American Psychological Association

Journal of Experimental Psychology:
Human Perception and Performance

ISSN: 0096-1523

2020, Vol. 46, No. 2, 131–154
http://dx.doi.org/10.1037/xhp0000704

Dissociating Expectancy-Based and Experience-Based Control in Task Switching

Chialun Liu and Nick Yeung
University of Oxford

The ability to switch tasks flexibly plays a critical role in goal-directed behavior. The present study tested the hypothesis that task switching is subject to higher-level "metacontrol" regulation that is reflected, for example, in contextual influences on switching efficiency, such as the global probability of task switches. This hypothesis was tested in 5 experiments using an instruction manipulation to dissociate expectancy-based control from experience-based practice effects: Participants' beliefs about switch probability were manipulated across trial sequences via explicit instruction, while objective frequency was matched for a subset of sequences. The behavioral results of Experiments 1–3 indicated that instruction played a role above experience in modulating task switching efficiency, and that this effect was motivation-dependent. Experiment 4 used electroencephalogram (EEG) methods to characterize the mechanism by which instructions affected processing via established event-related potential and oscillatory markers of task preparation. Experiment 5 demonstrated that the influence of instructions extended to participants' voluntary task choices. Collectively, the present findings demonstrate that instruction-induced expectancy prompts the adoption of distinct metacontrol modes across sequences, but does not modulate trial-by-trial, task-specific motor preparation.

Public Significance Statement

The research highlights the importance of the hierarchical structure of cognitive control. Results demonstrated that the cognitive system is able to adapt to various context supporting by high-level of cognitive control. These results provide new insight into cognitive control, and introduce a new method to study these processes.

Keywords: task switching, cognitive control, hierarchy, switch frequency, EEG

Mental flexibility plays a critical role in many daily activities. For instance, writing an academic article requires constant alternation between activities such as checking data, referring to published papers, and writing text. Studies using task-switching methods have provided valuable insight into flexible cognitive control by requiring the fluent, goal-directed switching that characterizes these everyday behaviors. In a typical task switching study, participants make frequent, rapid switches between simple categorization tasks (e.g., classifying presented digits as odd/even or high/low) according to a predictable schedule (e.g., Rogers & Monsell, 1995) or following cues that indicate the required task on each trial (e.g., Meiran, 1996). Flexible switching is presumed to tax control processes that focus attention on task-relevant stimulus attributes, establish mappings from those stimuli to required responses, and enable response-appropriate effectors—that is, to impose an appropriate *task set*. Consistent with this interpretation, switching is associated with performance costs—increased RTs and error rates when the task switches versus repeats from the previous trial—as well as increased activity in fronto-parietal brain regions thought to underpin flexible, goal-directed behavior (e.g., Richter & Yeung, 2014; Sakai, 2008).

However, standard task-switching designs lack a critical feature of most naturalistic settings: that there is high-level structure to the tasks being switched between. For example, when drafting an article, component activities such as writing a paragraph, checking data, and referring to published papers, are not performed in random and unpredictable order. Instead, people tend to order tasks with similar content to be completed close in time to increase efficiency. Moreover, the frequency and rapidity of switching might change over time, for example as a deadline approaches. Thus, a task can be viewed as an overall plan (writing a paper) comprising several subtasks (writing text, checking data, reading, etc.) that are directed and scheduled toward the fulfillment of a common goal. This form of hierarchical structure is found in several cognitive domains including cognitive control (e.g., Cooper & Shallice, 2000; Lien & Ruthruff, 2004; Norman, 1981),

Chialun Liu and Nick Yeung, Department of Experimental Psychology, University of Oxford.

Chialun Liu was sponsored by Ministry of Education Studying Aboard Scholarship from Taiwan. The authors thank Anne-Marike Schiffer and Raluca David for comments on experiments and technical support on data collection.

Correspondence concerning this article should be addressed to Chialun Liu, who is now at School of Life Sciences, University of Science and Technology of China, Huangshan Road 443, Hefei, Anhui 230027. E-mail: cllustc@ustc.edu.cn

memory (e.g., Anderson, Bothell, Lebiere, & Matessa, 1998), and action control (e.g., Botvinick & Plaut, 2004; Vallacher & Wegner, 1987). High-level structure may increase efficiency in planning and performance, but necessitates additional control signals that must be maintained over time to ensure the ultimate goal is properly followed (e.g., Desrochers, Chatham, & Badre, 2015). This idea of hierarchically ordered control signals is supported by recent neuroimaging evidence regarding functional specialization along the anterior-posterior axis of prefrontal cortex (Badre & D'Esposito, 2009; Koechlin & Summerfield, 2007; Koechlin, Ody, & Kouneiher, 2003).

Much previous research has investigated hierarchical structure in terms of task-subtask organization. In contrast, the focus of the present research is on a related but distinct form of adaptive higher-level control, which involves setting parameters relating to how tasks should be performed and scheduled—for example, whether there is time pressure (so that individual steps should be executed quickly, and optional steps skipped), or whether the task must be combined with others or performed alone. Henceforth we use the term "metacontrol" (cf. Hommel, 2015) to refer this form of organization, which we conceptualize as operating hierarchically above task-level control processes typically studied in task switching experiments.

The series of experiments reported here investigate this type of metacontrol parameter setting. In the context mentioned above, of drafting an academic article, this control might differ in the early and later stages of writing: In the early stages, people might switch frequently between checking data, writing short paragraphs, and reading published papers, whereas later on they may switch less frequently and instead sustain focus on reading paragraphs for clarity. Thus, the plan of writing a paper remains the same over time, but the metacontrol that coordinates subtasks changes.

Metacontrol in Task Switching

Evidence of metacontrol influence can be found in previous task switching studies. For example, Monsell, Sumner, and Waters (2003) observed differences in task switching performance when task order was predictable versus unpredictable: When task switches were fully predictable, the entire cost of switching was borne on the first trial of a new task, whereas when task order was unpredictable (being cued on each trial) they observed a gradual reduction in RTs across successive task repetitions. The authors suggest that participants commit fully to a new task when they know it will be required for multiple trials, but when task order is unpredictable, they are cautious about committing to a task because they might need to switch away again immediately. Thus, task-set control is subject to strategic modulation according to expectations about the probability of upcoming task switches.

Consistent with this idea, and of particular relevance here, several studies have shown that task switching efficiency is influenced by the likelihood of switches occurring (Dreisbach & Haider, 2006; Logan, Schneider, & Bundesen, 2007; Mayr, Kuhns, & Rieter, 2013; Monsell & Mizon, 2006). For example, Monsell and Mizon (2006) had separate groups of participants perform a standard task-switching paradigm in which task switches occurred on 25, 50, or 75% of trials. They found that switching costs reduced as switch probability increased, and interpreted this reduction as a reflecting change in strategy: When task switches are frequent, participants tend to switch away from the task they have just performed in anticipation of an upcoming switch. By contrast, when task repetition is probable, participants instead tend to remain in the same task set from the previous trial until cued otherwise. These findings suggest that trial-to-trial level switching process can be modified by a higher-level control process that is sensitive to the broader context; thus, falling within our definition of metacontrol.

Dreisbach and Haider (2006) similarly manipulated switch probability, using a within-subject design. Specifically, they compared a "global" expectancy condition, in which the ratio of task-switch to task-repeat trials was shown at the beginning of each block, against a "local" condition in which participants were informed about switch probability via cues presented before each stimulus. Both manipulations influenced task switching performance, suggesting that there are at least two routes for the preparatory adjustment of cognitive control: triggered by explicit cues on single trials or by global information about the context as a whole. Preparation via contextual information that is sustained across trials again hints at the possibility of higher-level control operating across longer time windows.

Providing converging evidence using neuroimaging methods, Braver, Reynolds, and Donaldson (2003) compared functional magnetic resonance imaging (fMRI) activity as participants performed standard task switching blocks (mixed task) against activity in blocks in which only a single task was performed (single task). Event-related analyses revealed transient activation in dorsolateral PFC (DLPFC) on each trial that was greater in mixed-task blocks than single-task blocks, whereas anterior PFC (APFC) did not show this transient response. In contrast, when contrasting sustained activity across blocks, they found higher sustained activity in APFC across entire mixed-task blocks compared with single-task blocks, whereas DLPFC showed little or no sustained activity in this comparison. Braver et al. interpreted these findings as suggesting that DLPFC supports trial-by-trial maintenance and switching of task sets, whereas APFC plays a contextual role in maintaining a heightened level of control over an extended period of task switching (i.e., a metacontrol function).

Together, these studies suggest that context modulates task-level control. However, several interpretations of the switch frequency effect are possible. It could be that this effect reflects metacontrol of the kind we define above, with a high-level process exerting sustained influence over lower-level switching mechanisms (e.g., reducing the strength with which task sets are applied when task switches are likely, to facilitate efficient switching). Alternatively, the effects may reflect more local trial-by-trial strategic control; for example, knowing that switches are likely, and that Task A was just performed, it is now best to prepare for Task B. Finally, the effects might have little to do with high-level control at all, but rather reflect the effects of experience and practice. For example, participants might benefit from performing extended runs of trials at a task when switching is infrequent (cf. Monsell et al., 2003), thus, inflating measured switch costs as task repetitions become increasingly efficient. Conversely, frequent task switching might lead participants to form associative links between the two tasks as a task-level equivalent of well-studied learning of response sequences (Cleeremans & Mcclelland, 1991), without any explicit representation of switch frequency context. Thus, at present, it is not clear that switch frequency effects result from low-level practice effects, dynamic cognitive control adjusted trial-to-trial, or a long-lasting adjustment over trials (or some combination of all of these).

The Present Study

Here we introduce a novel manipulation to study the influence of metacontrol on task switching. In particular, we used instructions to de-confound high-level influence from bottom-up effects of local practice and recent experience (such as the benefits of successive repetition of tasks when switching is rare, or practice at regular task transitions when switching is frequent). In our experiments, participants performed standard cued task switching in short sequences of trials, with instructions about switch probability that were generally informative but that were misleading in some individual sequences. When instructed that task switches would be frequent, participants experienced sequences with an overall switch probability of 66%; when instructed that switches would be rare, participants experienced sequences with an overall switch probability of 33%. However, these overall probabilities came about through a mix of sequences types: In sequences with "frequent switch" instructions, objective switch probability was either 81% ("Real Frequent") or 50% ("Fake Frequent"). Similarly, in sequences with "rare switch" instructions, objective switch probability was either 19% ("Real Rare") or 50% ("Fake Rare"). This design enables us to contrast two conditions in which low-level experience is matched but high-level expectation differs—the Fake Frequent and Fake Rare conditions—thus, isolating relatively pure effects of metacontrol. We used short sequences of trials following each instruction, reasoning that this would allow expression of any instruction effects that reflected the rapid adoption of new metacontrol parameters, while reducing the likelihood that participants would detect discrepancies between instructed and actual switch frequency in the crucial Fake Instruction conditions.

We hypothesized that information about switch probability should encourage people to adopt different task-set control strategies. For example, following frequent switch instructions, participants might commit less strongly to the required task on any given trial, knowing that they will soon be required to switch to a different one, and proactively prepare a switch after consecutive task repetitions. If task switching depends on metacontrol parameters in this way, we would expect lower switching costs in the Fake Frequent condition than in the Fake Rare condition, even though these conditions are matched for objective switch frequency. Experiment 1 aimed to test these core predictions. Experiments 2 and 3 extended the approach to test the dependence of instruction effects on motivation, manipulated via reward incentives.

Experiment 4 used electroencephalogram (EEG) methods to characterize the mechanisms by which instructions influence task switching performance. In particular, we looked for evidence of two contrasting (but not mutually exclusive) ways in which effects of metaparameters might be expressed. The first is via strategic preparation on a trial-by-trial basis: Knowing, for example, that switch frequency is high, a participant who just performed Task A might then proactively prepare for Task B (and vice versa) in anticipation that this task will be required. If so, then established neural markers of task switching preparation ought to be enhanced when instructions indicate high switch frequency. As a marker of task-specific preparation, we measured the lateralized readiness potential (LRP; Coles, 1989) in a design in which the tasks were assigned to different hands.

We also looked for evidence that participants adopt a global metacontrol set that is conducive either to stable task performance or task switching according to expected switch frequency, such that they commit less strongly to the current task when switch frequency is high (facilitating switching) or more strongly when switching is rare (facilitating repeated task performance). This idea relates to the hypothesis that task sets serve as attentional filters that shield the current task from interference but increase the cost of switching (e.g., Dreisbach & Haider, 2006, 2009), as well as to the hypothesis that the strength of attentional filtering of irrelevant information varies strategically according to task context (e.g., Botvinick, Braver, Barch, Carter, & Cohen, 2001; Entel, Tzelgov, & Bereby-Meyer, 2014). According to this view, the strength of filtering should depend on high-level expectations about the likelihood of task switches. We measured parieto-occipital alpha (8–14 Hz) power as a candidate index of this general task preparation and filtering (e.g., Hughes, Mathan, & Yeung, 2013; Macdonald, Mathan, & Yeung, 2011). Alpha power typically varies inversely with the degree of exerted attention or control, for example being reduced after experiencing response conflict (Compton, Arnstein, Freedman, Dainer-Best, & Liss, 2011) or during preparation for an upcoming task switch (Gladwin & de Jong, 2005; Poljac & Yeung, 2014). Thus, we predicted that when switch frequency is high, reduced alpha will be observed. On the other hand, when switch probability is low, and conflict is expected to be low, increased alpha power should be observed. Together, these EEG markers enable us to dissociate two levels of control by which instructions affect task switching processes.

In Experiment 5, we sought converging evidence for metacontrol effects by combining our instruction design with a voluntary task switch (VTS) procedure, in which participants were sometimes asked to select between tasks according to their own will or preference, rather than being cued to perform a specific task (Arrington & Logan, 2004). Recently, Fröber and Dreisbach (2017) explored voluntary task switching behavior using a design in which voluntary choice trials were interspersed among cued trials and in which switch frequency on cued trials varied across participants. Paralleling the switch frequency effects observed in cued switching designs (Dreisbach & Haider, 2006; Monsell & Mizon, 2006), Fröber and Dreisbach found increased rates of voluntary task switching in participants forced to make more frequent switches on the other, cued trials. Experiment 5 tested the prediction that corresponding effects would be observed as a function of pure instruction, even when controlling for bottom-up effects that arise as a function of real differences in switch frequency.

Experiment 1

The primary goal of our first experiment was to test for the influence of metacontrol while controlling for experience-driven control and practice effects. We asked our participants to switch between tasks of classifying digits as odd/even or low/high in short sequences of 17 trials, with instructions preceding each sequence that could signal task switches would be frequent or rare, or provide no information about switch likelihood. Crucially, half of the sequences with each frequency instruction had the identical objective switch probability (50%).

Method

Participants. Twenty students of the University of Oxford took part in this study (11 females; all right-handed; $M_{age} = 23.2$ years, $SD = 4.43$) for payment or course credit. All reported normal or corrected-to-normal vision and no color-blindness, and gave written informed consent. Given that we are studying a novel effect of instruction, we were not able to set our sample size based on an observed effect size from previous studies. As a guide, we expected the effect of instruction in our critical contrast—that is, the comparison of switch costs across Fake Instruction conditions—to be smaller than the effect of real differences in switch frequency, given that the latter effect should reflect bottom-up effects as well as metacontrol. Real switch frequency effects have been found to be large in previous studies with comparable sample sizes to ours, in both between-participants designs (Monsell & Mizon, 2006: $N = 16$ per group, $\eta_p^2 = .27$ for the contrast between 25 and 50% switch rates, and $\eta_p^2 = .20$ for the contrast between 50 and 75% switch rates) and within-participant designs (Dreisbach & Haider, 2006: $N = 24$, $\eta_p^2 = .45$, for the contrast of switch costs across 25 vs. 75% global switch frequencies). With $N = 20$, our design is powered to detect medium-large within-participant effect sizes ($d > 0.65$, $\eta_p^2 > .18$) with a power of 80% ($1 - \beta$) at a significance criterion of 5% ($\alpha = .05$), which we deemed appropriately conservative relative to previously observed effects of real instructions.

