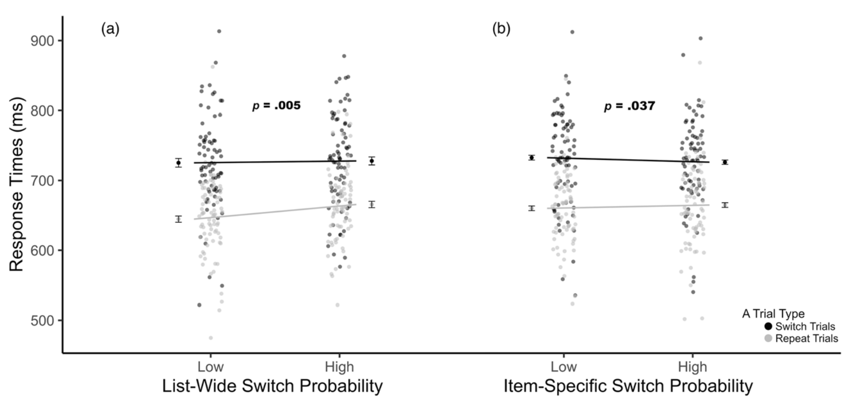

Fig. 2 Response times as a function of (**a**) List-Wide Switch Probability × Transition and (**b**) Item-Specific Switch Probability × Transition in Experiment 1. Error bars indicate within-subjects standard error of the mean (Franz & Loftus, 2012)

probability items (M = 61.4, SD = 41.4) than for low switch probability items (M = 72.6, SD = 44.7), resulting in an ISSP effect of 11.2 ms (SD = 45.7), Cohen's d = .25 (see Fig. 2b and Table 1).

The results were similar with the smaller data set after *excluding trials following incorrect trials*. We observed a significant main effect of transition, $F(1, 74) = 226.77$, $p < .001$, $\eta_p^2 = .75$, a nonsignificant main effect of item-specific switch probability, $F(1, 74) = 1.61$, $p = .209$, $\eta_p^2 = .02$, and a marginally significant item-specific switch probability x transition interaction, $F(1, 74) = 3.95$, $p = .051$, $\eta_p^2 = .05$. Switch costs were smaller for high switch probability items (M = 61.3, SD = 45.8) than for low switch probability items (M = 74.3, SD = 50.4), Cohen's d = .23.

Accuracy While participants responded less accurately on switch trials than on repeat trials, $F(1, 74) = 105.94$, $p < .001$, $\eta_p^2 = .59$, no other effects were significant (i.e., main effect of item-specific switch probability, $F(1, 74) = 1.90$, $p = .172$, $\eta_p^2 = .03$; item-specific switch probability x transition, $F(1, 74) = 0.78$, $p = .381$, $\eta_p^2 = .01$).

Correlation between proactive and reactive metacontrol

To assess whether participants with a large LWSP effect also exhibit a large ISSP effect, we computed the correlation between the two effects across participants. To do so, we first calculated the LWSP effect (i.e., RT switch costs on diagnostic items in the low switch probability list—RT switch costs on diagnostic items in the high switch probability list) and the ISSP effect (i.e., RT switch costs on low switch probability items in the medium switch probability list—RT switch costs on high switch probability items in the medium switch probability list) for each participant, and then correlate these effect scores across participants. The result showed that the size of the LWSP effect did not predict the size of the ISSP effect, Pearson's r = .08, $t(73) = .70$, $p = .487$ (see Fig. 3).

However, to make sure the lack of correlation was not due to having a noisy dataset to begin with, we conducted two split-half correlations to assess the internal consistency of the LWSP and the ISSP effects, respectively. First, for the LWSP effect, we split each participant's data into an odd-trial half and an even-trial half (odd vs. even was considered within each condition). We then calculated an interaction score (i.e., List × Transition) for each half in each participant, and correlated the two interaction scores across participants. This analysis revealed a significant correlation between the two estimates of the LWSP effect—that is, Pearson's r = .59, $t(73) = 6.29$, $p < .001$. As for the ISSP effect, we randomly paired one high switch probability item with one low switch probability item to calculate an interaction score (i.e., Item × Transition). Because there were four unique items, we

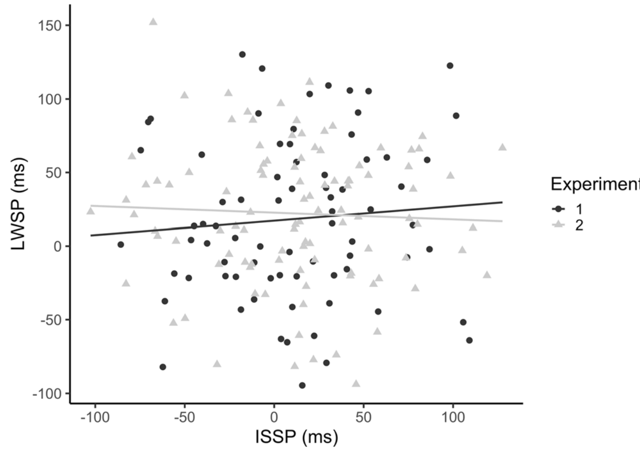

Fig. 3 Correlation between the LSWP and ISSP effects (calculated with RT) in Experiments 1 and 2. LWSP = switch costs of the diagnostic items in the low switch probability list − switch costs of the diagnostic items in the high switch probability list. ISSP = switch costs of the low switch probability items in the unbiased list − switch cost of the high switch probability item in the unbiased list

obtained two estimates of the ISSP effect in each participant. Finally, the two estimates were correlated across participants. Similar to the first analysis, the correlation was significant—that is, Pearson's r = .24, $t(73) = 2.15$, $p = .035$. Taking these results together, the lack of correlation between the LWSP and the ISSP effect was unlikely due to a noisy data set.

Lastly, to further assess the nonsignificance of the correlation between the LWSP and ISSP effects, we calculated the Bayes Factor (BF) in the form of BF_{01} (Bayes factor favoring H_0 over H_1) using the correlationBF function in the BayesFactor package (Version 0.9.12.4.2. in R) with a default prior scale (i.e., rscale = "medium"; Morey et al., 2015). A BF_{01} between 1 and 3 means anecdotal, and a value between 3 and 10 means substantial evidence for the null hypothesis. We obtained BF_{01} = 3.03 with this sample, indicating that the evidence substantially supported the null hypothesis (i.e., no correlation). Participants who demonstrated a larger benefit from list-control associations did not appear to exhibit a similar benefit from item–control associations.

Discussion

In Experiment 1, we observed reduced switch costs in the RT of diagnostic items in the high switch probability list compared with those in the low switch probability list, i.e., a LWSP effect, which indexes proactive metacontrol. Similarly, RT switch costs were reduced in the high switch probability items than in the low switch probability items in the unbiased list, i.e., an ISSP effect, which indexes reactive metacontrol. Namely, we demonstrated that participants proactively and reactively implemented the appropriate control states in response to the list-based and item-specific contextual cues, respectively. Furthermore, we did not find a dependence between proactive and reactive metacontrol, suggesting dissociable mechanisms may be responsible for the two modes of metacontrol.