Apparatus and stimuli. The experiment was run using Psychtoolbox (Psychology Software Tools, Sharpsburg, PA) in Matlab (MathWorks, Inc.) on a 17-in. CRT display (resolution at 1280 × 1024 pixels) with a 75Hz refresh rate. Responses were recorded with a standard QWERTY-keyboard, using "f" and "j" as left and right response keys.

On each trial, a single digit (1–9 except 5) was presented, with its color signaling the required task. For half of the participants, digits in red (RGB code, [255, 0, 0]) or blue (RGB code, [0, 0, 255]) were to be categorized as lower or higher than 5, whereas green (RGB code, [0, 255, 0]) and purple (RGB code, [255, 0, 255]) digits were to be categorized as odd or even. For the other half of participants, these color-task assignments were reversed. Two colors were assigned to each task to dissociate task switching and cue switching effects (Schneider & Logan, 2011). Digit color never repeated across trials even when the task remained unchanged. All stimuli were displayed in Courier font with a size of 42 on a gray background (RGB code, [168, 168, 168]).

Design and procedure. Participants completed a series of nine experimental blocks, each comprising five sequences of 17 trials, for a total of 765 trials. Switch frequency and validity of instruction were manipulated across sequences (see Figure 1). Two sequences per block were preceded by the instruction "Frequent switch (66%)." In one of these sequences, switch frequency was 50% (termed Fake Frequent, FF); in the other, the switch frequency was 81% (termed Real Frequent, RF). Two sequences per block were preceded by the instruction "Rare switch (33%)." In one of these sequences, switch frequency was 50% (Fake Rare, FR); in the other, the switch frequency was 19% (Real Rare, RR). Thus, for each instruction type considering both sequences, the overall switch frequency matched the instruction [(81% + 50%)/2 ∼= 66%, and (19% + 50%)/2 ∼= 33%], thereby encouraging participants to make use of the instructions. The remaining sequence in each block was preceded by the instruction "No Instruction," and had an objective switch probability of 50%. The first trial in each sequence was a warm-up trial (for which switch/repeat transition is undefined); switch probabilities were fixed over the remaining 16 trials based on the sequence assigned. The order of the five sequence types was randomly assigned separately for each block. In particular, no constraints were imposed regarding within-block ordering of Fake and Real Instruction sequences, or Rare and Frequent switch instructions, such that Fake Frequent and Fake Rare sequences were no more likely to follow their corresponding Real Instruction equivalents as other sequence types.

Each short sequence was announced by an instruction screen for 3 s, after which participants completed 17 trials of digit classification. Each trial in the test phase started with a white rectangular frame for 1 s and was followed by a colored digit at the center of the frame (see Figure 2). The target digit remained on the screen for up to 5 s until a response was detected. Immediately after the

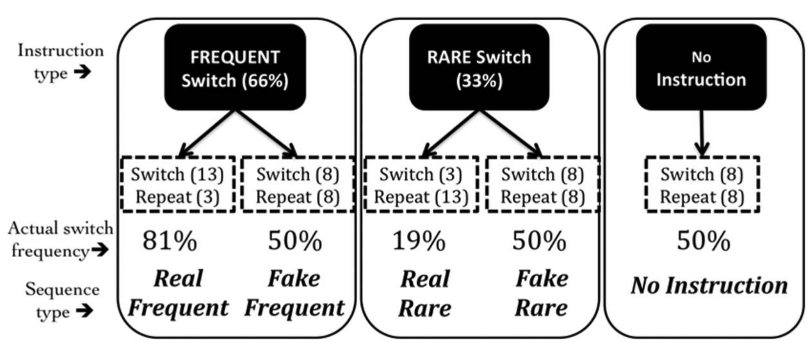

Figure 1. Overview of the task design. There were three overall instruction conditions, with 66, 33, and 50% switch probabilities. Within the frequent switch condition, there were two sequence types, one in which switches were very frequent (on 13/16 trials) and one in which switches actually occurred on 50% of trials (8/16 trials). In the rare switch condition, again there were two types of sequences, one with very low number of switches (3/16 trials) and another one with equal number of switches. Sequence types were randomly ordered within blocks.

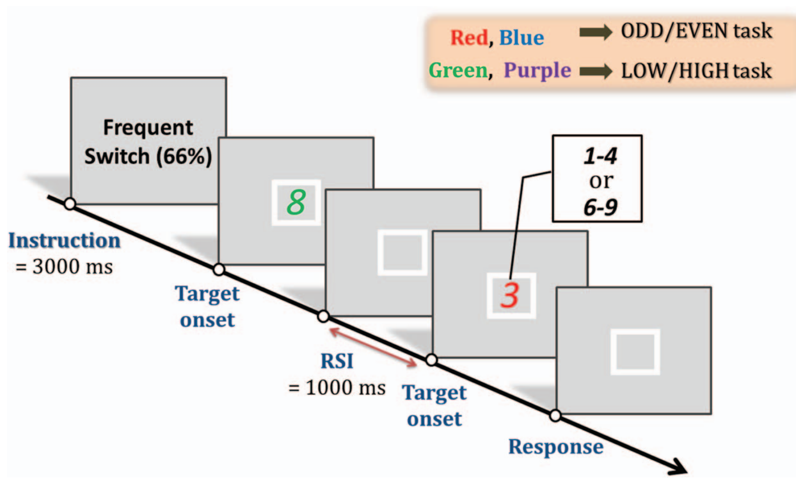

Figure 2. An example of the time-course of task presentation in Experiment 1. After showing an instruction for 3 s, each trial started with a colored digit and participants responded with keypresses. The digits were colored to indicate the required task. RSI = response stimulus interval. See the online article for the color version of this figure.

response, the colored digit vanished. There then followed a fixed 1,000 ms intertrial interval, after which the next target digit appeared. The same intertrial interval was also applied to the last trial of each sequence and followed by next instruction image. At the end of each experimental block, participants were given short break and feedback regarding their performance in that block.

Before these experimental blocks, participants practiced both tasks separately in two short practice blocks (16 trials each), then both tasks together in a block of 17 trials with tasks mixed in random order, then two further blocks of 17 trials in which switch frequency was 66% and 33%, with corresponding (valid) instructions at the start of these sequences. Participants had to perform at 90% accuracy or better in each block to proceed to the next part. The whole experiment lasted about 60 min.

Preprocessing and data analysis. Analyses excluded the first trial of each sequence, trials following errors and, for RT analyses, the error trials themselves. There was little effect of the particular task performed (low/high vs. odd/even) and this variable was not included as a factor in the final data analyses, both to ensure robust trial numbers in each cell of our factorial design and to simplify the presentation and interpretation of our factorial analyses (where task was not a crucial factor of interest). An alpha level of .05 was used to determine statistical significance. Because our main interest was to compare the two Fake Instruction conditions, we conducted separate analyses of variance (ANOVAs) for the Real and the Fake Instruction conditions and included the control (No Instruction) condition together with real instruction data.

Results

Real/No Instruction sequences. Across-participant average RT and proportion of errors (PE) are plotted in Figure 3, separately for the Real Instruction and No Instruction sequences (the Fake Instruction data appear in a separate Figure 4). We first performed repeated-measures ANOVAs on RTs and error rates in these sequences, with factors of Task Transition (repeat, switch) and Sequence Type (Real Frequent, Real Rare, No Instruction) to assess if our paradigm replicates switch frequency effects observed previously (e.g., Dreisbach & Haider, 2006; Monsell & Mizon, 2006). Consistent with this, the RT analysis revealed reliable main

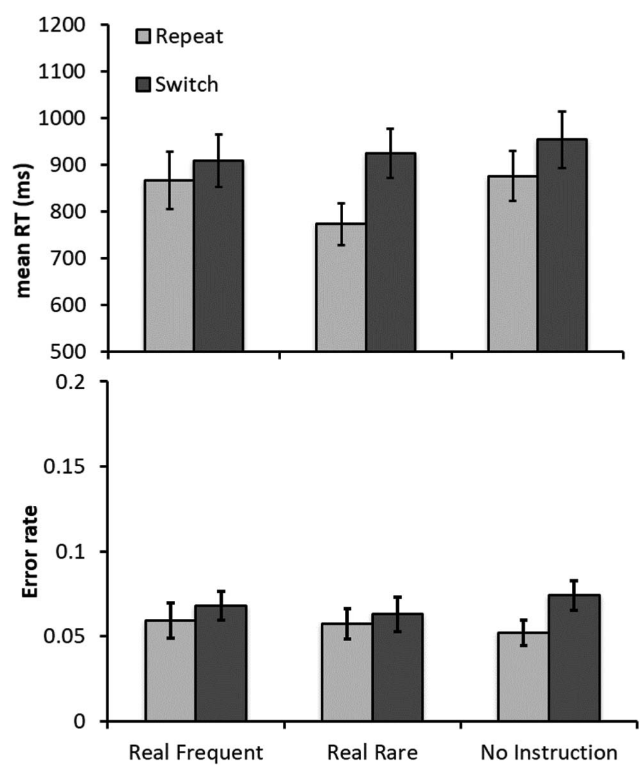

Figure 3. Data from the Real/No Instruction sequences from Experiment 1. Mean RT and mean error rate separately for switch and repeat trials. Error bars represent standard errors of the mean.

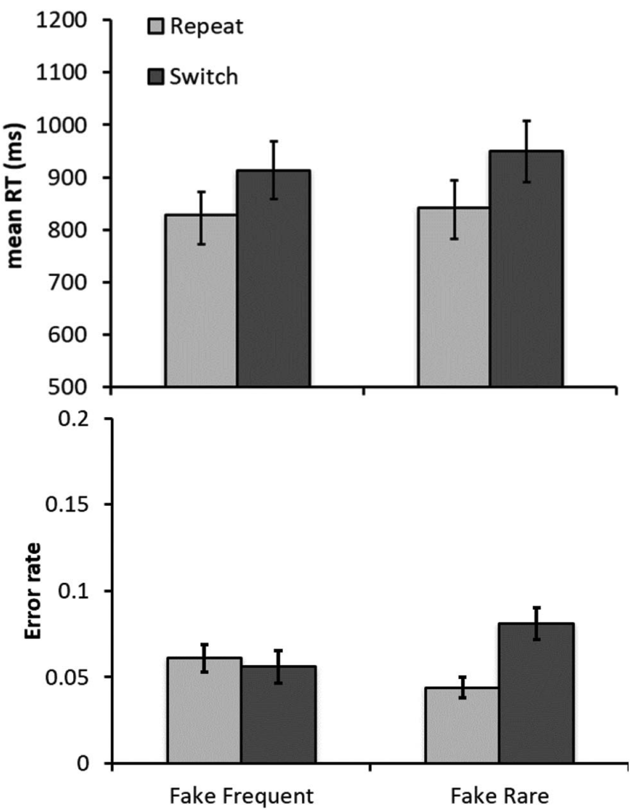

Figure 4. Performance in the Fake Instruction sequences in Experiment 1. Mean RT and mean error rate separately for switch and repeat trials. Error bars represent standard errors of the mean.

effects of Task Transition, $F(1, 19) = 24.0$, $MSE = 244{,}363$, $p < .01$, $\eta_p^2 = .56$, indicating a robust switching cost of 90 ms overall, a reliable main effect of Sequence Type, $F(2, 38) = 9.1$, $MSE = 43{,}938$, $p < .01$, $\eta_p^2 = .32$, and a reliable interaction between these factors, $F(2, 38) = 8.8$, $MSE = 30{,}689$, $p < .01$, $\eta_p^2 = .14$. A follow-up pairwise test revealed greater switch costs in Real Rare than Real Frequent sequences, $t(19) = 3.4$, $p < .01$.

For the error data, the ANOVA revealed only a reliable main effect of Task Transition, $F(1, 19) = 5.1$, $MSE = .004$, $p = .04$, $\eta_p^2 = .21$, with participants making more errors on switch than repeat trials. Numerically, this error cost of switching was largest in No Instruction sequences, but the interaction between Sequence Type and Task Transition was not reliable, $F < 1$.

Fake Instruction sequences. The crucial analysis assessed whether switching costs are greater in Fake Rare sequences (in which task switches were unexpected) than in Fake Frequent sequences (in which task switches were expected) despite having the same objective switch frequency. A repeated measures ANOVA with factors of Task Transition (repeat, switch) and Sequence Type (Fake Frequent, Fake Rare) revealed reliable main effects of Task Transition, $F(1, 19) = 22.0$, $MSE = 187{,}197$, $p < .01$, $\eta_p^2 = .54$, indicating the typical switching cost, and Sequence Type, $F(1, 19) = 4.7$, $MSE = 12{,}153$, $p = .04$, $\eta_p^2 = .20$, with slower RTs overall in Fake Rare sequences, but no significant interaction, $F(1, 19) = 2.4$, $MSE = 2{,}555$, $p = .14$, $\eta_p^2 = .11$. Thus, although switching costs were numerically larger in Fake Rare sequences (108 ms) than in Fake Frequent sequences (85 ms), this difference was not consistently observed across participants. This pattern was, however, consistently observed in the proportion of errors (see Figure 4), where there was no reliable main effect of Sequence Type, $F < 1$, but a main effect of Task Transition, $F(1, 19) = 8.1$, $MSE = 0.009$, $p = .01$, $\eta_p^2 = .30$, and a significant interaction between these factors, $F(1, 19) = 15.1$, $MSE = 0.008$, $p < .01$, $\eta_p^2 = .44$. This interaction was driven by a greater error cost of switching in Fake Rare than Fake Frequent sequences.

Discussion

This experiment introduced a novel paradigm to obtain evidence of metacontrol relating to variations in switch frequency, using an instruction manipulation to control for confounding effects that are inevitably present when switch rate objectively varies. Overall, the results supported the prediction of increased switching costs, both when switches are objectively rare and, crucially, also when instructions indicate that task switches will be rare, even in the absence of differences in objective switch frequency. Unexpectedly, this effect of instruction (in the critical Fake Rare vs. Fake Frequent contrast) was restricted to the error cost data, and was not reliably observed in RT switch costs. This pattern contrasts with the one observed in Real Instruction sequences, in which switch frequency effects were only consistently observed in the RT data.

As will become apparent, although initially unexpected, we replicated this pattern in subsequent experiments. The error cost difference between Fake Rare and Fake Frequent sequences also proved stable in follow-up analyses of the Experiment 1 data suggested by reviewers: It did not differ consistently across the first versus second half of trials within sequences ($F < 1$), suggesting it was more than a short-lived adjustment to each instruction provided (e.g., a transient decrease in response criterion when switches are expected to be rare, but turn out not to be). Nor did it differ consistently across the first versus second half of the experiment ($F < 1$), suggesting that participants continued to use instructions even after they had a few hundred trials of practice and task experience (as we intended that they would, through the inclusion of Real Instruction sequences in each block).

As a robust effect, the impact of instructions on error switching costs seems revealing of underlying mechanisms. In particular, whereas differences in RT switching costs across Real Instruction conditions arise through objective differences in the experienced sequences of trials (i.e., bottom-up effects), error cost differences across Fake Instruction conditions are driven by the way that expectations about switch frequency play out across task transition sequences (i.e., top–down effects). Thus, with Real Instructions, effects of switch frequency are primarily apparent as faster task repetition RTs when switches are rare (vs. frequent), with much smaller between-condition differences in switch trial RTs (cf. Figure 3). This speeding of task repetitions is a simple consequence of having longer sequences of task repetitions in Real Rare than Real Frequent sequences, with RTs known to decrease across successive repetitions of a task in cued switching designs (e.g., Monsell et al., 2003).