Experiment 2

Using a single task-switching paradigm, we were able to induce both proactive and reactive metacontrol in Experiment 1. Although this metacontrol process was demonstrated in a paradigm involving two semantic categorization rules on objects, it is possible that one could observe similar effects in paradigms using other stimuli, tasks or nonverbal domains as the control for task-sets is likely to be domain-general (cf. Capizzi et al., 2016). In Experiment 2, our goal was to replicate these results using a different set of stimuli (i.e., face images). However, we also made three minor changes in our design to ensure that the results we found in Experiment 1 were robust regardless. First, we include both response compatible and response incompatible stimuli in the task. It was aimed to address if response compatibility (i.e., producing same or different responses according to the two categorization rules) will affect the learning and execution of the two modes of metacontrol. Secondly, to maximize item-specific learning and the link between the LWSP and the ISSP effects, we reuse the inducer items from the high and low switch probability lists in the medium switch probability list. By contrast, we used four unique items for each list in Experiment 1, which was an attempt to minimize any potential facilitation or interference between lists. Lastly, we used more extreme switch probabilities (10%, 90%) in an attempt to induce stronger context–control learning.

Method

Participants

A total of 107 Purdue undergraduate students (M_{age} = 18.70, years SD_{age} = 1.03 years, 51 males, 55 females) consented to participate in the study approved by the Purdue University Institutional Review Board. Two credits were given for an hour of participation. Data from 101 participants were included in the analysis after excluding six participants due to their poor performance (i.e., mean accuracy outside the range of ± 2 standard deviations of the group mean accuracy).

Stimuli We used 16 individuals' full-color face images with neutral emotion from a database (Ebner et al., 2010). Each image belonged to one of the following four categories (i.e., female and young, female and old, male and young, male and old) as a result of the two categorization rules (gender & age). A different set of eight images (from another eight individuals) was used for practice exclusively. The images were displayed at a size of 325 pixels in width and 405 pixels in height.

Design and procedure Similar to Experiment 1, participants categorized face stimuli according to gender or age, cued by the color of a frame surrounding the stimulus (see Fig. 1b). The trial progression and other counterbalancing procedures were identical to those of Experiment 1, except that keys 'G' & 'J' were used here.

In the main experiment, participants completed two task-switching lists of 240 trials, each of which was associated with low and high switch probability lists (order counterbalanced across participants), and one list of 320 trials, which was associated with a 50% chance of switching at the list level. In the low switch probability list, half of the items were associated with a 10% chance of switching (four items, 108 repeat trials and 12 switch trials per item), and half were associated with a 50% chance of switching (four items, 60 repeat trials and 60 switch trials per item). Similarly, in the high switch probability list, half of the items were associated with a 50% chance of switching (four items, 60 repeat trials and 60 switch trials per item) and half with a 90% chance of switching (four items, 12 repeat trials and 108 switch trials per item). Just as in Experiment 1, items in the high and the low switch probability lists were unique (i.e., item images were of different individuals). Additionally, the diagnostic items in the low and high switch probability lists were analyzed to index proactive metacontrol, as was the case in Experiment 1. The medium switch probability list was essentially an ISSP design with half of the items associated with a 10% chance of switching (four items, 144 repeat trials and 16 switch trials per item) and a half with a 90% chance of switching (four items, 16 repeat trials and 144 switch trials per item). These items in the medium switch probability list were the same inducer items from the high and the low switch probability lists. As in Experiment 1, the high and low switch probability items in the medium switch probability list were analyzed to index reactive metacontrol. Participants were not informed about the list-wide nor the item-specific switch probabilities. We also did not inform them that the faces they have encountered in the high/low switch probability lists would re-appear in the medium switch probability list. We followed the same trial randomization procedure as Experiment 1.

Before the main experiment, participants started with practice trials to familiarize themselves with the assigned stimulus–response mapping, which was counterbalanced across participants. They were required to reach a mean accuracy of 85% or higher before moving on to the main experiment. After the practice, participants went through a quick burn-in phase with two short high and low switch probability lists (order counterbalanced across participants) of 80 trials each. The stimuli used in this phase were the same ones used in the main experiment. The goal of this phase was to allow participants to experience a difference in switch probabilities between lists. However, we did not inform them explicitly about the list-wide switch probability differences but simply included these trials as burn-ins.

Data analysis We performed the same outlier exclusion procedure and the same set of statistical analyses as Experiment 1 to assess proactive and reactive metacontrol. As in Experiment 1, data from the medium switch probability list was not included in the ANOVAs assessing proactive metacontrol, and data from the high/low switch probability lists was not included in the ANOVAs assessing reactive metacontrol. In addition, as a key point of Experiment 2, we formally examined whether pure proactive metacontrol and reactive metacontrol is modulated by response compatibility by comparing the LWSP/ISSP effects between response compatible and response incompatible items. That is, data of diagnostic items in the high/low switch probability lists were subject to a 2 (response compatibility: compatible, incompatible) × 2 (list-wide switch probability: low, high) × 2 (transition: switch, repeat) rmANOVA analysis. Likewise, data of switch probability-biased items in the medium switch probability list were subject to a 2 (response compatibility: compatible, incompatible) × 2 (item-specific switch probability: low, high) × 2 (transition: switch, repeat) rmANOVA.

Results

Proactive metacontrol

Response times Participants were slower on switch trials than on repeat trials, $F(1, 100) = 185.72$, $p < .001$, $\eta_p^2 = .65$. Participants responded similarly to diagnostic items in the high and in the low switch probability lists, $F(1, 100) = 0.04$, $p = .836$, $\eta_p^2 < .01$. Notably, the LWSP effect was replicated, as reflected in a significant List-Wide Switch Probability × Transition interaction, $F(1, 100) = 21.94$, $p < .001$, $\eta_p^2 = .18$. Switch costs were reduced for diagnostic items in the high switch probability list ($M = 29.3$, $SD = 36.9$) as compared with those in the low switch probability list ($M = 51.4$, $SD = 39.1$), resulting in a LWSP effect of 22.1 ms ($SD = 47.4$), Cohen's $d = .47$ (see Fig. 4a and Table 2).

The results remained the same with the dataset *excluding trials following incorrect trials*. RT were longer on switch trials than on repeat trials, $F(1, 100) = 169.92$, $p < .001$, $\eta_p^2 = .63$. RT were similar between the high and the low list-wide switch probability lists, $F(1, 100) = 0.03$, $p = .874$, $\eta_p^2 < .01$, and the LWSP effect was significant, $F(1, 100) = 16.88$, $p < .001$, $\eta_p^2 = .14$. The diagnostic items in the high switch probability list incurred smaller switch costs ($M = 30.2$, $SD = 38.9$) as compared with those in the low switch probability list ($M = 50.6$, $SD = 40.9$), resulting in a LWSP effect of 20.4 ms ($SD = 50.0$), Cohen's $d = .41$.

To determine whether *response compatibility* might have interacted with the list-wide switch probability manipulation, a separate rmANOVA was performed including response compatibility as an additional variable. As expected, there was a main effect of response compatibility, $F(1, 100) = 511.78$, $p < .001$, $\eta_p^2 = .84$, a main effect of transition, $F(1, 100) = 228.17$, $p < .001$, $\eta_p^2 = .70$, and an List-Wide Switch Probability × Transition interaction, $F(1, 100) = 19.69$, $p < .001$, $\eta_p^2 = .16$. An expected significant Response Compatibility × Transition interaction was observed, $F(1, 100) = 19.69$, $p < .001$, $\eta_p^2 = .16$, which was due to larger switch costs on response incompatible items than on response compatible items (response incompatible: $M = 52.1$, $SD = 38.5$; response compatible: $M = 35.2$, $SD = 34.3$). Importantly, the three-way Response Compatibility × List-Wide Switch Probability × Transition interaction was not significant, $F(1, 100) = 1.42$, $p = .236$, $\eta_p^2 = .01$. No other effects were significant, main effect of list-wide switch probability, $F(1, 100) < 0.01$, $p = .951$, $\eta_p^2 < .01$; Response Compatibility × List-Wide Switch Probability interaction, $F(1, 100) = 1.09$, $p = .298$, $\eta_p^2 = .01$. The result suggests that the magnitude of the LWSP effect is similar between response compatible and response incompatible items. This result also suggests that findings in Experiment 1 were not confounded by our paradigm including only response incompatible items.

Lastly, to see if the magnitude of the LWSP effect differs between inducer and diagnostic items, a separate rmANOVA was performed including *item type* (i.e., diagnostic items: 50% switch probability items, inducer items: 10/90% switch probability items) as an additional variable. As expected, there was a significant main effect of transition, $F(1, 100) = 181.29$, $p < .001$, $\eta_p^2 = .64$, and a significant List-Wide Switch Probability × Transition interaction, $F(1, 100) = 44.54$, $p < .001$, $\eta_p^2 = .31$. Importantly, similar to Experiment 1, the item type did not interact with the LWSP effect as supported by a nonsignificant three-way interaction, $F(1, 100) = 1.48$, $p = .227$, $\eta_p^2 = .01$. There were no other significant effects, main effect of list-wide switch probability, $F(1, 100) = 0.23$, $p = .634$, $\eta_p^2 < .01$; main effect of item type, $F(1, 100) < 0.01$, $p = .976$, $\eta_p^2 < .01$; interaction effect of Item Type × List-Wide Switch Probability, $F(1, 100) = 2.09$, $p = .151$, $\eta_p^2 = .02$; interaction effect of Item Type × Transition, $F(1, 100) = 0.61$, $p = .438$, $\eta_p^2 < .01$. This suggests that there was not a statistically significant difference in the magnitude of the LWSP effect between the inducer items ($M = 30.9$, $SD = 59.6$) and the diagnostic items ($M = 22.1$, $SD = 47.4$).

Accuracy Similar to the RT results, accuracy on switch trials was lower than on repeat trials, $F(1, 100) = 99.34$, $p < .001$, $\eta_p^2 = .50$. Other effects had marginal patterns, main effect of list-wide switch probability, $F(1, 100) = 3.89$, $p = .051$, $\eta_p^2 =$

Table 2 Descriptive statistics in Experiment 2, mean (standard deviation)

Switch probability	Transition	RT (ms)	RT* (ms)	ACC (%)
Low switch probability list	Repeat	684.6 (74.7)	683.0 (76.0)	90.9 (6.3)
	Switch	736.0 (86.4)	733.6 (86.5)	85.1 (7.6)
High switch probability list	Repeat	694.7 (73.5)	692.5 (74.2)	88.7 (6.8)
	Switch	724.0 (79.0)	722.7 (77.7)	84.4 (8.6)
Low switch probability items	Repeat	676.9 (63.8)	675.2 (64.7)	89.8 (5.8)
	Switch	709.8 (77.3)	708.2 (77.6)	87.5 (10.0)
High switch probability items	Repeat	682.1 (73.3)	684.0 (76.0)	91.1 (8.2)
	Switch	703.4 (70.6)	702.4 (70.9)	87.0 (7.8)

RT* = mean response times with a data set excluding trials following incorrect trials

.04; List-Wide Switch Probability × Transition interaction, $F(1, 100) = 3.68$, $p = .058$, $\eta_p^2 = .04$.

Reactive metacontrol

Response times Participants responded slower on switch trials than on repeat trials, $F(1, 100) = 54.29$, $p < .001$, $\eta_p^2 = .35$. They responded similarly on trials with high switch probability items and on those with low switch probability items, $F(1, 100) = 0.05$, $p = .826$, $\eta_p^2 < .01$. Importantly, we replicated the ISSP effect as we found a significant Item-Specific Switch Probability × Transition interaction, $F(1, 100) = 5.70$, $p = .019$, $\eta_p^2 = .05$. The interaction was due to smaller switch costs on the high switch probability items ($M = 21.3$, $SD = 44.7$) as compared with the low switch probability items ($M = 32.9$, $SD = 43.8$), resulting in an ISSP effect of 11.6 ms ($SD = 48.8$), Cohen's $d = .24$ (see Fig. 4b and Table 2).

The results were the same with a smaller dataset *excluding trials following incorrect trials*: A significant main effect of transition, $F(1, 100) = 45.11$, $p < .001$, $\eta_p^2 = .31$, a nonsignificant main effect of item-specific switch probability, $F(1, 100) = 0.27$, $p = .607$, $\eta_p^2 < .01$, and a significant ISSP effect, $F(1, 100) = 7.88$, $p = .006$, $\eta_p^2 = .07$. Switch costs for the high switch probability items ($M = 18.4$, $SD = 48.1$) were smaller than those for the low switch probability items ($M = 33$, $SD = 44.8$), resulting in an ISSP effect of 14.5 ms ($SD = 52.1$), Cohen's $d = .28$.

Similar to the LWSP effect, the ISSP effect was also not modulated by *response compatibility*. The separate rmANOVA with an additional response compatibility variable revealed a significant main effect of response compatibility, $F(1, 100) = 444.38$, $p < .001$, $\eta_p^2 = .82$, a significant main effect of transition, $F(1, 100) = 67.43$, $p < .001$, $\eta_p^2 = .40$, and a significant Item-Specific Switch Probability × Transition interaction, $F(1, 100) = 4.91$, $p = .029$, $\eta_p^2 = .05$. A significant Response Compatibility × Transition interaction was also observed, $F(1, 100) = 7.27$, $p = .008$, $\eta_p^2 = .07$, which was driven by larger switch costs for response incompatible items than for response compatible items (response incompatible: $M = 36.9$, $SD = 45$; response compatible: $M = 22.5$, $SD = 45.6$). Other effects were not significant, main effect of item-specific switch probability, $F(1, 100) = 0.10$, $p = .748$, $\eta_p^2 < .01$; interaction effect of Response Compatibility × Item-Specific Switch Probability, $F(1, 100) = 0.51$, $p = .479$, $\eta_p^2 < .01$. Notably, the three-way interaction involving Response Compatibility × Item-Specific Switch Probability ×