In contrast, task and transition probabilities are equated across Fake Instruction conditions, so these RT differences are not observed. Differences across conditions arise instead through the interaction between participants' expectations and the objectively experienced task and transition probabilities. Specifically, a characteristic feature of Fake Rare sequences is that participants should anticipate extended runs of a task having switched to it (as occurs in Real Rare sequences) such that they should strongly impose the corresponding task set (Dreisbach & Haider, 2006), strongly inhibit the previous one (Mayr & Keele, 2000), and perhaps adopt a more liberal response threshold (Schmitz & Voss, 2012) in anticipation of relatively easy task repetitions. All of these factors will make errors likely if, in fact, the task then switches unexpectedly. Crucially, these unexpected switches occur often in Fake Rare sequences (e.g., with *ABA* task sequences occurring as frequently as all other three-trial task orderings). As a consequence, participants make frequent task switching errors in Fake Rare sequences, creating the pattern of error costs observed. In contrast, rapid switches back to a task occur very infrequently in Real Rare sequences, so that error rates remain low in this condition.

In this way, the effects of objective versus expected differences in switch frequency are primarily apparent in different behavioral measures (RTs vs. errors, respectively). Regardless, the results of Experiment 1 suggest that our instruction manipulation can successfully modulate metacontrol parameters, such that participants were particularly likely to make errors on task switch trials when instructions led them to expect frequent task repeats. Experiment 2 built on this instruction effect to test whether metacontrol could be influenced by levels of motivation.

Experiment 2

Experiment 2 introduced a reward incentive manipulation that placed emphasis on fast responding but with a parallel requirement to make fewer than 10% errors, with two aims. First, it was intended to encourage participants to act on instructions to maximize their performance. As such, we anticipated that the effect of instructions might increase. At the same time, the error rate limit should encourage participants to slow down when necessary, such that instruction effects might emerge in RT data as well as, or instead of, the error rate effects seen in Experiment 1. The second aim was more conceptually motivated. To the extent that instruction effects reflect high-level control, we would expect them to depend on participants' motivation to act on instructions, given the proposal that control is effortful and, therefore, only exerted when benefits outweigh costs (e.g., Botvinick & Braver, 2015; Holroyd & Yeung, 2012; Shenhav, Botvinick, & Cohen, 2013). Thus, we predicted that switching cost differences between Fake Frequent and Fake Rare sequences should be enhanced with reward incentives compared with a no reward control.

Method

Participants. An additional 20 participants were recruited for this study (11 females; $M_{\text{age}} = 26.4$ years, $SD = 3.41$). The sample size was the same as in Experiment 1, reflecting the success of that experiment in detecting an effect in the key contrast of interest (switch cost difference between Fake instruction conditions) that clearly exceeded the smallest effect detectable with our chosen sample size ($\eta_p^2 = .44$ for the error cost effect in Experiment 1, against a minimum detectable effect of $\eta_p^2 = .18$ with $N = 20$, $1 - \beta = 0.8$ and $\alpha = .05$). All participants signed informed consent and were debriefed after the session. Participants were either paid £8 or received course credits for their participation plus £0–16 extra reward depending on their performance, as described below.

Apparatus, stimuli, design, and procedure. The design followed that of Experiment 1, except for introduction of a reward manipulation. Thus, in half of the blocks, participants were given the opportunity to gain reward (£0.50) for good performance in each 17-trial sequence. This opportunity was signaled to them at the start of each sequence with "Reward in this sequence" added to the screen with switch probability information, which appeared at the beginning of each sequence for 3,000 ms. The criteria to gain reward were: achieve above 90% accuracy and a mean RT lower than the previous same type of instruction without reward. At the end of each Reward sequence, £0.50 was awarded and shown on the screen if these criteria were met; otherwise the experiment proceeded to the next sequence. In No Reward sequences, participants were simply told to emphasize both speed and accuracy, with no additional incentive.

There were 11 experimental blocks for a total of 935 trials. The first block was used for measuring the RT reward criterion and, thus, was always a No Reward condition. This block was treated as a warm-up block and excluded from further analysis. For the remaining 10 blocks, five included only No Reward sequences and five included only Reward sequences, randomly ordered. Performance feedback, including reward gained, was delivered at the end of each block.

Results

Real/No Instruction sequences. We first report data from Real Instruction sequences, in which objective switch probability varied substantially and in line with the instructions (see Figure 5). An ANOVA with factors of Task Transition (repeat, switch), Sequence Type (Real Frequent, Real Rare, and No Instruction) and a new factor of Reward (Reward, No Reward sequence) was performed. RT analysis revealed a small mean switch cost overall of 59 ms that was not consistently observed across participants, $F(1, 19) = 3.0$, $MSE = 16{,}043$, $p = .10$, $\eta_p^2 = .14$. RTs were overall faster in Reward than No Reward blocks, $F(1, 19) = 14.6$, $MSE = 206{,}917$, $p < .01$, $\eta_p^2 = .44$, and also differed between instruction conditions, $F(2, 38) = 10.3$, $MSE = 72{,}410$, $p < .01$, $\eta_p^2 = .35$. The interaction between Sequence Type and Task Transition was highly significant, $F(2, 38) = 7.4$, $MSE = 70{,}161$, $p < .01$, $\eta_p^2 = .28$, reflecting greater switch costs in Real Rare and No Instruction sequences than Real Frequent sequences (54 and 24 vs. −29 ms, respectively, Figure 5). This effect was not further modulated by Reward, $F(2, 38) = 1.3$, $MSE = 5{,}823$, $p = .30$, $\eta_p^2 = .06$, nor were any other interaction terms significant, all Fs < 1. For the proportion error data, reward reduced error rates, $F(1, 19) = 5.3$, $MSE = .007$, $p = .03$, $\eta_p^2 = .22$, and participants made fewer errors on task-repeat trial than task-switch trials, $F(1, 19) = 9.3$, $MSE = .017$, $p < .01$, $\eta_p^2 = .33$, but no interaction term reached significance, ps > .30. Thus, collectively the RT and error rate data replicate the switch frequency effect and reveal a robust speed and accuracy benefit of reward motivation.

Fake Instruction sequences. A corresponding three-way repeated-measures ANOVA applied to RT data from the Fake Instruction sequences (see Figure 6) revealed a highly significant performance benefit of Reward, $F(1, 19) = 8.2$, $MSE = 119{,}326$, $p < .01$, $\eta_p^2 = .30$, again indicating the success of the reward

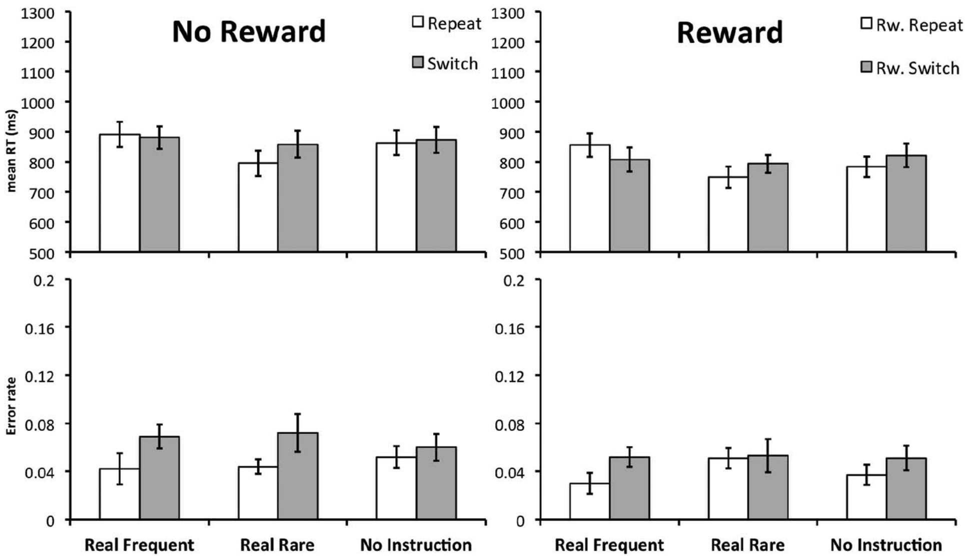

Figure 5. Data from Real/No Instruction sequences from Experiment 2. Mean RTs and error rates on switch and repeat trials for the three instruction conditions, separately for No Reward and Reward blocks. Error bars represent standard errors of the mean.

manipulation. The switching cost was again small in Fake Instruction sequences (33 ms) but this difference was reliable, $F(1, 19) = 11.8$, $MSE = 43{,}836$, $p < .01$, $\eta_p^2 = .38$. Overall RTs were similar between Fake Rare and Fake Frequent sequences, $F(1, 19) = 3.1$, $MSE = 11{,}083$, $p = .10$, $\eta_p^2 = .14$. No interactions reached significance, including the critical interaction between Sequence Type and Task Transition, $F(1, 19) = 2.0$, $MSE = 4{,}285$, $p = .17$, $\eta_p^2 = .10$, although its numerical trend (overall switch costs for Fake Frequent and Fake Rare sequences of 23 vs. 43 ms) was in accordance with the pattern seen in Real Instruction sequences. Nor was there a reliable three-way interaction between Reward, Instruction, and Task Transition, $F < 1$. These results indicate that instructions had little consistent effect on RT switch costs.

Error rates in the Fake Instruction sequences were numerically lower in Reward blocks, 4.7% versus 5.7%; $F(1, 19) = 3.3$, $MSE = .003$, $p = .08$, $\eta_p^2 = .15$. A marginal main effect of Task Transition was found, $F(1, 19) = 4.4$, $MSE = .009$, $p = .05$, $\eta_p^2 = .19$, with a small but reasonably consistent error cost of 1.5%. No

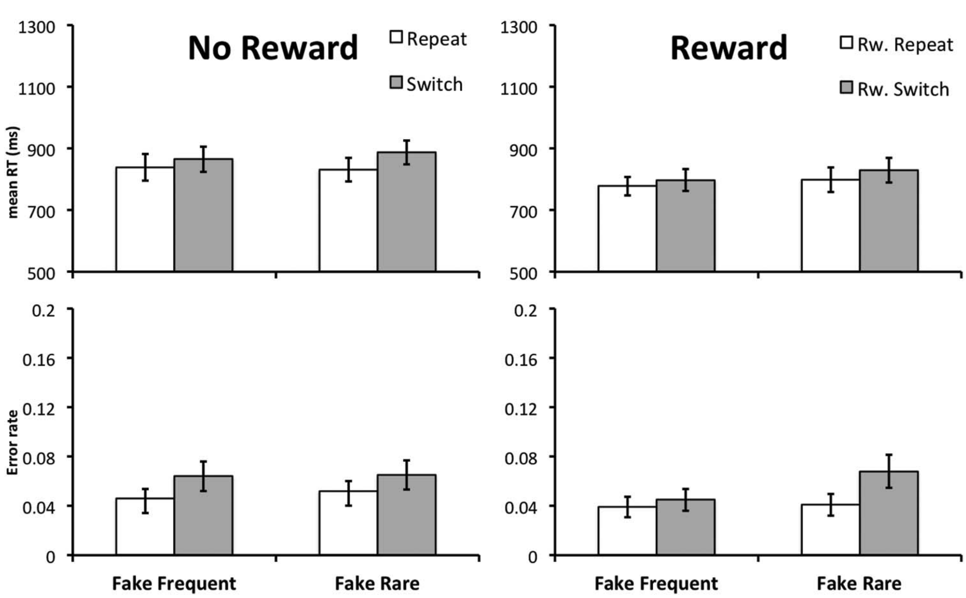

Figure 6. Data from the Fake Instruction sequences from Experiment 2. Mean RTs and error rates for switch and repeat trials in the two instruction conditions, separately for No Reward and Reward blocks. Error bars represent standard errors of the mean.

two-way interactions, all Fs < 1, $p > .50$, nor the three-way interaction, $F(1, 19) = 1.3$, $MSE = .001$, $p = .27$, $\eta_p^2 = .06$, reached significance. Numerically, error costs were similar across the two Fake Instruction conditions in No Reward blocks but quite different in Reward blocks. In particular, the larger switching error cost in the Fake Rare sequences (vs. Fake Frequent sequences) in reward blocks mirrored the results of Experiment 1. However, these effects were not statistically reliable.

Discussion

This experiment used reward motivation to encourage attention to instructions and fast and accurate responding. Reward was effective in improving task performance, reducing both RTs and error rates (cf. Manohar et al., 2015). Also, a robust switch frequency effect on RTs in the Real Instruction sequences was replicated. However, we did not find an instruction modulation effect on switch costs across Fake Instruction sequences, although the numerical trends were in the predicted direction.

It is difficult to interpret the weak instruction effects observed because switching costs in this experiment were very small: on average just 23 ms and 1.6% error difference, as compared with typical RT switching costs of 100–200 ms in both alternating-runs (e.g., Rogers & Monsell, 1995) and task-cueing studies (e.g., Dreisbach, Haider, & Kluwe, 2002). The reason for these small switching costs is unclear given that the tasks were identical to those used in Experiment 1, in which robust costs were observed and overall RTs were comparable to those observed here (particularly in the No Reward condition, which closely replicated the design of Experiment 1). However, previous studies using the same tasks have observed robust switching costs using standard cued switching designs, in which the required task is signaled by a cue that is presented separately from the stimuli (as a colored cue frame within which the digit appears; e.g., Monsell et al., 2003), rather than using the color of the digit itself as the task cue. Our own pilot testing confirmed this. Experiment 3, therefore, used the same instruction design combined with a reward incentive manipulation, but adopted a standard task cueing procedure with the expectation of observing robust switch costs to provide a more secure basis for investigating our effects of interest.

Experiment 3

In Experiment 3, the task cue was now a colored frame that preceded the target digit by 100 ms, a short interval that should maximize switching cost (e.g., Monsell & Mizon, 2006). We also used one color cue per task, rather than two. Although this choice means that task switches and repeats are always accompanied by cue change versus repetition, respectively, which may complicate the interpretation of measured switch costs (e.g., Schneider & Logan, 2011), we were concerned that including two cues per task in Experiments 1 and 2 might have artificially lowered switch costs by disrupting participants' ability to form effective task sets when the task is repeated. More important, our main contrast, between Fake Rare and Fake Frequent sequences, involves conditions that are matched in terms of objective task switching frequency and, therefore, cue change/repetition likelihood, so that cue repetition effects should have little impact on our key analyses. The crucial prediction was the same as in the previous experiment, of an impact of Fake Instructions that should be manifest in particular when motivation is high.

Method

Participants. Nineteen participants (13 females; $M_{age} = 21.05$ years, $SD = 4.16$) from the University of Oxford completed this experiment, after one participant failed to complete the session from the original sample of $N = 20$ determined based on the criteria described above. They were either paid £8 or course credit for their participation plus £0–16 extra reward depending on their performance.

Procedure. The apparatus, design, stimuli, and procedure were very similar to those of Experiment 2. However, the required task was now cued on each trial by a colored frame that appeared 100 ms before the digit inside a white fixation frame. Each task was associated one color only, either red or blue (counterbalanced across participants). Following the response on each trial (or a 5 s timeout period), the digit and colored frame disappeared to leave only the white fixation frame for a 1,000 ms intertrial interval. The crucial instruction and reward manipulations were the same as in Experiment 2.

Result

Real/No Instruction sequences. We begin with the results of the Real/No Instruction sequences (see Figure 7). The RT data were entered into a repeated measure ANOVA with factors of Task Transition (repeat, switch), Sequence Type (Real Frequent, Real Rare, and No Instruction) and Reward (no reward, reward). A reliable main effect of Reward confirmed that the reward manipulation was successful in reducing RTs, 719 versus 639 ms, $F(1, 18) = 23.4$, $MSE = 360{,}453$, $p < .01$, $\eta_p^2 = .57$. There were significant main effects of both Sequence Type, $F(2, 36) = 9.3$, $MSE = 58{,}347$, $p < .01$, $\eta_p^2 = .34$, and Task Transition, $F(1, 18) = 105.0$, $MSE = 1{,}158{,}211$, $p < .01$, $\eta_p^2 = .85$, the latter indicating that a robust and a substantial switching cost (of 143 ms) was observed. The interaction between Sequence Type and Task Transition was significant, $F(2, 36) = 9.1$, $MSE = 30{,}143$, $p < .01$, $\eta_p^2 = .34$, again replicating the switch frequency effect. The interaction between Reward and Task Transition also reached significance, $F(1, 18) = 11.9$, $MSE = 43{,}000$, $p < .01$, $\eta_p^2 = .06$, indicating that reward motivation decreased switching costs. No other interaction terms were significant, all Fs < 1.