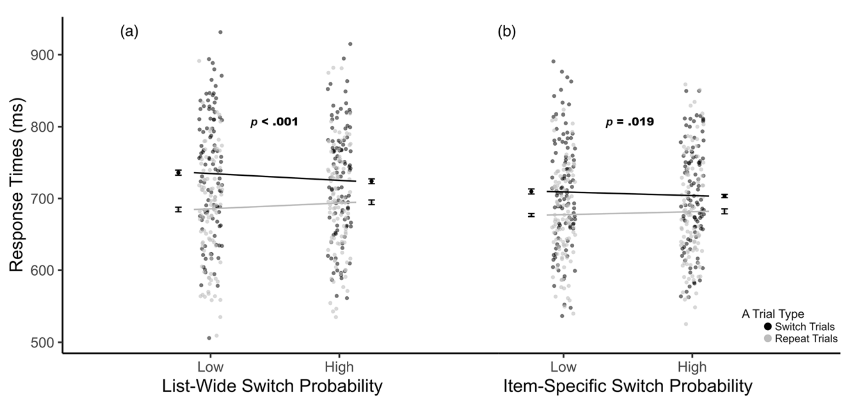

Fig. 4 Response times as a function of (**a**) List-Wide Switch Probabilty × Transition and (**b**) Item-Specific Switch Probability × Transition in Experiment 2. Error bars indicate within-subjects standard error of the mean (Franz & Loftus, 2012)

Transition was not significant, $F(1, 100) = 0.26$, $p = .609$, $\eta_p^2 < .01$, suggesting that the magnitude of the ISSP effect is not different between response compatible or response incompatible stimuli. This finding again suggests that the significant ISSP effect reported in Experiment 1 was not confounded by a design including only response incompatible stimuli.

Accuracy While participants responded less accurately on switch trials than on repeat trials, $F(1, 100) = 30.31$, $p < .001$, $\eta_p^2 = .23$, no other effects reached statistical significance, main effect of item-specific switch probability, $F(1, 100) = 0.56$, $p = .455$, $\eta_p^2 < .01$; Item-Specific Switch Probability × Transition interaction, $F(1, 100) = 3.05$, $p = .084$, $\eta_p^2 = .03$.

Correlation between proactive and reactive metacontrol

Similar to Experiment 1, both the frequentist and Bayesian approaches supported that there is no reliable correlation between the LWSP and the ISSP effects in RT across subjects, Pearson's $r = -.05$, $t(99) = -.47$, $p = .641$, $BF_{01} = 3.94$ (see Fig. 3). Like in Experiment 1, we examined the internal consistency of the LWSP and the ISSP effects by computing the split-half correlations for each effect. This analysis revealed a significant split-half correlation in the LWSP effect, $r = .24$, $t(99) = 2.41$, $p = .018$. However, the split-half correlation did not reach significance in the ISSP effect, $r = -.06$, $t(99) = -.59$, $p = .554$.

Discussion

In Experiment 2, we replicated the list-based and item-specific switch probability effects (i.e., LWSP and ISSP effects) that are indicative of proactive and reactive metacontrol, as well as their lack of dependence. Furthermore, the LWSP and ISSP effects were similar across the response compatible and response incompatible items, demonstrating that the results from Experiment 1 were not derived from a design including only the response incompatible items. Interestingly, as in Experiment 1, the size of LWSP effects were not different between the diagnostic and inducer items. In other words, we did not find additivity in inducer items. We speculated that proactive metacontrol is more dominant in the low/high switch probability lists, precluding reactive metacontrol to be expressed in inducer items when they appear in a biased switch probability list. This finding again resonates greatly with the observation that the two modes of metacontrol appear to be independent.

Across experiment analyses

Data analysis We performed an across-experiment analysis with experiment as a between-subjects variable to statistically assess any difference between the two experiments. To assess the difference in proactive metacontrol across two experiments, the diagnostic items (50% switch probability) from the low and the high switch probability lists were subject to a 2 (experiment: Experiment 1, Experiment 2) × 2 (list-wide switch probability: low, high) × 2 (transition: switch, repeat) mixed rmANOVA analysis. To assess the difference in reactive metacontrol across two experiments, switch probability-biased items from the medium switch probability list were subject to a 2 (experiment: Experiment 1, Experiment 2) × 2 (item-specific switch probability: low, high) × 2 (transition: switch, repeat) mixed rmANOVA.

Results

Proactive and reactive metacontrol

Response times We replicated the LWSP effect (i.e., proactive metacontrol) as well as the ISSP effect (i.e., reactive metacontrol), as evident by the significant List-Wide/Item-Specific Switch Probability × Transition interactions, LWSP: $F(1, 174) = 27.47$, $p < .001$, $\eta_p^2 = .14$; ISSP: $F(1, 174) = 9.91$, $p = .002$, $\eta_p^2 = .05$. The main effect of experiment was marginally significant in the ANOVA assessing proactive metacontrol, $F(1, 174) = 3.89$, $p = .05$, $\eta_p^2 = .02$, which was due to the longer mean RT in Experiment 2 ($M = 709.8$, $SD = 81.0$) than in Experiment 1 ($M = 690.9$, $SD = 71.1$). However, the main effect of experiment was not significant in the ANOVA assessing reactive metacontrol, $F(1, 174) = 0.09$, $p = .759$, $\eta_p^2 < .01$. The three-way interaction in both ANOVAs was not significant, proactive: $F(1, 174) = 0.24$, $p = .622$, $\eta_p^2 < .01$; reactive: $F(1, 174) < 0.01$, $p = .958$, $\eta_p^2 < .01$, suggesting that the magnitude of the LWSP and the ISSP effects turned out to be similar across the two experiments. With a much larger sample size, we still did not observe any correlation between the LWSP and the ISSP effects in RT across participants, Pearson's $r = .01$, $t(174) = .13$, $p = .894$, $BF_{01} = 5.67$ (see Fig. 3).

Accuracy While the LWSP effect was significant, $F(1, 174) = 9.05$, $p = .003$, $\eta_p^2 = .05$, the ISSP effect was not significant, $F(1, 174) = 0.20$, $p = .659$, $\eta_p^2 < .01$. The main effect of experiment was also significant in both ANOVAs assessing proactive and reactive metacontrol, proactive: $F(1, 174) = 56.70$, $p < .001$, $\eta_p^2 = .25$; reactive: $F(1, 174) = 25.09$, $p < .001$, $\eta_p^2 = .13$, which was due to lower accuracy in Experiment 1 (proactive: $M = 80.9$, $SD = 11.3$, reactive: $M = 83.2$, $SD = 11$) than in Experiment 2 ($M = 87.3$, $SD = 7.8$, reactive: $M = 88.9$, $SD = 8.2$). The three-way interaction of List-Wide Switch Probability × Transition × Experiment was significant, $F(1, 174) = 4.34$, $p = .039$, $\eta_p^2 = .02$, which was driven by a larger LWSP effect in Experiment 1 ($M = 4.4$, $SD = 11.4$) than in Experiment 2 ($M = 1.6$, $SD = 8.5$).

Whereas, the three-way interaction of Item-Specific Switch Probability × Transition × Experiment was not significant, $F(1, 174) = 3.26$, $p = .073$, $\eta_p^2 = .02$.

General discussion

Our study investigated two different types of context–control learning in terms of the LWSP and the ISSP effects as they are hypothesized to reflect proactive and reactive metacontrol, respectively. In two experiments, we employed a basic cued task-switching protocol that involves switching back-and-forth between two categorization tasks. Without informing participants about the regularities in switch probabilities, we were able to induce linking a particular control demand (e.g., frequent switching) either to a temporal episode (i.e., a list of trials) or to an individual stimulus. Namely, we observed behavioral patterns indicative of proactive and reactive metacontrol: Switch costs were reduced on the diagnostic items in the high switch probability list compared with those in the low switch probability list (i.e., a LWSP effect), and switch costs were reduced on the high switch probability items compared with the low switch probability items (i.e., an ISSP effect) in the 50% switch probability list. Additionally, there were no differences in proactive and reactive metacontrol across the response compatible and response incompatible items in Experiment 2, suggesting that the observed LWSP and ISSP effects in Experiment 1 were not due to a task-switching paradigm including only response incompatible items. These results support our hypothesis that list-based and item-based switch probability manipulations respectively induce proactive and reactive metacontrol, suggesting that participants recruit different modes of metacontrol in accordance with contextual variations in cognitive control demands.

One of the core features of cognitive control is that it enables behavioral and cognitive flexibility by selecting proper responses in accordance with the current behavioral goals (Cohen, 2017; Meiran et al., 2015; Miller & Cohen, 2001). Metacontrol or regulation of cognitive control, (Goschke & Bolte, 2014; Hommel, 2015) is hierarchically above cognitive control and enables the selection of control operations (e.g., task switch, selective attention) in accordance with the most relevant cognitive control demand. Piecing together these ideas, while the goal of cognitive control is to generate adaptive responses, the goal of metacontrol is to generate adaptive control. Building on the cognitive system that has dual modes of cognitive control (Braver, 2012), our findings documented dual modes of metacontrol that capitalize on distinct types of contextual cues (e.g., lists, items). Note that in our study participants were not informed about the control demand probabilities. As a result, proactive/reactive metacontrol observed here likely emerged naturally through experience. Yet some recent studies have shown that, in addition to experience, metacontrol can also be induced via explicit instruction—that is, an expectancy-based (as opposed to experience-based) metacontrol (e.g., Liu & Yeung, 2020). Together, our study joined a group of prior studies demonstrating that performance and behavior are modulated by metacontrol acquired through experience-based, context–control associative learning (Abrahamse et al., 2016; Braem et al., 2019; Bugg & Crump, 2012; Chiu & Egner, 2019; Egner, 2014).

Consistent with previous findings (Siqi-Liu & Egner, 2020), we also did not find reliable differences in the LWSP effects between inducer and diagnostic items. We suspect that proactive metacontrol might have been the dominant mode in lists with a relatively obvious switch probability bias (e.g., <35% or >65%). The DMC framework posits that reactive control is more susceptible to proactive interference since it relies on cues recognizable upon the stimulus onsets and the relevant control can only be applied during poststimulus processing (Braver et al., 2007). It seems that a similar argument can be made in the context of metacontrol. In switch probability-biased lists, the appropriate control state can already be instantiated prior to the stimulus onset, precluding the learning and/or the retrieval of the appropriate item-specific control state. Whereas, in unbiased lists, item-specific control associations are more likely to be formed and retrieved to benefit performance.

Our correlation results suggest that proactive metacontrol might be independent of reactive metacontrol. That is, the extent to which a cognitive system's ability to instantiate a control state (e.g., higher level of switch readiness) in anticipation of meeting a control demand (e.g., a high switch probability list) before the demand occurs cannot predict a system's ability to instantiate an optimal control state to meet a demand just in time. This independence might suggest that different forms of metacontrol (i.e., proactive, reactive) might modulate different processes that contribute to switch costs (e.g., task-set inertia processes or associative retrieval processes) in addition to the common task-set reconfiguration processes (Monsell, 2003). However, proactive and reactive metacontrol was inferred from a "double" difference score (i.e., the difference in switch costs between lists/items, while switch cost is a RT difference between switch and repeat RT). Therefore, the presence of metacontrol can be driven by a difference in either repeat RT, switch RT, or both between lists/items. In Experiment 2, the LWSP effect appears to be driven by the differences in both switch and repeat RT whereas, in Experiment 1, the effect appears to be mainly driven by the difference in repeat RT. We suspect the specific list-wide switch probabilities we had in each experiment might play a role (e.g., Experiment 1 used 65/35% whereas Experiment 2 used 70/30%), but we are not certain. Also, we note that the two lists were administered closer in time for Experiment 2 while the two lists were separated by the medium list in

Experiment 1. Therefore, it is difficult to infer from our results whether metacontrol reflects a modulation of an active task-set configuration process (Meiran et al. 2015; Rogers & Monsell, 1995), or retrieval of a previous task-set and responses (Allport et al., 1994; Waszak et al., 2003, 2004, 2005). Future studies could consider including a pure baseline measure (e.g., unbiased items in an unbiased list) to formally address this question (for addressing this question by including a third task, see Siqi-Liu & Egner, 2020).

The independence of the two modes aligns with the DMC framework, positing that the two modes of cognitive control are potentially relying on independent information processing modes, and therefore having distinct computational characteristics, temporal dynamics, and underlying neural mechanisms (Braver et al., 2007; De Pisapia & Braver, 2006; Grandjean et al., 2012). For example, using fMRI and EEG, the two modes of cognitive control were shown to be independent as they can be differentiated in terms of temporal dynamics and underlying neural mechanisms (Braver et al., 2007). While the transient activation of the lateral prefrontal cortex (PFC) was associated with reactive control, a sustained lateral PFC activation was associated with proactive control (Braver, 2012; Braver et al., 2007; De Pisapia & Braver, 2006). Functional hemispheric asymmetries in sustained versus phasic cognitive control were reported: While right PFC and right-lateralized intrinsic brain activity was associated with sustained cognitive control, left lateral PFC and left-lateralized intrinsic brain activity was engaged in phasic cognitive control (Ambrosini & Vallesi, 2016; Braver et al., 2003). Furthermore, distinct brain regions might engage in the two modes. MacDonald et al. (2000) demonstrated that the dorsal anterior cingulate cortex (dACC) was more activated when it was followed by incongruent trials than when it was followed by congruent trials (i.e., trial-wise conflict modulation), whereas the dorsal lateral prefrontal cortex (dlPFC) was more activated in a context where frequent incongruent trials were expected (i.e., list-wide preparatory modulation). ACC was also detected to be more activated on incongruent trials in a mostly congruent list than those in a mostly incongruent list implicating engagement of the ACC in trial-wise reactive conflict resolution (Carter et al., 2000; Kerns et al., 2004), while previous studies consistently indicated that the dlPFC is the area which keeps task-related information active (Bunge et al., 2002; Miller & Cohen, 2001). These prior neuroimaging findings thus implicate that neural mechanisms underlying reactive metacontrol might interact with the dACC, relying on its ability to detect a trial-wise conflict. Whereas, neural mechanisms underlying proactive metacontrol might interact with the dlPFC as it is thought to maintain control states across time in a preparatory manner.