For the error rate data (bottom panels of Figure 7), all main effects were significant, including Reward, $F(1, 18) = 3.1$, $MSE = .051$, $p < .01$, $\eta_p^2 = .32$, with reduced errors with reward incentive, Sequence Type, $F(2, 36) = 4.1$, $MSE = .007$, $p = .03$, $\eta_p^2 = .18$, and Task Transition, $F(1, 18) = 7.3$, $MSE = .037$, $p = .01$, $\eta_p^2 = .29$, with an overall switching error cost of 2.5%. The interaction between Sequence Type and Task Transition was not reliable, $F(2, 36) = 1.2$, $MSE = .003$, $p = .30$, $\eta_p^2 = .06$, nor were other two-way interaction terms, all Fs < 1.2, all ps $> .30$, but the three-way interaction between Reward, Sequence Type and Task Transition reached significance, $F(1, 18) = 4.3$, $MSE = .007$, $p = .02$, $\eta_p^2 = .19$. This effect was mainly driven by a larger switching error cost difference between the two Real Instruction conditions in no reward blocks (costs of −0.8 vs. 3.5% for Real Frequent vs. Real Rare sequences) than in reward blocks (costs of 3.2 vs. 2.0%).

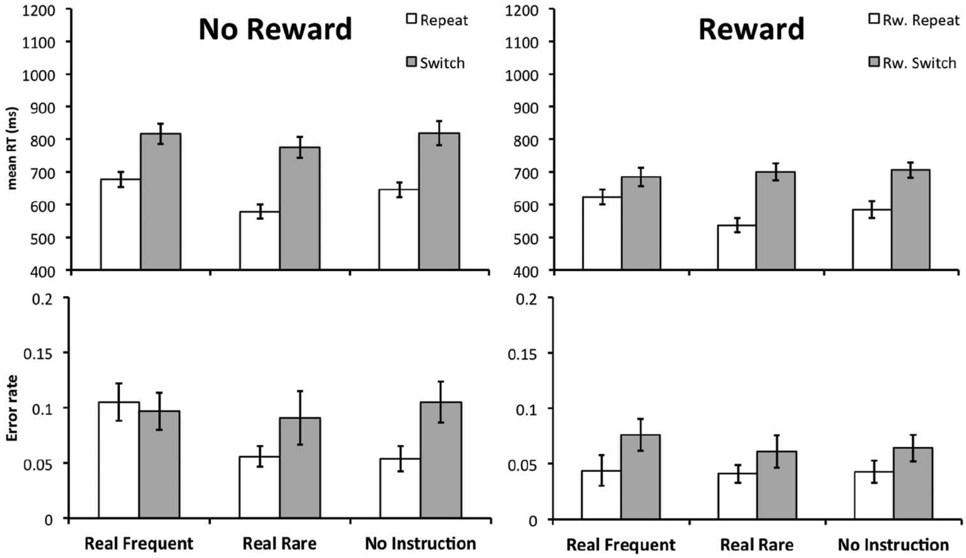

Figure 7. Performance in the Real/No Instruction sequences from Experiment 3. Mean RT and mean proportion of errors separately for switch and repeat trials in blocks without or with reward incentive. Error bars represent standard errors of the mean.

In summary, in Real Instruction sequences we again observed a switch frequency effect and reward benefit, and importantly the magnitude of switching costs on RTs was comparable to past studies. Thus, the necessary preconditions are in place to investigate instruction effects in the Fake Instruction sequences.

Fake Instruction sequences. Mean RTs from Fake Instruction sequences (see Figure 8) were subjected to a repeated measures ANOVA with factors of Reward (no reward, reward), Sequence Type (Fake Frequent, Fake Rare), and Task Transition (repeat, switch). The results revealed that RTs decreased overall with Reward, $F(1, 18) = 49.8$, $MSE = 252{,}603$, $p < .01$, $\eta_p^2 = .73$. A reliable overall switching cost of 139 ms was found, as reflected in a significant main effect of Task Transition, $F(1, 18) = 60.0$, $MSE = 738{,}845$, $p < .01$, $\eta_p^2 = .77$. There was no significant main effect of Sequence Type, $F < 1$. For the interaction terms, only a significant interaction between Reward and Task Transition was observed, $F(1, 18) = 13.5$, $MSE = 23{,}720$, $p < .01$, $\eta_p^2 = .04$, with smaller switching costs in Reward blocks (115 ms) than No Reward blocks (164 ms). RT switching costs were almost identical between Fake Frequent and Fake Rare sequences, $F < 1$, in a manner that was unaffected by reward incentive as reflected in a nonsignificant three-way interaction, $F < 1$.

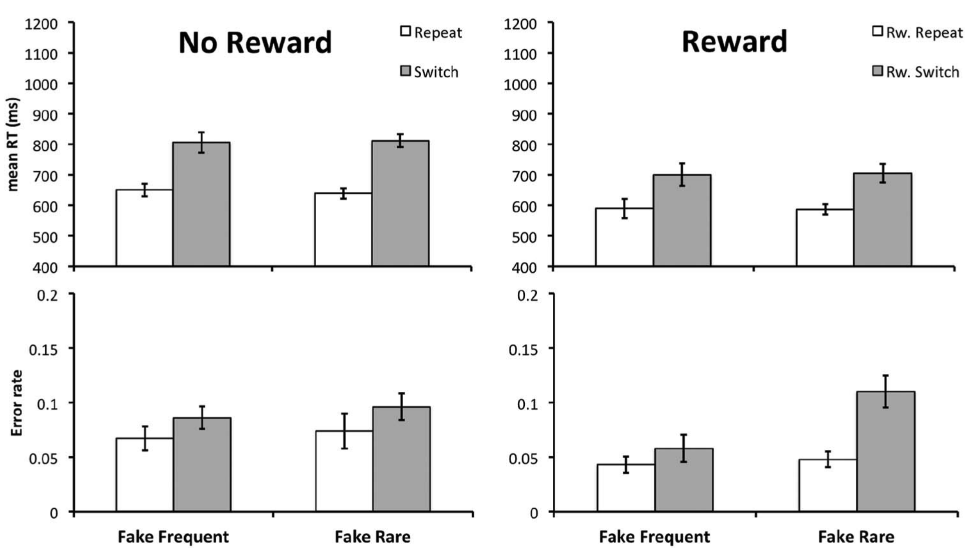

Figure 8. Performance in the Fake Instruction sequences of Experiment 3. Mean RT and mean proportion of errors as a function of switch and repeat trials are shown separately for No Reward and Reward blocks. Error bars represent standard errors of the mean. Rw. = reward.

A corresponding analysis of the error rate data revealed a greater proportion of errors overall in Fake Rare (8.2%) than Fake Frequent (6.3%) sequences, $F(1, 18) = 4.5$, $MSE = 0.013$, $p < .01$, $\eta_p^2 = .37$. More errors were made on switch trials than repeat trials, 8.7 versus 5.8%, $F(1, 18) = 20$, $MSE = 0.033$, $p < .01$, $\eta_p^2 = .52$. Error rates were numerically lower in Reward than No Reward blocks (6.5 vs. 8.1%), but the difference was not significant, $F(1, 18) = 3.2$, $MSE = 0.01$, $p = .10$, $\eta_p^2 = .15$. Two-way interactions between Reward and Sequence Type, $F(1, 18) = 6.3$, $MSE = 0.004$, $p = .02$, $\eta_p^2 = .26$, and between Sequence Type and Task Transition, $F(1, 18) = 4.8$, $MSE = 0.006$, $p = .04$, $\eta_p^2 = .21$, were qualified by a reliable three-way interaction, $F(1, 18) = 4.9$, $MSE = .005$, $p = .04$, $\eta_p^2 = .21$, which confirmed the prediction of a reward-modulated instruction effect on error costs of switching. Analysis of No Reward blocks alone revealed no reliable interaction between Sequence Type and Task Transition, $F < 1$. In contrast, this interaction was reliable in Reward blocks, $F(1, 18) = 6.7$, $MSE = .011$, $p = .02$, $\eta_p^2 = .27$, indicating that a larger error cost of switching was found in Fake Rare than Fake Frequent sequences.

Discussion

The design of Experiment 3 was successful in creating robust switching costs. In this context, we replicated the predicted effect of instruction on switching performance observed in Experiment 1 (and apparent numerically in Experiment 2), but only in blocks with reward. Once again, the effect of pure instruction (i.e., in the Fake Rare vs. Fake Frequent contrast) was evident as errors on task switch trials when these were unexpected. Overall, these findings suggest an instruction-induced global metacontrol influence in task switching that is only observed when participants are motivated to use instructions.

It is somewhat surprising that effects of instruction—in terms of increased switch costs in Fake Rare versus Fake Frequent sequences—were absent in No Reward blocks in this experiment, given that the effect was observed in Experiment 1 in which reward was never available. However, there is substantial evidence that people encode rewards relative to expectation rather than in absolute terms (D'Ardenne et al., 2008; Zaghloul et al., 2009), such that neutral (no reward) outcomes are viewed as punishment when reward is expected, but as reward when punishment is expected (Nieuwenhuis et al., 2005). Thus, the No Reward condition here is not identical to Experiment 1, in which reward was never available. Along similar lines, Kleinsorge and Rinkenauer (2012) found that when reward was associated with a specific task during switching, performance only improved on that task, whereas performance actually worsened for the nonrewarded task. They concluded that performance enhancement through reward incentive is selective and adaptive, and our results are certainly in line with this conclusion.

A methodological detail of the present experiment was that we used one cue per task, rather than two as in Experiments 1 and 2. This design was intended to increase observed switch costs—that were indeed robustly observed here—but it entails that task transitions (switch/repeat) are confounded with cue transitions (switch/repeat), such that measured switch costs may be contaminated by changes in the speed of cue encoding as a function of whether the cue repeats or changes from the previous trial (Schneider & Logan, 2011). However, we are confident that cue repetition effects do not drive our critical effects of interest, which instead reflect the impact of high-level metacontrol parameters. First, the effects of Fake Instructions were qualitatively and quantitatively similar in the present experiment as in Experiment 1, where cue repetitions never occurred. Second, priming of cue encoding is an inherently bottom-up process that should depend only on the objective sequence of cues presented, something that was matched by design across Fake Instruction sequences. Third, there is little reason to expect priming of cue encoding to depend on reward, unlike top–down control that is known to be highly sensitive to motivation (Botvinick & Braver, 2015). Thus, given the success of the design of this experiment in creating robust switch costs, Experiments 4 and 5 adopted the same task cueing design to explore different aspects of metacontrol influences on task switching: Experiment 4 used EEG measures of task preparation to characterize the mechanisms by which instructions influence task switching; Experiment 5 used a behavioral measure of task choice, in a voluntary switching design, to seek converging evidence of instruction-induced changes in metacontrol in task switching.

Experiment 4

In this experiment, the two tasks were mapped to different hands, enabling us to track task-specific preparation via a well-characterized EEG marker of hand-specific motor activity, the lateralized readiness potential (LRP). If participants' expectations about switch frequency guide their strategic task preparation, we should observe a larger LRP toward the same hand on successive trials when switches are expected to be rare, because using the same hand (i.e., preparing for task repetition) is a better strategy. Conversely, we would expect lateralization toward the other hand after each response when switches are expected to occur frequently. We had originally planned to complement this LRP analysis with analyses of oscillatory EEG markers of motor preparation (De Jong, Gladwin, & M't Hart, 2006), but we surprisingly failed to observe consistent lateralization of these markers and, therefore, omit these analyses here.

As well as prompting task-specific preparation, instructions could influence global control states that operate over a sustained period (cf. Braver et al., 2003). In particular, when switches are frequent, one could expect high levels of between-task interference (e.g., Yeung, Nystrom, Aronson, & Cohen, 2006) and, thus, a need for increased attentional filtering of task-irrelevant information (Kiesel et al., 2010; Vandierendonck, Liefooghe, & Verbruggen, 2010). In this way, the global control state might adjust goal shielding (e.g., Dreisbach & Haider, 2009) to prevent interference from switching task goals. Our index of global control state was EEG alpha (8–12 Hz) power, because alpha has been commonly associated with general task preparation or task focus (e.g., Hughes et al., 2013; Macdonald et al., 2011). Specifically, alpha power reduces under conditions of increased cognitive demand, for example during effortful task switching (Gladwin & de Jong, 2005), leading to the idea that alpha reflects cortical "idling" (Clayton et al., 2018). Thus, we predicted that alpha power should be reduced in Fake Frequent compared with Fake Rare sequences, reflecting the expectation of increased attentional demands in the former case.

Method

Participants. Twenty-two additional volunteers (14 females; $M_{\text{age}} = 22.23$ years, $SD = 4.48$) were recruited from the University of Oxford community. They were either paid £10 per hour or awarded course credit for their participation, plus £0–16 performance-contingent reward. None reported a history of neurological or psychological disorder.

Apparatus, design, stimuli, and procedure. The procedure followed the same general design as Experiment 3, but with two important changes. First, to allow measurement of task preparation via lateralized motor potentials, responses for the two tasks were associated with different hands (rather than using the same keys, as in Experiments 1–3), with task-to-hand mappings counterbalanced across participants. Second, participants completed 14 blocks for a total of 1,190 trials (vs. 11 blocks and 935 trials in the previous experiment) because more trials were required to obtain stable EEG waveforms. Participants sat in a dimly lit, electrically shielded room. Stimuli were presented on a 20-in. CRT (Trinitron, Dell) monitor with a 75 Hz refresh rate using the MATLAB toolbox Psychtoolbox3. Stimuli were viewed from approximately 70 cm.

EEG data acquisition. EEG data were recorded from Ag-AgCl electrodes embedded in a fabric cap (QuikCap, Neuroscan, El Paso, TX) from 32 channels: FP1, FPz, FP2, F7, F3, Fz, F4, F8, FT7, FC3, FCz, FC4, FT8, T7, C3, Cz, C4, T8, TP7, CP3, CPz, CP4, TP8, P7, P3, Pz, P4, P8, POz, O1, Oz, O2. Additional electrodes were placed on the right mastoid, above and below the left eye, and on the outer canthi of both eyes. The ground was placed at location AFz. All electrode recordings were referenced to the left mastoid and offline re-referenced to linked mastoids. Electrode impedances were kept below 50 kΩ. The data were continuously recorded using SynAmps2 amplifiers (Neuroscan), sampled at 1,000 Hz and bandpass filtered at 0.1–200 Hz, with gain of 2816 and 29.8 nV resolution.

EEG data analysis. Ocular artifacts were corrected using a regression-based approach (Semlitsch, Anderer, Schuster, & Presslich, 1986). After ocular artifact correction, the EEG data were downsampled to 250 Hz. For LRP analyses, the data were further bandpass filtered from 0.1–15 Hz. Trials were rejected if the voltage change in the epoch was larger than 100 μV in the electrodes: Fz, FCz, Cz, CPz, and Pz. We also excluded the first trial of each instruction sequence and trials with errors or following errors.

In our paradigm, participants can start to prepare for the upcoming task immediately after the response of the preceding task. EEG and ERP analysis focused on the period between the response on trial n-1 and onset of the task cue on trial n, which is a 1 s response-cue interval (RCI) in which participants could in principle begin to prepare for next trial (e.g., by anticipating the task that will be required). Response-locked epochs were extracted from the continuous data in time windows from −1,000 ms before each response to 1,200 ms afterward (that includes the RCI and the subsequent 200 ms). The LRP was calculated using averaged EEG amplitude at electrodes C3 and C4 following the equation (Coles, 1989):

$$\frac{(\text{C3} - \text{C4})\text{right hand} + (\text{C4} - \text{C3})\text{left hand}}{2},$$

in a window from 400 to 1,000 ms relative to response onset. For this analysis, epochs from each channel were baseline corrected relative to the period between −1,000 and −800 ms before the response on trial $n - 1$. This baseline was chosen to be distant from activity related to the response on the previous trial (that would occur on average around −1,900 ms before the response on trial n) but before events of interest on the current trial (e.g., retrieval of stimulus-response rule, reconfiguration processes), as confirmed via visual inspection of waveforms. Similar results were observed with different baselines. To avoid distortion at the edges of epochs in calculations of EEG oscillatory power, power was calculated on the continuous data before response-locked epochs were extracted. Alpha (8–12 Hz) power was calculated using the Hilbert transform (Hilbert function in Matlab), averaged across posterior scalp electrodes P7, P3, Pz, P4, P8, and POz.