As we have demonstrated a neat task-switching paradigm to induce both proactive and reactive metacontrol within-subjects, future studies could harness such a paradigm to investigate the individual differences in metacontrol, which could be due to cognitive (e.g., working memory capacity) or noncognitive factors (e.g., affective processing, personality traits). The reason that both cognitive and noncognitive factors could modulate metacontrol is because of the hub property of the anterior cingulate cortex (ACC) (Tang et al., 2019). Activation in the ACC during a cognitive control task that relies on working memory, has been linked to self-reported behavioral approach/inhibition sensitivity measures (Gray & Braver, 2002). As the ACC has been shown to play a role in adjusting cognitive control on a trial-by-trial basis (i.e., a form of reactive metacontrol), we hypothesize that the ACC might mediate the relationship between individual difference and metacontrol.

On the other hand, considering the benefit of bottom-up retrieval of metacontrol along with the lack of cognitive flexibility in some neuropsychiatric disorders (e.g., obsessive-compulsive disorder, schizophrenia, and autism spectrum disorders)(Champagne-Lavau et al., 2012; Gruner & Pittenger, 2017; Sanders et al., 2008), future studies can target clinical populations to study context–control learning. For example, such studies could compare clinical and nonclinical populations in terms of how they exhibit proactive and reactive metacontrol, behaviorally or neurocognitively. In addition, future studies can further investigate the independence between proactive and reactive metacontrol. Comparison of the neural correlates of the LWSP and ISSP effects can be used to address if proactive and reactive metacontrol are mediated by the same or different brain regions, or by different temporal dynamics, such as tonic versus phasic components. Finally, future studies should also address whether metacontrol can be acquired purely via a top-down mechanism (e.g., explicit instruction; cf. Liu & Yeung) in combination with one-shot learning (cf. Spinelli et al., 2019; Whitehead et al., 2020).

Conclusion

In conclusion, we demonstrated that both proactive and reactive metacontrol is achieved in response to variations in cognitive control demands. These findings are in line with the contemporary theorizing of associative learning-guided control, suggesting that cognitive control can be regulated by contextual cues predictive of goal-relevant cognitive control demands, which has traditionally been assumed to be deployed in a top-down manner. The two forms of metacontrol appear to be dissociable and independent, which maximize cognitive and behavioral flexibility in an environment that is complex (e.g., the real world). Our results support the idea that we interact with the environment (e.g., contextual cues) to exert sustained and transient attention in the form of proactive and reactive metacontrol. These two modes of metacontrol enable optimal efficiency by interlocking flexible cognitive control and fast associative learning.

Acknowledgments We thank Hyun Joo Shin for her help with programming a part of the experiment. We adapted codes from van Langen (2020; Open-visualizations in R and Python; https://github.com/jorvlan/open-visualizations) to generate Figs. 2 and 4.

Code availability The codes are available from the corresponding author on reasonable request.

Author's contribution M.S. Kang and Y.-C. Chiu conceived the study design. M.S. Kang programmed the experiments, collected and analyzed the data. M.S. Kang wrote the initial draft of the manuscript. M.S. Kang and Y.-C. Chiu both revised and edited the submitted manuscript.

Funding The authors did not receive support from any organization for the submitted work.

Data availability The raw data is available on the Open Science Framework (https://osf.io/yrjtv/).

Declarations

Conflicts of interest The authors declare no competing financial interests.

Ethics approval This study was performed in line with the principles of the Declaration of Helsinki. Approval was granted by the Ethics Committee of Purdue University (IRB #: 1808020939; Approval date 9/12/2019).

Consent to participate Informed consent was obtained from all individual participants included in the study.

Consent for publication Informed consent was obtained from all individual participants and the data were collected and analyzed anonymously.

References

Abrahamse, E., Braem, S., Notebaert, W., & Verguts, T. (2016). Grounding cognitive control in associative learning. *Psychological Bulletin*, *142*(7), 693–728. https://doi.org/10.1037/bul0000047

Allport, A., Styles, E. A., & Hsieh, S. (1994). Shifting intentional set: Exploring the dynamic control of tasks. In C. Umilta & M. Moscovitch (Eds.), *Conscious and nonconscious information processing: Attention and performance XV* (pp. 421–452). MIT Press.

Ambrosini, E., & Vallesi, A. (2016). Asymmetry in prefrontal resting-state EEG spectral power underlies individual differences in phasic and sustained cognitive control. *NeuroImage*, *124*, 843–857. https://doi.org/10.1016/j.neuroimage.2015.09.035

Braem, S., Bugg, J. M., Schmidt, J. R., Crump, M. J. C., Weissman, D. H., Notebaert, W., & Egner, T. (2019). Measuring adaptive control in conflict tasks. *Trends in Cognitive Sciences*, *23*(9), 769–783. https://doi.org/10.1016/j.tics.2019.07.002

Braver, T. S. (2012). The variable nature of cognitive control: A dual mechanisms framework. *Trends in Cognitive Sciences*, *16*(2), 106–113. https://doi.org/10.1016/j.tics.2011.12.010

Braver, T. S., Reynolds, J. R., & Donaldson, D. I. (2003). Neural Mechanisms of Transient and Sustained Cognitive Control during Task Switching. *Neuron*, *39*, 713–726. https://doi.org/10.1016/S0896-6273(03)00466-5

Braver, T. S., Gray, J. R., & Burgess, G. C. (2007). Explaining the many varieties of working memory variation: Dual mechanisms of cognitive control. In A. R. A. Conway, C. Jarrold, M. J. Kane, A. Miyake, & J. N. Towse (Eds.), *Variation in working memory* (pp. 76–106). Oxford University Press.

Braver, T. S., Paxton, J. L., Locke, H. S., & Barch, D. M. (2009). Flexible neural mechanisms of cognitive control within human prefrontal cortex. *Proceedings of the National Academy of Sciences of the United States of America, 106*(18), 7351–7356. https://doi.org/10.1073/pnas.0808187

Bugg, J. M. (2012). Dissociating levels of cognitive control: The case of Stroop interference. *Current Directions in Psychological Science*, *21*(5), 302–309. https://doi.org/10.1177/0963721412453586

Bugg, J. M., & Crump, M. J. C. (2012). In support of a distinction between voluntary and stimulus-driven control: A review of the literature on proportion congruent effects. *Frontiers in Psychology*, *3*, 1–16. https://doi.org/10.3389/fpsyg.2012.00367

Bugg, J. M., & Hutchison, K. A. (2013). Converging evidence for control of color-word Stroop interference at the item level. *Journal of Experimental Psychology: Human Perception and Performance*, *39*(2), 433–449. https://doi.org/10.1037/a0029145

Bugg, J. M., Jacoby, L. L., & Chanani, S. (2011). Why it is too early to lose control in accounts of item-specific proportion congruency effects. *Journal of Experimental Psychology: Human Perception and Performance, 37*(3), 844–859. https://doi.org/10.1037/a0019957