Results

In what follows, we first present replication of the behavioral results of Experiment 3, showing the impact of instructions and sensitivity to reward incentives. We then present analyses of the EEG data to provide insight into the mechanisms underpinning the observed behavioral effects.

Performance in Real/No Instruction sequences. As above, our analysis began with the Real and No Instruction sequences (see Figure 9), using the same ANOVA with factors of Reward (no reward, reward), Sequence Type (Real Frequent, Real Rare, and No Instruction), and Task Transition (repeat, switch). In the RT analysis, all main effects and interactions reached significance. In particular, the reward manipulation successfully improved overall performance, $F(1, 21) = 20.9$, $MSE = 135{,}320$, $p < .01$, $\eta_p^2 = .50$, and the switch frequency manipulation affected switching costs, $F(1, 21) = 13.4$, $MSE = 34{,}645$, $p < .01$, $\eta_p^2 = .39$, in the usual manner. In a corresponding analysis of error rate data, reliable main effects of Reward, $F(1, 21) = 9.2$, $MSE = .024$, $p < .01$, $\eta_p^2 = .31$, and Task Transition, $F(1, 21) = 9.7$, $MSE = .016$, $p < .01$, $\eta_p^2 = .32$, indicated reduced errors rates with reward incentive and on repeat compared with switch trials.

Performance in Fake Instruction sequences. Mean RTs and error rates in Fake Instruction sequences were entered into separate three-way repeated measures ANOVAs with factors of Reward (no reward, reward), Sequence Type (Fake Frequent, Fake Rare) and Task Transition (repeat, switch). Analysis of the RT data (see Figure 10) revealed that RTs decreased overall with Reward, $F(1, 21) = 20.2$, $MSE = 126{,}658$, $p < .01$, $\eta_p^2 = .49$, and were increased on switch versus repeat trials, $F(1, 21) = 74.6$, $MSE = 798{,}281$, $p < .01$, $\eta_p^2 = .78$. Switch costs were lower in reward blocks than no reward blocks, $F(1, 21) = 12.4$, $MSE = 49{,}860$, $p < .01$, $\eta_p^2 = .37$. The three-way interaction was not reliable, $F < 1$. Thus, as in the previous experiment, the RT analysis revealed a reliable overall effect of reward but no consistent modulation of performance according to instruction.

In a corresponding analysis of error rates, all main effects and interactions were significant. Error rates were lower in Reward blocks than No Reward blocks, $F(1, 21) = 12.2$, $MSE = .03$, $p < .01$, $\eta_p^2 = .37$, higher on switch than repeat trials, $F(1, 21) = 30.7$, $MSE = .072$, $p < .01$, $\eta_p^2 = .59$, and higher in Fake Rare than Fake Frequent sequences, $F(1, 21) = 36.7$, $MSE = .069$, $p < .01$, $\eta_p^2 = .64$. Of principal interest was the significant three-way interaction between Reward, Sequence Type, and Task Transition, $F(1, 21) = 9.5$, $MSE = .018$, $p < .01$, $\eta_p^2 = .31$, which replicated the previous experiment showing a reward-dependent difference between

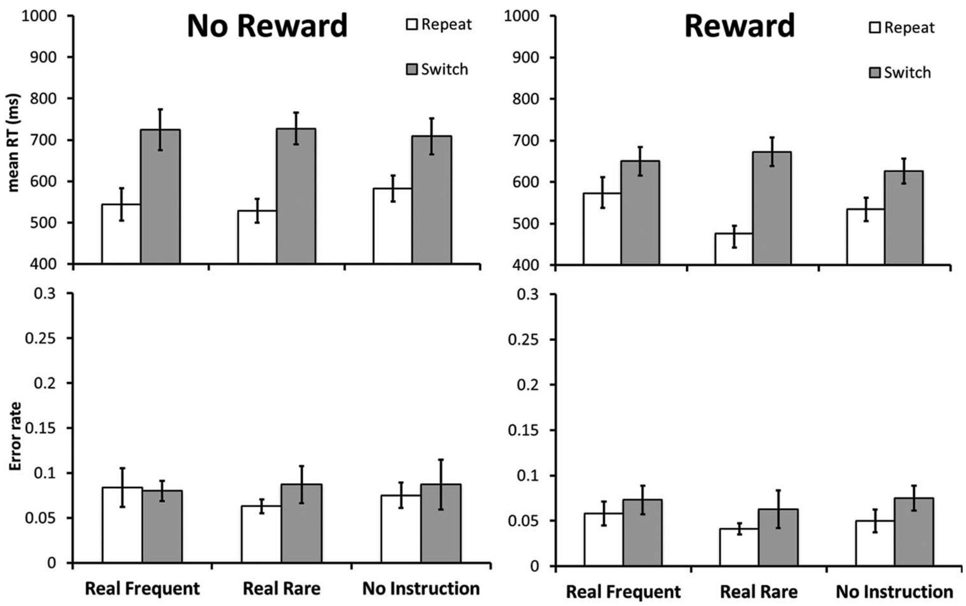

Figure 9. Performance in the Real and No Instruction conditions from Experiment 4. Mean RT and mean proportion of errors are shown for switch and repeat trials in the three instruction conditions separately for No Reward and Reward blocks. Error bars represent standard errors of the mean.

error costs in Fake Rare versus Fake Frequent sequences. Separate ANOVAs on data from Reward and No Reward blocks indicated that the error cost difference between the two Fake Instruction sequences was clearly apparent in Reward blocks, $F(1, 21) = 9.3$, $MSE = .033$, $p < .01$, $\eta_p^2 = .2$, but not in No Reward blocks, $F < 1$.

Analysis of error types. The two tasks were mapped to separate hands in this experiment to allow measurement of the LRP as an index of task-specific preparation. This design also enabled us to perform a new behavioral analysis, to determine whether the error cost pattern we have replicated across experiments reflects participants performing the wrong task (that would be evident as responding with the incorrect hand) versus performing the required task but choosing the wrong response within that task (i.e., respond with the correct hand but incorrect finger). This approach has been used previously (e.g., by

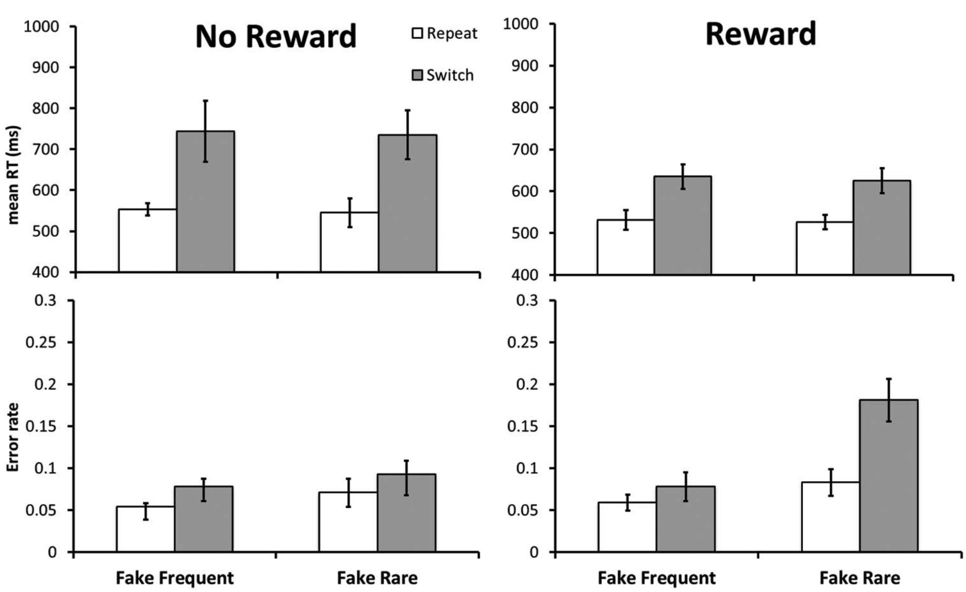

Figure 10. Performance in Fake Instruction sequences in Experiment 4. Mean RT and mean proportion of errors are shown for switch and repeat trials in the two instruction conditions, separately for No Reward and Reward blocks. Error bars represent standard errors of the mean.

Muhle-Karbe, Andres, & Brass, 2014) to show distinct preparation for tasks versus actions.

The results were clear cut in indicating that the effect of instructed switch frequency occurred at the task level (see Figure 11). Thus, an analysis of response errors (Wrong finger) revealed only a small switch cost, $F(1, 21) = 6.5$, $MSE = .007$, $p = .02$, $\eta_p^2 = .24$ and a tendency for more errors in Fake Rare sequences, $F(1, 21) = 4.2$, $MSE = .006$, $p = .05$, $\eta_p^2 = .17$, but no other reliable effects. In contrast, in an analysis of task-level errors (Wrong hand), all factors and interactions reached significance, including the critical three-way interaction between Reward, Sequence Type, and Task Transition, $F(1, 21) = 23.3$, $MSE = .022$, $p < .01$, $\eta_p^2 = .53$.

Summary of behavioral findings. Collectively, these results replicate those of the previous experiments in showing reliable effects of instructions on switch frequency, even when controlling for the switch rates actually experienced, that are strongly modulated by performance incentives. The new analysis of error types indicates further that this effect is driven almost exclusively by participants performing the wrong task when making unexpected task switches. These findings indicate once again that instructions can be effective in inducing metacontrol states that influence task switching performance. Of interest, then, are the neural correlates of these metacontrol states as they are reflected in the EEG.

EEG results: LRPs. By mapping the two tasks to separate hands, we were able to measure preparation for a particular task in terms of the lateralization of cortical motor activity (cf. De Jong et al., 2006; Poljac & Yeung, 2014). Figure 12 presents grand-averaged LRPs, with waveforms plotted according to the hand used for the response on the previous trial. The classical LRP is apparent as a negative-going potential that rises sharply to peak slightly before the recorded keypress response (at 0 ms, *R*, on the *x*-axis of the plots). The peak occurs slightly before the response, reflecting the discrepancy between formation of the intention to move in motor cortex (as measured by the LRP) and the overt button-press (to which the ERP waveforms are time-locked). Of interest here was the continuation of this lateralized activity after the response, following an initial oscillatory rebound (seen here in the period 0–200 ms postresponse) but before cue presentation for the next trial (at 1,000 ms, *C*, on the *x*-axis of Figure 12). Our main hypothesis was that preparatory activity should vary according to instructions and will be more pronounced in reward trials. More specifically, when participants expect frequent switches, we predicted anticipatory motor preparation of the opposite hand to the one just used; thus, a more positive LRP, when switches are frequent than when they are rare.

LRPs in Real Instruction sequences are plotted in Figure 12 (averaging across Reward and Task Transition conditions), in which a separation between Frequent and Rare switch condition waveforms is apparent from 800 ms before the response until long afterward (Figure 12, top panels). A repeated-measures ANOVA with factors of Reward (No Reward, Reward) and Sequence Type (Real Frequent, Real Rare) revealed that this overall difference between sequence types was reliable in the time window of interest, which is the period leading up to the cue and stimulus on the next trial, $F(1, 21) = 57$, $MSE = 15.2$, $p < .01$, $\eta_p^2 = .73$, whereas neither the main effect of Reward ($F < 1$) nor the two-way interaction term reached significance, $F(1, 21) = 2.5$, $MSE = .39$,

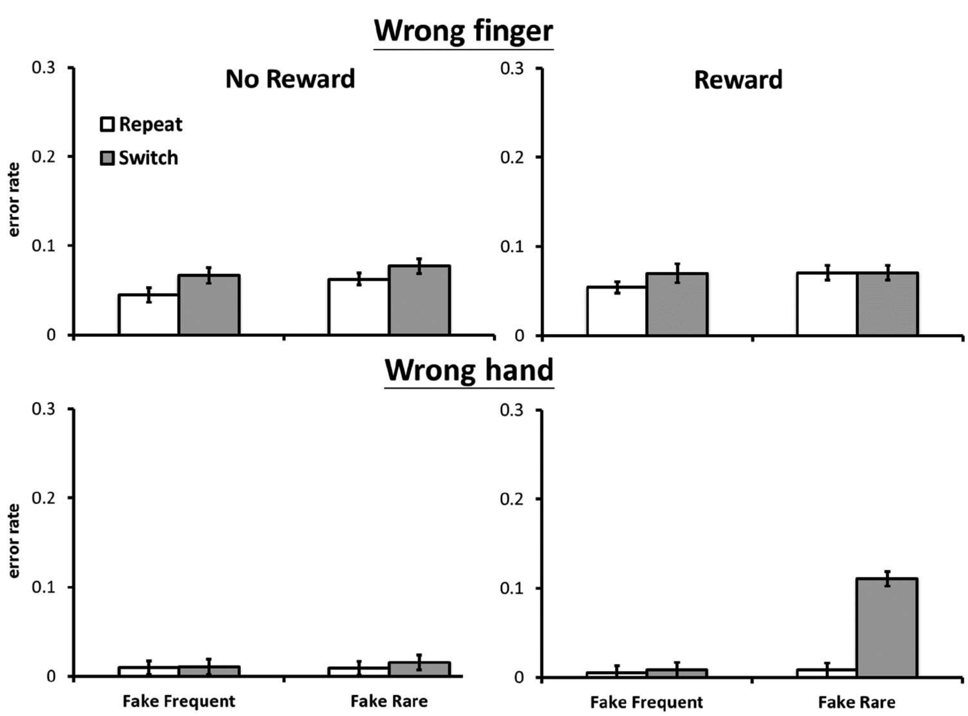

Figure 11. Analysis of error types in Experiment 4. Across conditions, errors are split according to whether they occurred through participants responding with the wrong finger of the hand associated with correct (cued) task (upper panels) or through participants responding with the wrong hand (lower panels).

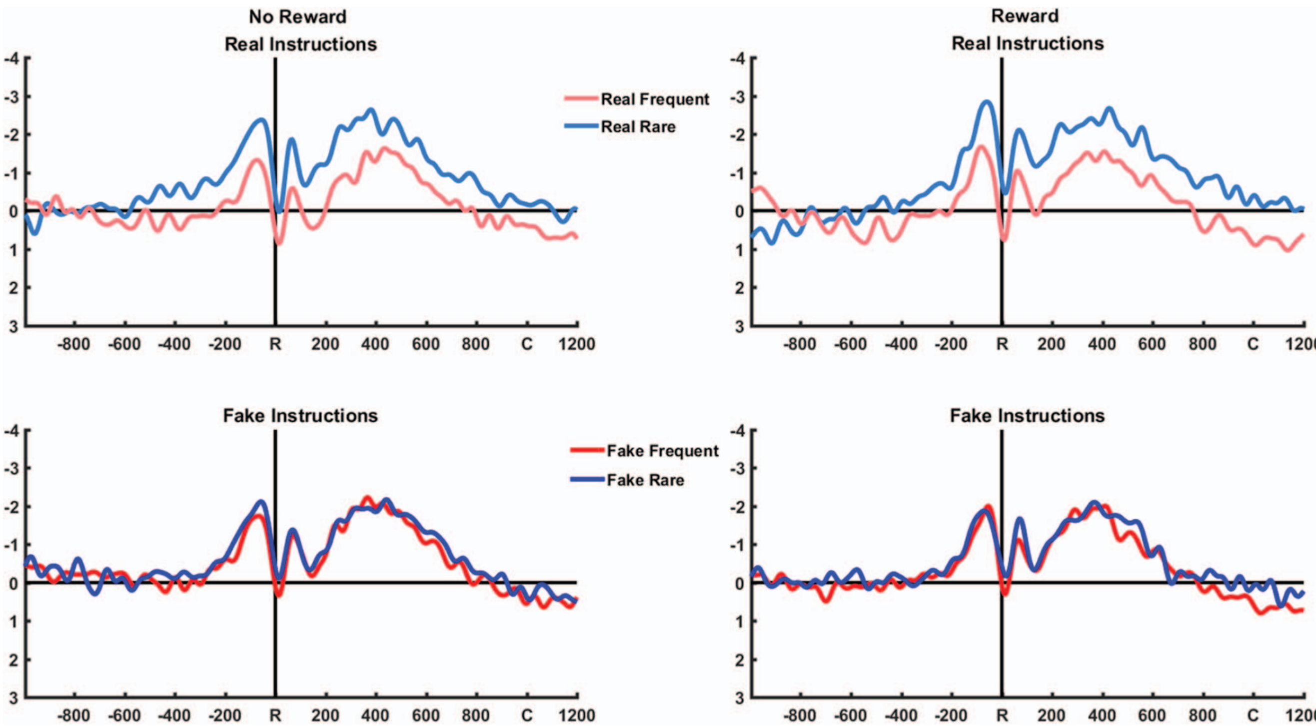

Figure 12. Grand-averaged lateralized readiness potential (LRP) in Real Instruction (top panels with light colors) and Fake Instruction (bottom panels with dark color set) sequences, separately for No Reward blocks (left panels) and Reward blocks (right panels). The signal is time-locked to the response on one trial (labeled R on the *x*-axis), with analysis focusing on the period between this event and the task cue on the subsequent trial (labeled C on the *x*-axis). See the online article for the color version of this figure.

p = .13, η_p^2 = .11. Thus, more negative LRPs in the waveform from Real Rare sequences indicates that participants tended to prepare to perform the same task again after each response, that is, with the hand used in the previous trial, when the sequence involved frequent task repetitions.