Bunge, S. A., Dudukovic, N. M., Thomason, M. E., Vaidya, C. J., & Gabrieli, J. D. E. (2002). Immature frontal lobe contributions to cognitive control in children: Evidence from fMRI. *Neuron*, *33*(2), 301–311. https://doi.org/10.1016/S0896-6273(01)00583-9

Capizzi, M., Ambrosini, E., Arbula, S., Mazzonetto, I., & Vallesi, A. (2016). Electrophysiological evidence for domain-general processes in task-switching. *Frontiers in Human Neuroscience*, *10*, 1–14. https://doi.org/10.3389/fnhum.2016.00124

Carter, C. S., Macdonald, A. M., Botvinick, M., Ross, L. L., Stenger, V. A., Noll, D., & Cohen, J. D. (2000). Parsing executive processes: Strategic vs. evaluative functions of the anterior cingulate cortex. *Proceedings of the National Academy of Sciences of the United States of America*, *97*(4), 1944–1948. https://doi.org/10.1073/pnas.97.4.1944

Champagne-Lavau, M., Charest, A., Anselmo, K., Rodriguez, J. P., & Blouin, G. (2012). Theory of mind and context processing in schizophrenia: The role of cognitive flexibility. *Psychiatry Research*, *200*(2/3), 184–192. https://doi.org/10.1016/j.psychres.2012.06.011

Chiu, Y.-C. (2019). Automating adaptive control with item-specific learning: Psychology of learning and motivation. In K. Federmeier (Ed.), *Advances in research and theory* (Vol. 71, pp. 1–37). Elsevier.

Chiu, Y.-C., & Egner, T. (2017). Cueing cognitive flexibility: Item-specific learning of switch readiness. *Journal of Experimental Psychology: Human Perception and Performance*, *43*(12), 1950–1960. https://doi.org/10.1037/xhp0000420

Chiu, Y. -C., & Egner, T. (2019). Cortical and subcortical contributions to context–control learning. *Neuroscience and Biobehavioral Reviews*, *99*, 33–41. https://doi.org/10.1016/j.neubiorev.2019.01.019

Chiu, Y.-C., Fröber, K., & Egner, T. (2020). Item-specific priming of voluntary task switches. *Journal of Experimental Psychology: Human Perception and Performance, 46*(4), 434–441. https://doi.org/10.1037/xhp0000725

Cohen, J. (2017). Cognitive control. In T. Egner (Ed.), *The Wiley handbook of cognitive control* (pp. 3–28). Wiley. https://doi.org/10.1002/9781118920497.ch1

Cohen, J. D., Braver, T. S., Nystrom, L. E., Noll, D. C., Jonides, J., Smith, E. E., & Perlstein, W. M. (1997). Temporal dynamics of brain activation during a working memory task. *Nature*, *386*, 604–608. https://doi.org/10.1038/386604a0

Crump, M. J. C., & Logan, G. D. (2010). Contextual control over task-set retrieval. *Attention, Perception, & Psychophysics, 72,* 2047–2053. https://doi.org/10.3758/BF03196681

Crump, M. J., & Milliken, B. (2009). Short article: The flexibility of context-specific control: Evidence for context-driven generalization of item-specific control settings. *Quarterly Journal of Experimental Psychology, 62*(8), 1523–1532. https://doi.org/10.1080/17470210902752096

de Pisapia, N., & Braver, T. S. (2006). A model of dual control mechanisms through anterior cingulate and prefrontal cortex interactions. *Neurocomputing*, *69*(10/12), 1322–1326. https://doi.org/10.1016/j.neucom.2005.12.100

Dreisbach, G., & Haider, H. (2006). Preparatory adjustment of cognitive control in the task switching paradigm. *Psychonomic Bulletin & Review*, *13*(2), 334–338. https://doi.org/10.3758/BF03193853

Dreisbach, G., Haider, H., & Kluwe, R. H. (2002). Preparatory processes in the task-switching paradigm: Evidence from the use of probability cues. *Journal of Experimental Psychology: Learning Memory and Cognition*, *28*(3), 468–483. https://doi.org/10.1037/0278-7393.28.3.468

Ebner, N. C., Riediger, M., & Lindenberger, U. (2010). FACES-a database of facial expressions in young, middle-aged, and older women and men: Development and validation. *Behavior Research Methods, 42*(1), 351–362. https://doi.org/10.3758/BRM.42.1.351

Egner, T. (2014). Creatures of habit (and control): A multi-level learning perspective on the modulation of congruency effects. *Frontiers in Psychology*, *5*, 1–11. https://doi.org/10.3389/fpsyg.2014.01247

Franz, V. H., & Loftus, G. R. (2012). Standard errors and confidence intervals in within-subjects designs: Generalizing Loftus and Masson (1994) and avoiding the biases of alternative accounts. *Psychonomic Bulletin & Review*, *19*(3), 395–404. https://doi.org/10.3758/s13423-012-0230-1

Fröber, K., & Dreisbach, G. (2020). How sequentially changing reward prospect modulates meta-control: Increasing reward prospect promotes cognitive flexibility. *Cognitive, Affective, & Behavioral Neuroscience*, 1–15. Advance online publication. https://doi.org/10.3758/s13415-020-00825-1

Gonthier, C., Braver, T. S., & Bugg, J. M. (2016). Dissociating proactive and reactive control in the Stroop task. *Memory & Cognition*, *44*(5), 778–788. https://doi.org/10.3758/s13421-016-0591-1

Goschke, T. (2003). Voluntary action and cognitive control from a cognitive neuroscience perspective. In S. Maasen, W. Prinz, & G. Roth (Eds.), *Voluntary action: Brains, minds, and sociality* (pp. 49–85). Oxford University Press.

Goschke, T., & Bolte, A. (2014). Emotional modulation of control dilemmas: The role of positive affect, reward, and dopamine in cognitive stability and flexibility. *Neuropsychologia*, *62*, 403–423. https://doi.org/10.1016/j.neuropsychologia.2014.07.015

Grandjean, J., D'Ostilio, K., Phillips, C., Balteau, E., Degueldre, C., Luxen, A., Maquet, P., Salmon, E., & Collette, F. (2012). Modulation of brain activity during a Stroop inhibitory task by the kind of cognitive control required. *PLOS ONE*, *7*(7), Article e41513. https://doi.org/10.1371/journal.pone.0041513

Gray, J. R., & Braver, T. S. (2002). Personality predicts working-memory-related activation in the caudal anterior cingulate cortex. *Cognitive, Affective, & Behavioral Neuroscience, 2*(1), 64–75. https://doi.org/10.3758/CABN.2.1.64

Gruner, P., & Pittenger, C. (2017). Cognitive inflexibility in obsessive-compulsive disorder. *Neuroscience*, *345*, 243–255. https://doi.org/10.1016/j.neuroscience.2016.07.030

Hommel, B. (2015). Between persistence and flexibility: The Yin and Yang of action control. In A. Elliot (Ed.), *Advances in motivation science* (Vol. 2, pp. 33–67). Elsevier.

Jacoby, L. L., Lindsay, D. S., & Hessels, S. (2003). Item-specific control of automatic processes: Stroop process dissociations. *Psychonomic Bulletin and Review*, *10*(3), 638–644. https://doi.org/10.3758/BF03196526

Jersild, A. T. (1927). Mental set and shift. *Archives of Psychology, 14*, 5–82.

Kerns, J. G., Cohen, J. D., MacDonald, A. W., Cho, R. Y., Stenger, V. A., & Carter, C. S. (2004). Anterior cingulate conflict monitoring and adjustments in control. *Science*, *303*(5660), 1023–1026. https://doi.org/10.1126/science.1089910

Leboe, J. P., Wong, J., Crump, M., & Stobbe, K. (2008). Probe-specific proportion task repetition effects on switching costs. *Perception and Psychophysics*, *70*(6), 935–945. https://doi.org/10.3758/PP.70.6.935

Liu, C., & Yeung, N. (2020). Dissociating Expectancy-Based and Experience-Based Control in Task Switching. *Journal of Experimental Psychology: Human Perception and Performance, 46*(2), 131–154. https://doi.org/10.1037/xhp0000704

Logan, G. D., & Bundesen, C. (2003). Clever Homunculus: Is There an Endogenous Act of Control in the Explicit Task-cuing Procedure? *Journal of Experimental Psychology: Human Perception and Performance*, *29*(3), 575–599. https://doi.org/10.1037/0096-1523.29.3.575

Logan, G. D., & Zbrodoff, N. J. (1979). When it helps to be misled: Facilitative effects of increasing the frequency of conflicting stimuli in a Stroop-like task. *Memory & Cognition*, *7*(3), 166–174. https://doi.org/10.3758/BF03197535

Logan, Posner, M. I., & Snyder, C. R. R. (1975). Attention and cognitive control. In R. L. Solso (Ed.), *Information processing and cognition: The Loyola symposium*. Erlbaum. http://philpapers.org/rec/POSAAC

MacDonald, A. W., Cohen, J. D., Andrew Stenger, V., & Carter, C. S. (2000). Dissociating the role of the dorsolateral prefrontal and anterior cingulate cortex in cognitive control. *Science*, *288*(5472), 1835–1838. https://doi.org/10.1126/science.288.5472.1835

MacLeod, C. M., & Dunbar, K. (1988). Training and Stroop-like interference: Evidence for a continuum of automaticity. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 14*, 126–135. https://doi.org/10.1037//0278-7393.14.1.126

Mayr, U., Kuhns, D., & Rieter, M. (2013). Eye movements reveal dynamics of task control. *Journal of Experimental Psychology: General*, *142*(2), 489–509. https://doi.org/10.1037/a0029353

Meiran, N., Pereg, M., Kessler, Y., Cole, M. W., & Braver, T. S. (2015). The power of instructions: Proactive configuration of stimulus–response translation. *Journal of Experimental Psychology: Learning Memory and Cognition*, *41*(3), 768–786. https://doi.org/10.1037/xlm0000063

Miller, E. K., & Cohen, J. D. (2001). An integrative theory of prefrontal cortex function. *Annual Review of Neuroscience, 24*(1), 167–202. https://doi.org/10.1146/annurev.neuro.24.1.167

Monsell, S. (2003). Task switching. *Trends in Cognitive Sciences, 7*(3), 134–140. https://doi.org/10.1016/S1364-6613(03)00028-7

Monsell, S., & Mizon, G. A. (2006). Can the task-cuing paradigm measure an endogenous task-set reconfiguration process? *Journal of Experimental Psychology: Human Perception and Performance, 32*(3), 493–516. https://doi.org/10.1037/0096-1523.32.3.493

Moreno-Martínez, F. J., & Montoro, P. R. (2012). An ecological alternative to Snodgrass & Vanderwart: 360 high quality colour images with norms for seven psycholinguistic variables. *PloS one, 7*(5), e37527. https://doi.org/10.1371/journal.pone.0037527

Morey, R. D., Rouder, J. N., & Jamil, T. (2015). *BayesFactor: Computation of Bayes factors for common designs* (Version 0.9.12-4.2). https://cran.rproject.org/web/packages/BayesFactor/

Rogers, R. D., & Monsell, S. (1995). Costs of a predictable switch between simple cognitive tasks. *Journal of Experimental Psychology: General, 124*(2), 207–231. https://doi.org/10.1037/0096-3445.124.2.207

Sanders, J., Johnson, K. A., Garavan, H., Gill, M., & Gallagher, L. (2008). A review of neuropsychological and neuroimaging research in autistic spectrum disorders: Attention, inhibition and cognitive flexibility. *Research in Autism Spectrum Disorders*, *2*(1), 1–16. https://doi.org/10.1016/j.rasd.2007.03.005

Schmidt, J. R., & Besner, D. (2008). The Stroop effect: Why proportion congruent has nothing to do with congruency and everything to do with contingency. *Journal of Experimental Psychology: Learning Memory and Cognition*, *34*(3), 514–523. https://doi.org/10.1037/0278-7393.34.3.514

Schneider, D. W., & Logan, G. D. (2006). Priming cue encoding by manipulating transition frequency in explicitly cued task switching. *Psychonomic Bulletin & Review*, *13*(1), 145–151. https://doi.org/10.3758/bf03193826

Siqi-Liu, A. & Egner, T. (2020). Contextual adaptation of cognitive flexibility is driven by task- and item-level learning. *Cognitive, Affective, & Behavioral Neuroscience, 20*, 757–782. https://doi.org/10.3758/s13415-020-00801-9

Spinelli, G., Perry, J. R., & Lupker, S. J. (2019). Adaptation to conflict frequency without contingency and temporal learning: Evidence from the picture-word interference task. *Journal of Experimental Psychology: Human Perception and Performance*, *45*(8), 995–1014. https://doi.org/10.1037/xhp0000656

Tang, W., Jbabdi, S., Zhu, Z., Cottaar, M., Grisot, G., Lehman, J. F., Yendiki, A., & Haber, S. N. (2019). A connectional hub in the rostral anterior cingulate cortex links areas of emotion and cognitive control. *ELife, 8,* 1–25. https://doi.org/10.7554/eLife.43761.001

Waszak, F., Hommel, B., & Allport, A. (2003). Task-switching and long-term priming: Role of episodic stimulus–task bindings in task-shift costs. *Cognitive psychology, 46*(4), 361–413. https://doi.org/10.1016/S0010-0285(02)00520-0

Waszak, F., Hommel, B., & Allport, A. (2004). Semantic generalization of stimulus-task bindings. *Psychonomic Bulletin & Review, 11*(6), 1027–1033. https://doi.org/10.3758/BF03196732

Waszak, F., Hommel, B., & Allport, A. (2005). Interaction of task readiness and automatic retrieval in task switching: Negative priming and competitor priming. *Memory & cognition, 33*(4), 595–610. https://doi.org/10.3758/BF03195327

Whitehead, P. S., Pfeuffer, C. U., & Egner, T. (2020). Memories of control: One-shot episodic learning of item-specific stimulus-control associations. *Cognition*, *199*, 104–220. https://doi.org/10.1016/j.cognition.2020.104220