In contrast, there was little evidence of between-condition differences across Fake Instruction sequences (Figure 12, bottom panels). In a corresponding ANOVA on averaged LRP amplitudes as a function of Reward (No Reward, Reward) and Sequence Type (Fake Frequent, Fake Rare), neither main effect was statistically reliable, both $ps > .27$, nor was the interaction, $F < 1$. A very small trend toward a more negative LRP can be observed in the Fake Rare condition in a late 200-ms period just before task cue onset (see Figure 12, bottom-right panel). This trend is in accordance with the prediction that participants should prepare to respond again with the hand associated with the same task (task repeat) when expecting switches to occur only rarely, but the effect was weak and inconsistently observed across participants.

EEG results: Alpha power. We next looked at alpha (8–12 Hz) oscillatory power data. The core hypothesis was that instructions should influence attentional states as reflected in an adjustment of alpha power. Figure 13 plots grand-averaged alpha power at posterior scalp sites. One clear feature of these data is that alpha power is suppressed around response initiation and then gradually returns to a relatively stable level between trials (during the RCI). The key measure of interest is the magnitude of such rebounds as a function of instruction type. In the following analysis, data from No Instruction sequences were excluded to focus on contrasting the two switch frequencies instructions and maximize statistical sensitivity.

An ANOVA on data from Real Instruction sequences with factors of Reward (no reward, reward) and Sequence Type (Real Frequent, Real Rare) revealed that both main effects were reliable. We observed reduced alpha power in Reward blocks compared with No Reward blocks, $F(1, 21) = 8.5$, $MSE = 2.13$, $p < .01$, $\eta_p^2 = .29$, consistent with the idea that reward induces greater task focus or task preparation. However, contrary to our predictions, we also observed increased rather than reduced alpha power in Real Frequent sequences compared with Real Rare sequences, $F(1, 21) = 6.9$, $MSE = .66$, $p = .02$, $\eta_p^2 = .25$. The two factors did not reliably interact, $F < 1$.

A corresponding two-way repeated measures ANOVA on alpha power data from Fake Instruction sequences (see Figure 13) likewise revealed significant main effects of both Reward, $F(1, 21) = 19.5$, $MSE = 3.90$, $p < .01$, $\eta_p^2 = .48$, and Sequence Type, $F(1, 21) = 5.6$, $MSE = .31$, $p = .03$, $\eta_p^2 = .22$. Replicating the results observed in Real Instruction sequences, alpha power was substantially reduced in Reward blocks as compared with No Reward blocks. The reliable main effect of Sequence Type indicated that different control states might operate between frequent and rare switch instructions. However, again contrary to our original predictions, but consistent with the results from Real Instruction sequences, we found increased alpha power when participants expected switch trials to occur more frequently (i.e., in Fake

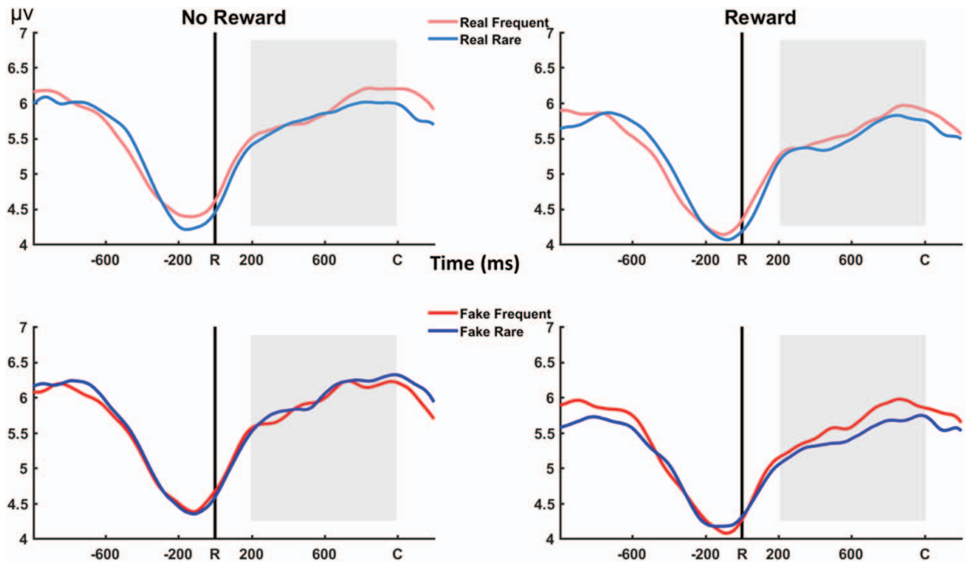

Figure 13. Grand-averaged electroencephalogram (EEG) alpha power, time-locked to the response (R) on trial $n - 1$. Each color represents different instruction condition. The gray region indicates the data used for statistical analysis. R = response; C = cue. See the online article for the color version of this figure.

Frequent vs. Fake Rare sequences). This pattern was only observed in the data from Reward blocks, as one might expect in light of the specificity of behavioral effects of instructions to these blocks, but the interaction between Reward and Sequence Type was not statistically significant, $F(1, 21) = 3.8$, $MSE = .33$, $p = .06$, $\eta_p^2 = .16$.

Overall, therefore, the alpha power results were consistent with the hypothesis that distinct control states operate when switches are expected to be rare versus frequent, regardless of objective switch frequency. However, the direction of the effect was surprising, a point we return to in the discussion below.

Discussion

The behavioral results replicated the key findings of the previous experiments, showing that task switching efficiency is modulated by both real and instruction-induced expectations about switch frequency, in a reward-dependent manner. An analysis of error types, made possible by mapping the two tasks to separate hands, indicated that instruction effects were apparent only in terms of participants responding with the wrong hand (i.e., performing the wrong task), not the wrong finger (i.e., performing the cued task incorrectly). These findings are consistent with our conception of instruction effects as task-level phenomena, reflecting the way in which task sets are selected, imposed and maintained according to expectations about switch frequency.

These behavioral effects of instruction were not mirrored in task-specific preparation as indexed via lateralized motor potentials. We observed no clear separation in LRP waveforms between the Fake Frequent and Fake Rare conditions during the response-cue interval. These null findings are necessarily inconclusive but, in the context of a clear replication of our key behavioral effects, they suggest that metacontrol influence was not expressed in terms of low-level motor preparation for an expected task. Instead, the alpha power results suggest that instructions modulate a more general level of control. We observed changes in alpha power during the response-cue (intertrial) interval according to switch frequency, both in Real and Fake Instruction sequences. However, the direction of the effect was surprising, with greater alpha power in sequences with higher objective or expected switch frequency, which might be expected to require higher levels of engagement (cf. Macdonald et al., 2011) and increased need for attentional control (e.g., Gladwin & de Jong, 2005; Poljac & Yeung, 2014), both of which should lead to reduced alpha power. Indeed, we found that reward incentives, which led to decreased RTs and error rates very consistently, led to reductions in alpha power. It is, therefore, surprising that the effects of switch frequency were not in accordance with this simple account.

Although necessarily speculative, we suggest that our alpha power results are consistent with an account that links the concept of *goal shielding* (e.g., Dreisbach & Haider, 2006) with our hypothesis about metacontrol. According to Dreisbach and Haider (2006), a core function of cognitive control is to reduce interference from competing stimulus dimensions by narrowing the focus of attention toward currently relevant features. Although this goal-shielding process reduces between-task interference, it is proposed to come at the cost of reduced flexibility, as reflected in switch costs. This theory, therefore, implies a trade-off between stability and flexibility in cognitive control: strong goal-shielding ensures good performance at the moment control is applied, but at the cost of slow and effortful task switching later. If so, we might expect the strength of goal-shielding to vary according to context as a crucial metacontrol parameter: Goal-shielding should be strong when task switches are rare, so that the benefits of stable task sets can be achieved in the context of little cost (switching will be slow, but required only rarely); goal-shielding should be relatively weak when task switches are frequent, where the benefits of stable task sets must be weighed against the performance costs they cause on frequent switch trials.

To the extent that goal-shielding is effortful and demanding—a common assumption about cognitive control processes (e.g., Botvinick et al., 2001; Shenhav et al., 2013)—this reasoning provides a coherent account of our alpha power findings: Reduced alpha power in Real Rare and Fake Rare sequences could reflect the demanding application of strong goal-shielding, which is applied in anticipation that stable task sets can be maintained across several trials (but which causes a high error rate when task switches are required, as in the Fake Rare condition). In contrast, alpha power will be relatively high in Real and Fake Frequent sequences, reflecting the reduced demand for effortful goal-shielding that would be counterproductive given the likelihood of task switching. In this way, our alpha power findings can be reconciled with the behavioral effects we observed within the framework of metacontrol.

Experiment 5

Experiment 5 aimed to provide convergent evidence of metacontrol influence on task switching, by studying the impact of switch frequency instructions on voluntary task choices. In this experiment, occasional trials requiring participants to choose the task to perform were introduced into the cued switching design used in the previous experiments. Fröber and Dreisbach (2017) have recently shown that voluntary task choice is sensitive to switch frequency in such designs, with participants more often voluntarily switching tasks when task cues on surrounding trials require frequent (vs. rare) switches. We predicted that instructions regarding switch frequency would likewise affect proportions of voluntary task repetitions and switches. Specifically, if Fake Rare instructions induce a metacontrol state that favors repeating the previous task, for example via strongly imposed goal-shielding that creates a stable (but also inflexible) task set, then participants should tend to repeat tasks more often when given choice over which task to perform. Conversely, if Fake Frequent instructions induce a metacontrol state that favors task switching, for example via weaker goal-shielding to promote efficient switching, then participants should make a higher rate of voluntary task switches. The present experiment tested these predictions. Aside from the inclusion of these voluntary choice trials, the design was similar to that of previous experiments, giving us the opportunity to replicate again the key findings described above. This included the analysis of error types introduced in Experiment 4, because again in Experiment 5 the two tasks were mapped to separate hands (here to allow us to determine which task was chosen on voluntary choice trials).

Method

Participants. Twenty-one students from the University of Oxford took part in this study (12 females; M_{age} = 19.1 years, SD = 1.20) for payment or course credit. All reported normal or corrected-to-normal vision and no color-blindness, and received payment or course credit for participating. They signed informed consent before the start of testing and were debriefed after the session.

Design and procedure. The design was generally similar to the previous experiments except that five voluntary task choice trials were introduced in each sequence. On these trials, a third gray cue (RGB code, [100,100,100]) was used, which indicated that participants had to choose for themselves which task to perform on the upcoming stimulus. Responses were recorded with a standard QWERTY-keyboard, using "z" and "x" as response keys with the left middle and index and fingers for one task, and "n" and "m" with the right index and middle fingers for the other task. The task selected by participants can, therefore, be inferred from the hand used on these voluntary trials, with errors defined as a response with the wrong finger of the chosen hand. The mapping of tasks to hands was counterbalanced across participants.

Switch frequency was calculated based on the cued trials and independent of the inclusion of voluntary trials. After the first trial in a sequence, in which participants were never given voluntary choice over the task to perform, 21 trials followed that consisted of 16 cued trials and five voluntary trials. The proportions of task switches and repeats on the cued trials were determined as in previous experiments. The five voluntary trials were randomly inserted into each instruction sequence with the constraint that they never occurred on consecutive trials. In these voluntary trials, participants were told to choose one of tasks without any restrictions. Performance on voluntary trials was included in the calculation for reward delivery in Reward blocks.

Preprocessing and data analysis. Data analysis focused on RTs and error rates as in previous experiments, but also on participants' task choices in voluntary selection trials. The first trial of each block, error trials, and trials following an error were excluded from the RT and choice analyses (15.3% of trials).

Results

Real Instruction conditions—Performance on cued trials. The first analysis aimed to replicate the basic effects of real switch frequency on cued task switching performance. A repeated measures ANOVA was performed on mean RTs (see Figure 14), with factors of Reward (reward vs. no reward), Sequence Type (Real Frequent, Real Rare, and No Instruction), and Task Transition (repeat, switch). This analysis replicated key findings reported above, notably a performance improvement with reward, $F(1, 20) = 63.4$ $MSE = 573{,}681$, $p < .01$, $\eta_p^2 = .76$ (see Figure 14), and the standard switch frequency effect on switching costs, $F(2, 40) = 3.9$, $MSE = 19{,}933$, $p = .03$, $\eta_p^2 = .16$, which here tended to be reduced in reward blocks, $F(2, 40) = 11.5$, $MSE = 33{,}473$, $p < .01$, $\eta_p^2 = .36$. The same ANOVA performed on the error rate data revealed a corresponding benefit of reward, $F(1, 20) = 12.7$, $MSE = .025$, $p < .01$, $\eta_p^2 = .39$, and fewer errors when the task repeated than when it switched, $F(1, 20) = 8.7$, $MSE = .028$, $p < .01$, $\eta_p^2 = .30$, but no other significant effects.

Fake Instruction—Performance on cued trials. Replicating the key analysis of the previous experiments, a repeated measures ANOVA was conducted on data from Fake Instruction sequences, using factors of Reward (no reward, reward), Sequence Type (Fake Frequent, Fake Rare), and Task Transition (repeat, switch). The RT analysis (see Figure 15) revealed two significant main effects, showing a performance benefit of reward, $F(1, 20) = 17.5$, $MSE = 98{,}297$, $p < .01$, $\eta_p^2 = .47$, and a robust switch cost of 157 ms, $F(1, 20) = 50.4$, $MSE = 1{,}029{,}070$, $p < .01$, $\eta_p^2 = .72$. As in previous experiments, RT switching costs in the Fake Frequent and

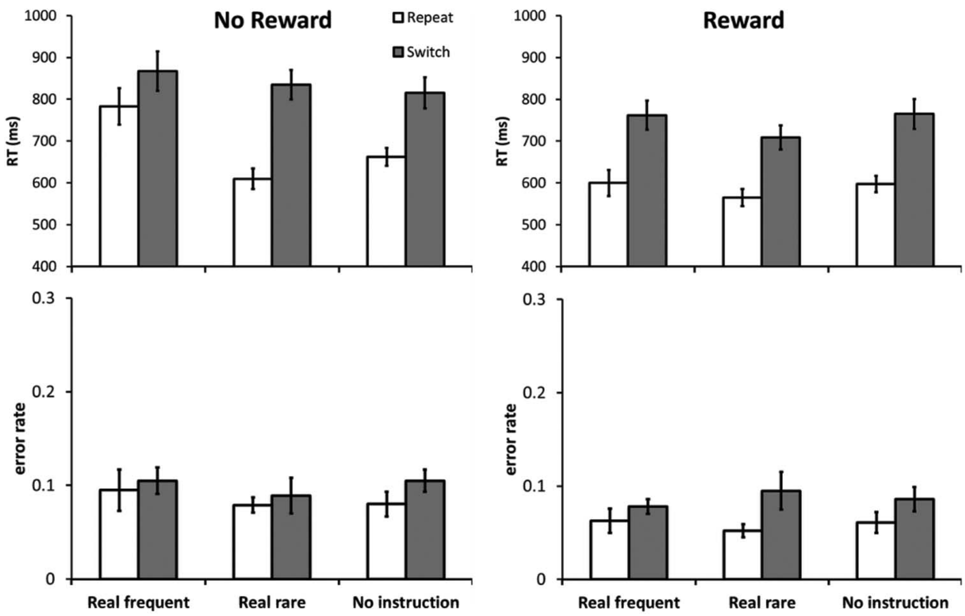

Figure 14. Mean RTs and error rates in the real instruction conditions in Experiment 5 as a function of reward (right vs. left panels), instruction type, and task transition. Error bars indicate standard errors of the mean.

Fake Rare conditions were of similar magnitude (interaction between Sequence Type and Task Transition, $F < 1$).

A corresponding analysis of error rates in Fake Instruction sequences (see Figure 15) revealed that participants overall made more errors in Fake Rare than Fake Frequent sequences, $F(1, 20) = 10.0$, $MSE = .03$, $p < .01$, $\eta_p^2 = .33$, and made more errors on switch trials than repeat trials, $F(1, 20) = 57.2$, $MSE = .21$, $p < .01$, $\eta_p^2 = .74$. There were reliable interactions between Reward and Sequence Type, $F(1, 20) = 7.3$, $MSE = .02$, $p = .01$, $\eta_p^2 = .27$, and between Sequence Type and Task Transition, $F(1, 20) = 10.9$, $MSE = .04$, $p < .01$, $\eta_p^2 = .35$. Most importantly, the critical three-way interaction was also

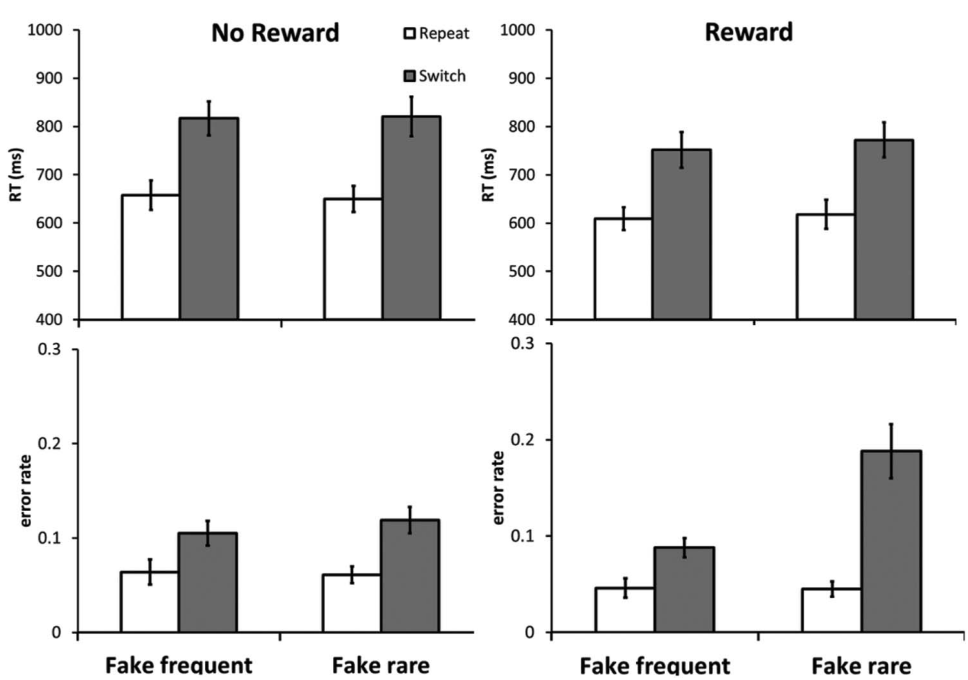

Figure 15. Mean RTs and error rates of the fake instruction conditions in Experiment 5 as a function of reward, instruction, and task transition. Error bars indicate standard errors of the mean.

reliable, $F(1, 20) = 6.6$, $MSE = .02$, $p = .02$, $\eta_p^2 = .25$, once again confirming the observation of a larger switching error cost in Fake Rare than Fake Frequent sequences in reward blocks, $F(1, 20) = 10.4$, $MSE = .18$, $p < .01$, $\eta_p^2 = .58$, but no such differences in no reward blocks, $F(1, 20) = 1.6$, $MSE = .002$, $p = .22$, $\eta_p^2 = .08$.

Error types on cued trials. The two tasks were mapped to separate hands to allow us to identify the task performed on voluntary choice trials. With this design, we can again distinguish task-level errors (when participants responded with the wrong hand) from those occurring at the response level (when participants responded with the wrong finger of the correct hand). The results were very similar to those in Experiment 4, with little evidence of an increased rate of response errors (wrong finger) in Fake Rare sequences under reward incentive (interaction between Reward, Task Transition and Sequence type, $F < 1$). Instead, the key pattern of interest, a reward-dependent increase in switch-trial errors under Fake Rare instructions, was apparent for task-level (wrong hand) errors, although the three-way interaction between Reward, Sequence Type and Task Transition was not statistically reliable, $F(1, 20) = 4.0$, $MSE = .004$, $p = .06$, $\eta_p^2 = .17$ (see Figure 16).

Task choices on voluntary trials. The main aim of this experiment was to assess voluntary task choice as a convergent measure of metacontrol effects in task switching. Voluntary task-switching trials were sorted into task transitions based on the hand used to respond. Of primary interest was the proportion of task repetitions and switches on these voluntary trials across sequence types. If metacontrol influences task selection, then the proportion of voluntary switches should be greater when instructions indicate that task switches will be frequent than when instructions indicate that switches will be rare. Crucially, the expected pattern should be apparent in both Real and Fake Instruction sequences.

As shown in Figure 17, participants overall exhibited a bias toward repeating the previous task when given voluntary choice (cf. Arrington & Logan, 2004; Mayr & Bell, 2006; Yeung, 2010). Since proportions of task repetition and task switch are complementary, a repeated measure ANOVA with factors Reward and Sequence Type was performed on the single measure of task switch proportion. Consistent with the prediction that the switch proportion would be higher in Real Frequent sequences, there was a significant main effect of Sequence Type, $F(1, 20) = 24.1$, $MSE = .60$, $p < .01$, $\eta_p^2 = .55$. Follow-up planned comparisons revealed that participants chose to switch tasks more often in Real Frequent sequences than Real Rare sequences, $p < .01$. Reward did not reliably affect switch proportions, $F(1, 20) = 3.0$, $MSE = .02$, $p = .10$, $\eta_p^2 = .13$, nor reliably interact with the effect of Sequence Type, $F < 1$. Thus, replicating recent findings by Fröber and Dreisbach (2017), albeit in a within-participant rather than between-participants design, we find that voluntary task choices are influenced by the overall context of switch frequency established by neighboring cued (forced task) trials.

For task choices in Fake Instruction sequences (see Figure 18), a corresponding ANOVA was performed with factors of Sequence Type (Fake Frequent vs. Fake Rare) and Reward (reward vs. no reward). A higher proportion of voluntary task switches was observed in Fake Frequent than Fake Rare sequences, which was confirmed by the significant main effect of Sequence Type: $F(1, 20) = 6.6$, $MSE = .13$, $p = .02$, $\eta_p^2 = .25$. Neither the main effect of Reward, $F < 1$, nor the interaction between Sequence Type and Reward, was statistically reliable, $F < 1$. The latter null result is surprising given that the error cost effects studied in previous experiments, and replicated again here, were specific to the Reward condition.

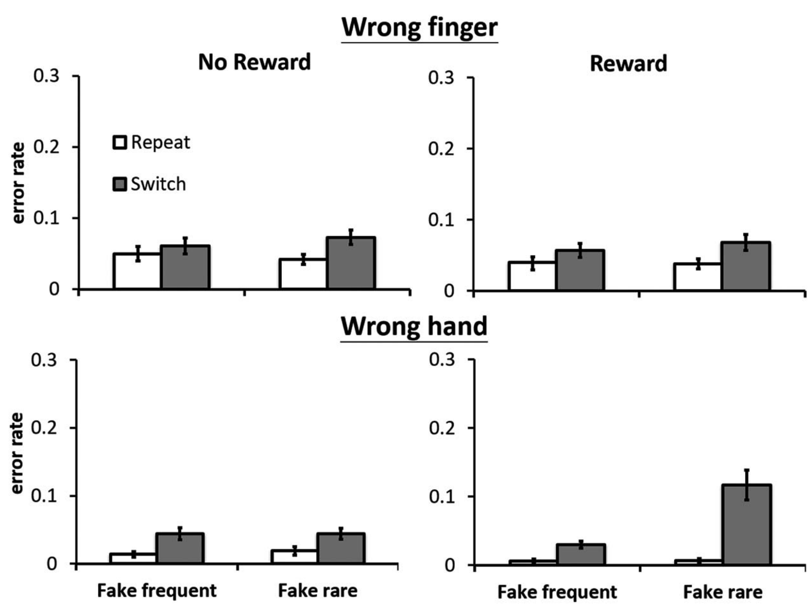

Figure 16. Mean error rates of Wrong finger type and Wrong hand errors in the Experiment 5 as a function of reward, instruction type, and task transition. Wrong finger errors were defined as using incorrect fingers while using the correct hand. Wrong hand errors were defined as using incorrect hands irrespective of fingers to respond. Error bars denote the standard errors of the mean.

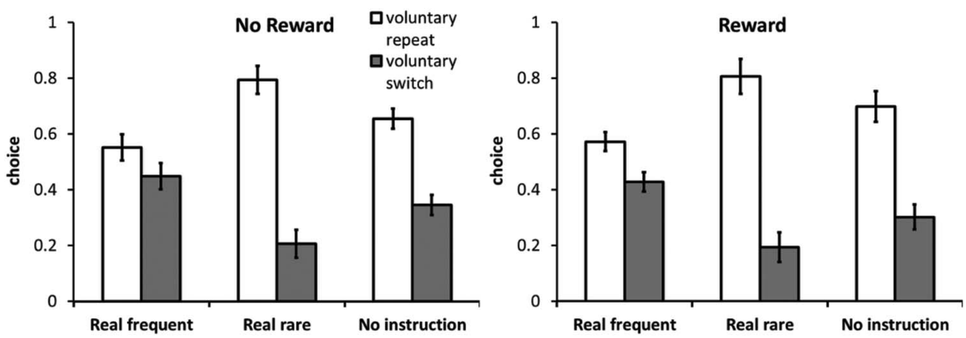

Figure 17. Proportions of task repetitions and task switches on the voluntary trials in Experiment 5 for the real instruction and no instruction conditions. Choices are plotted as a function of reward and instruction. Error bars denote the standard errors of the mean.

Discussion

Experiment 5 sought evidence of metacontrol by assessing task choices on voluntary trials in a cued multitasking environment. Performance on cued trials replicated the results of Experiments 1–4, showing increased error costs of switching when instructions indicated that task switches would be rare (regardless of objective likelihood). Further analysis of error types indicated that errors in Fake Instruction sequences were because of competition at the task level rather than the response level. Crucially, on voluntary choice trials, a corresponding effect was observed such that participants were more likely to make voluntary task switches when instructed that switches would occur frequently than rarely, even when comparing conditions that were matched for actually experienced switch frequencies. Unlike the error cost effect seen across experiments, this voluntary choice effect did not show reward sensitivity, indicating that, even in No Reward blocks, participants represented switch frequency instructions in a manner that could influence performance, albeit not to the extent needed to induce task selection errors (i.e., where the task performed was contrary to the one cued).

General Discussion

Five experiments investigated the influence of metacontrol in task switching—that is, the degree to which switching performance is subject to higher-level modulation according to the prevailing context in which it occurs. To this end, the experiments introduced a novel experimental design using verbal instructions: Participants were told about the frequency of switches in an upcoming sequence of trials, but in some trial sequences experienced the same objective switch frequency. Overall, the five experiments provide evidence that simple instructions can have a robust influence on switching costs. In particular, we observed high error rates when participants were required to switch tasks having been instructed that such switches would be rare (Fake Rare sequences). Consistent with this effect reflecting high-level, volitional control, it was sensitive to a reward incentive manipulation in Experiments 3, 4, and 5. The EEG data in Experiment 4 indicated further that the observed effects of instruction are more likely to reflect the application of a global control state—as reflected in oscillatory alpha power—than strategic trial-to-trial task preparation. Experiment 5 provided a converging measure of the influence of instructions, in terms of a biasing effect on voluntary task choices.

Across our experiments, we consistently replicated the finding that switch costs reduce as task switches become more frequent (Dreisbach & Haider, 2006; Monsell & Mizon, 2006; see Table 1). Our results extend this finding by demonstrating that the effect cannot be explained solely as a bottom-up effect of practice and experience, such as the beneficial effect of successive task repetitions when switches are rare, or simple associative learning that trials of Task A tend to be followed by trials of Task B (and vice

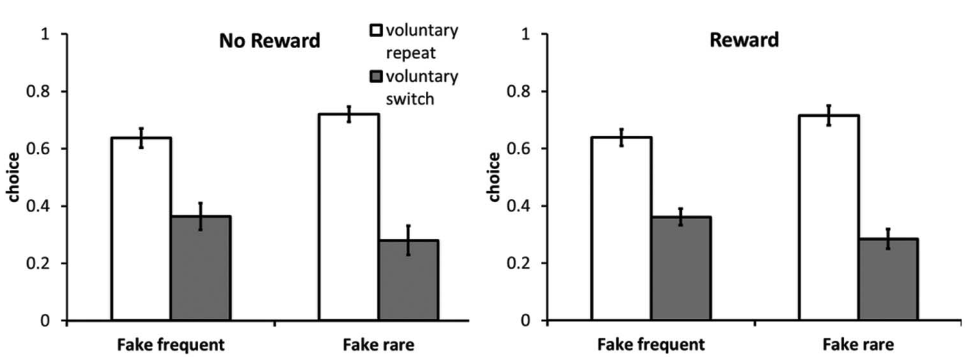

Figure 18. Proportion of task repetitions and switches on the voluntary trials in Experiment 5 for fake instruction sequences, as a function of reward and instruction. Error bars denote standard errors of the mean.

Table 1
Summary of RT Switch Costs (in Milliseconds) Across Conditions in Experiments 1–5

	Real instructions			Fake instructions		
Experiment	Frequent	Rare	Difference	Frequent	Rare	Difference
Exp 1	42	151	109* (31)	85	108	23 (14)
Exp 2						
No Rew	−10	63	73 (41)	26	56	30 (21)
Reward	−48	45	93** (24)	19	31	12 (26)
Exp 3						
No Rew	140	197	57 (39)	156	173	17 (29)
Reward	61	163	102** (16)	110	119	9 (21)
Exp 4						
No Rew	171	173	2 (26)	162	174	12 (15)
Reward	80	186	106** (20)	101	101	0 (15)
Exp 5						
No Rew	84	225	141** (30)	159	170	11 (25)
Reward	162	144	−18 (18)	143	154	11 (20)

Note. No Rew = no reward; Exp = experiment. Difference scores indicate the degree to which switch costs were greater in rare switch sequences than frequent switch sequences, with standard error of this critical contrast given in parentheses.
* $p < .05$. ** $p < .01$.

versa) when switches are frequent: Our design enabled us to study effects of top–down control induced by instruction, unconfounded with the actually experienced sequence of events. We observed effects of (expected) switch frequency that were induced flexibly and independent of objective switch frequency by verbal instruction. Conceptually, we suggest that these effects reveal the influence of metacontrol parameters (cf. Hommel, 2015), that modulate the operation of task-set control processes that are the typical focus of task switching research. Methodologically, our studies introduce a novel approach, based on verbal instructions, to study these kinds of metacontrol processes.

We conceive of metacontrol processes as operating in a flexible and goal-directed manner to optimize performance. This was reflected in our experimental approach of using relatively short trial sequences following each instruction, which should allow expression of instruction effects that reflect the rapid adoption of new metacontrol parameters, while making it less likely that participants would detect discrepancies between instructed and actual switch frequencies in the crucial Fake Instruction sequences. However, it is important to consider the potential contribution of associative learning processes to our results (e.g., De Houwer, Hughes, & Barnes-Holmes, 2016; Heyes, 2012; Mitchell, De Houwer, & Lovibond, 2009), given evidence that sensitivity to co-occurrence of environmental events and behavioral policies extends to control processes (e.g., Waszak, Hommel, & Allport, 2003). For example, in our experiments, perhaps associations formed between the respective instructions (frequent vs. rare switches) and adopting a high versus low response threshold (and thereby a tendency to respond slowly or quickly; cf. Karayanidis et al., 2009; Schmitz & Voss, 2012). However, although we do not rule out that associative learning effects might influence our data in subtle ways, they cannot explain our key findings. For example, if participants associated Frequent versus Rare switch instructions with different response thresholds, we would expect different RTs across the two Fake Instruction conditions, but in fact RTs were very similar (as indeed were error rates on task repeat trials). More broadly, associative learning accounts cannot easily explain the sensitivity of instruction effects to reward motivation—in contrast to top–down control effects that are known to exhibit this sensitivity (e.g., Botvinick & Braver, 2015; Fröber & Dreisbach, 2016)—nor why instructions influenced voluntary task choices in Experiment 5. These features instead favor a characterization of instruction effects as reflecting flexible and volitional application of top–down control. For related reasons, we are confident that our findings do not reflect priming of cue encoding (a relevant concern given our use of a single cue per task in Experiments 3–5; cf. Schneider & Logan, 2011).

Although our results were broadly in line with our original predictions, an initially unexpected finding was that effects of instruction (in the critical Fake Rare vs. Fake Frequent contrast) were primarily apparent as changes in error switching costs and were not reliably observed in RTs. That is not to claim that there is no RT effect: as shown in Table 1, RT switch cost differences were almost always in the predicted direction, being numerically larger in Fake Rare than Fake Frequent sequences. However, across participants the effects were sufficiently weak and inconsistent that we would not be powered to detect (or rule out) their existence without unreasonably large sample sizes. In contrast, the error rate pattern was robust—being replicated across all five experiments (see Table 2), albeit only numerically in Experiment 2 where overall switch costs were very low—suggesting that the relative specificity to errors is revealing of the underlying mechanisms. In particular, whereas the effects of real differences in switch frequency were evident as RT speeding on successive task repetitions when switches were rare, the effects of fake instructions were observed as errors when instruction-induced expectations were violated—specifically, in terms of errors on trials requiring a task switch when participants expected extended sequences of task repetitions. The results of Experiments 4 and 5 indicate that these errors primarily reflect selection of the incorrect task, as indicated

Table 2
Summary of Percentage Error Costs of Switching Across Conditions in Experiments 1–5

	Real instructions			Fake instructions		
Experiment	Frequent	Rare	Difference	Frequent	Rare	Difference
Exp 1	.9	.6	−.3 (1.3)	−.1	4.0	4.1 (1.0)**
Exp 2						
No Rew	2.7	2.8	.1 (1.9)	1.8	1.3	−.5 (1.7)
Reward	2.2	.3	−1.9 (1.9)	.6	2.3	1.7 (1.5)
Exp 3						
No Rew	−.8	3.5	4.3 (2.7)	1.8	2.2	.4 (1.1)
Reward	3.2	2	−1.2 (1.8)	1.5	6.3	4.8 (1.8)*
Exp 4						
No Rew	−.4	2.3	2.7 (1.8)	2.4	2.1	−.3 (1.4)
Reward	1.5	2.2	.7 (1.4)	1.9	9.8	7.9 (2.4)**
Exp 5						
No Rew	1	1	0 (2.9)	4.0	5.8	1.8 (1.3)
Reward	1.4	4.3	2.9 (2.0)	4.2	14.3	10.1 (3.1)**

Note. No Rew = no reward; Exp = experiment. Difference scores indicate the degree to which switch costs were greater in rare switch sequences than frequent switch sequences, with standard error of this critical contrast given in parentheses.
* $p < .05$. ** $p < .01$.

by responding with the wrong hand when the tasks were mapped to separate hands. This influence of instruction on task-selection was likewise apparent in Experiment 5 as a bias in voluntary task choices toward the task (or transition) that would be most likely required.

The EEG results from Experiment 4 provide insight into the mechanisms by which instructions affect task switching performance. The key difference we observed between instruction conditions was in terms of oscillatory alpha power in the intertrial interval, with greater power in Fake Frequent than Fake Rare sequences (as well as in Real Frequent vs. Real Rare sequences). As discussed above, we interpret this difference as reflecting the control process of task shielding, which is applied strongly to create stable and lasting task sets when switches are expected to be rare: The effort associated with this control process is reflected in suppression of alpha power. The connection between effort and shielding is consistent with Shenhav et al.'s (2013) proposal that the cost of control is assessed and balanced against its likely payoff. Thus, through instructions the participants could adjust task shielding (to focus attention on the now-relevant task-set and prevent interference from the now-irrelevant task) in accordance with current requirements (switching frequently or rarely)—a potential solution, via metacontrol, to the "shielding-shifting" control dilemma discussed by Goschke and colleagues (Goschke & Bolte, 2014).

The sensitivity of our instruction effect to reward incentive (numerically in Experiment 2, and significantly so in Experiments 3, 4 and 5) is consistent with this interpretation. Recent empirical and theoretical work has emphasized the links between cognitive control and reward motivation (Botvinick & Braver, 2015). In line with this perspective, we found that instruction effects were enhanced when reward incentivized fast and accurate performance. Indeed, instruction effects were absent in nonincentivized blocks when rewards were available elsewhere.

Based on their findings that reward can lead to improvements in both RT and accuracy simultaneously, Manohar et al. (2015) suggested that reward can "pay" the costs associated with acts of control. In this regard, it is notable that Experiments 3–5 provided evidence of reward effects at the level of basic task performance (reductions in overall RTs and error rates), task-level control (reductions in switch costs), and metacontrol (increases in instruction effects) simultaneously. As such, our findings indicate that principles of motivated control operate at multiple levels (Kouneiher, Charron, & Koechlin, 2009), consistent with the perspective that cognitive control exhibits hierarchical structure with common principles operating at different levels of behavioral organization (Choi, Drayna, & Badre, 2018; Fuster & Bressler, 2015; Koechlin & Summerfield, 2007).

Collectively, our findings converge on the conclusion that task-set control processes—as they are widely studied in task switching—are themselves subject to higher-level metacontrol. Here we have investigated the influence of this metacontrol in a series of five experiments that develop and test a novel experimental manipulation: using verbal instructions to induce different metacontrol states (e.g., reflecting expectations about switch likelihood) while controlling for objective features of the task context (e.g., objective switch frequency). Our findings demonstrate the influence of metacontrol states on task switching performance (particularly task-selection errors, as well as voluntary task choices) and accompanying oscillatory brain activity. We interpret these metacontrol processes as operating in a flexible and goal-directed manner to optimize performance.

References

Anderson, J. R., Bothell, D., Lebiere, C., & Matessa, M. (1998). An integrated theory of list memory. *Journal of Memory and Language, 38,* 341–380. http://dx.doi.org/10.1006/jmla.1997.2553

Arrington, C. M., & Logan, G. D. (2004). The cost of a voluntary task switch. *Psychological Science, 15,* 610–615. http://dx.doi.org/10.1111/j.0956-7976.2004.00728.x

Badre, D., & D'Esposito, M. (2009). Is the rostro-caudal axis of the frontal lobe hierarchical? *Nature Reviews Neuroscience, 10,* 659–669. http://dx.doi.org/10.1038/nrn2667

Botvinick, M., & Braver, T. (2015). Motivation and cognitive control: From behavior to neural mechanism. *Annual Review of Psychology, 66,* 83–113. http://dx.doi.org/10.1146/annurev-psych-010814-015044

Botvinick, M. M., Braver, T. S., Barch, D. M., Carter, C. S., & Cohen, J. D. (2001). Conflict monitoring and cognitive control. *Psychological Review, 108,* 624–652. http://dx.doi.org/10.1037/0033-295X.108.3.624

Botvinick, M., & Plaut, D. C. (2004). Doing without schema hierarchies: A recurrent connectionist approach to normal and impaired routine sequential action. *Psychological Review, 111,* 395–429. http://dx.doi.org/10.1037/0033-295X.111.2.395

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. http://dx.doi.org/10.1016/S0896-6273(03)00466-5

Choi, E. Y., Drayna, G. K., & Badre, D. (2018). Evidence for a functional hierarchy of association networks. *Journal of Cognitive Neuroscience, 30,* 722–736. http://dx.doi.org/10.1162/jocn_a_01229

Clayton, M. S., Yeung, N., & Cohen Kadosh, R. (2018). The many characters of visual alpha oscillations. *European Journal of Neuroscience, 48,* 2498–2508.

Cleeremans, A., & McClelland, J. L. (1991). Learning the structure of event sequences. *Journal of Experimental Psychology: General, 120,* 235–253. http://dx.doi.org/10.1037/0096-3445.120.3.235

Coles, M. G. (1989). Modern mind-brain reading: Psychophysiology, physiology, and cognition. *Psychophysiology, 26,* 251–269. http://dx.doi.org/10.1111/j.1469-8986.1989.tb01916.x

Compton, R. J., Arnstein, D., Freedman, G., Dainer-Best, J., & Liss, A. (2011). Cognitive control in the intertrial interval: Evidence from EEG alpha power. *Psychophysiology, 48,* 583–590. http://dx.doi.org/10.1111/j.1469-8986.2010.01124.x

Cooper, R., & Shallice, T. (2000). Contention scheduling and the control of routine activities. *Cognitive Neuropsychology, 17,* 297–338. http://dx.doi.org/10.1080/026432900380427

D'Ardenne, K., Mcclure, S. M., Nystrom, L. E., & Cohen, J. D. (2008). Bold responses reflecting dopaminergic signals in the human ventral tegmental area. *Science, 319,* 1264–1267.

De Houwer, J., Hughes, S., & Barnes-Holmes, D. (2016). Associative learning as higher order cognition: Learning in human and nonhuman animals from the perspective of propositional theories and relational frame theory. *Journal of Comparative Psychology, 130,* 215–225. http://dx.doi.org/10.1037/a0039999

De Jong, R., Gladwin, T., & M't Hart, B. (2006). Movement-related EEG indices of preparation in task switching and motor control. *Brain Research, 1105,* 73–82. http://dx.doi.org/10.1016/j.brainres.2006.03.030

Desrochers, T. M., Chatham, C. H., & Badre, D. (2015). The necessity of rostrolateral prefrontal cortex for higher-level sequential behavior. *Neuron, 87,* 1357–1368. http://dx.doi.org/10.1016/j.neuron.2015.08.026

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

Dreisbach, G., & Haider, H. (2009). How task representations guide attention: Further evidence for the shielding function of task sets. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 35,* 477–486. http://dx.doi.org/10.1037/a0014647

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,* 468–483. http://dx.doi.org/10.1037/0278-7393.28.3.468

Entel, O., Tzelgov, J., & Bereby-Meyer, Y. (2014). Proportion congruency effects: Instructions may be enough. *Frontiers in Psychology, 5,* 1108. http://dx.doi.org/10.3389/fpsyg.2014.01108

Fröber, K., & Dreisbach, G. (2016). How sequential changes in reward magnitude modulate cognitive flexibility: Evidence from voluntary task switching. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 42,* 285–295. http://dx.doi.org/10.1037/xlm0000166

Fröber, K., & Dreisbach, G. (2017). Keep flexible - Keep switching! The influence of forced task switching on voluntary task switching. *Cognition, 162,* 48–53. http://dx.doi.org/10.1016/j.cognition.2017.01.024

Fuster, J. M., & Bressler, S. L. (2015). Past makes future: Role of pFC in prediction. *Journal of Cognitive Neuroscience, 27,* 639–654. http://dx.doi.org/10.1162/jocn_a_00746

Gladwin, T. E., & de Jong, R. (2005). Bursts of occipital theta and alpha amplitude preceding alternation and repetition trials in a task-switching experiment. *Biological Psychology, 68,* 309–329. http://dx.doi.org/10.1016/j.biopsycho.2004.06.004

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. http://dx.doi.org/10.1016/j.neuropsychologia.2014.07.015

Heyes, C. (2012). Simple minds: A qualified defence of associative learning. *Philosophical Transactions of the Royal Society of London, Series B: Biological Sciences, 367,* 2695–2703. http://dx.doi.org/10.1098/rstb.2012.0217

Holroyd, C. B., & Yeung, N. (2012). Motivation of extended behaviors by anterior cingulate cortex. *Trends in Cognitive Sciences, 16,* 122–128. http://dx.doi.org/10.1016/j.tics.2011.12.008

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). New York, NY: Elsevier.

Hughes, G., Mathan, S., & Yeung, N. (2013). EEG indices of reward motivation and target detectability in a rapid visual detection task. *NeuroImage, 64,* 590–600. http://dx.doi.org/10.1016/j.neuroimage.2012.09.003

Karayanidis, F., Mansfield, E. L., Galloway, K. L., Smith, J. L., Provost, A., & Heathcote, A. (2009). Anticipatory reconfiguration elicited by fully and partially informative cues that validly predict a switch in task. *Cognitive, Affective & Behavioral Neuroscience, 9,* 202–215. http://dx.doi.org/10.3758/CABN.9.2.202

Kiesel, A., Steinhauser, M., Wendt, M., Falkenstein, M., Jost, K., Philipp, A. M., & Koch, I. (2010). Control and interference in task switching—A review. *Psychological Bulletin, 136,* 849–874. http://dx.doi.org/10.1037/a0019842

Kleinsorge, T., & Rinkenauer, G. (2012). Effects of monetary incentives on task switching. *Experimental Psychology, 59,* 216–226. http://dx.doi.org/10.1027/1618-3169/a000146

Koechlin, E., Ody, C., & Kouneiher, F. (2003). The architecture of cognitive control in the human prefrontal cortex. *Science, 302,* 1181–1185. http://dx.doi.org/10.1126/science.1088545

Koechlin, E., & Summerfield, C. (2007). An information theoretical approach to prefrontal executive function. *Trends in Cognitive Sciences, 11,* 229–235. http://dx.doi.org/10.1016/j.tics.2007.04.005

Kouneiher, F., Charron, S., & Koechlin, E. (2009). Motivation and cognitive control in the human prefrontal cortex. *Nature Neuroscience, 12,* 939–945. http://dx.doi.org/10.1038/nn.2321

Lien, M. C., & Ruthruff, E. (2004). Task switching in a hierarchical task structure: Evidence for the fragility of the task repetition benefit. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 30,* 697–713. http://dx.doi.org/10.1037/0278-7393.30.3.697

Logan, G. D., Schneider, D. W., & Bundesen, C. (2007). Still clever after all these years: Searching for the homunculus in explicitly cued task switching. *Journal of Experimental Psychology: Human Perception and Performance, 33,* 978–994. http://dx.doi.org/10.1037/0096-1523.33.4.978

Macdonald, J. S., Mathan, S., & Yeung, N. (2011). Trial-by-trial variations in subjective attentional state are reflected in ongoing prestimulus EEG alpha oscillations. *Frontiers in Psychology, 2,* 82. http://dx.doi.org/10.3389/fpsyg.2011.00082

Manohar, S. G., Chong, T. T.-J., Apps, M. A., Batla, A., Stamelou, M., Jarman, P. R., . . . Husain, M. (2015). Reward pays the cost of noise reduction in motor and cognitive control. *Current Biology, 25,* 1707–1716. http://dx.doi.org/10.1016/j.cub.2015.05.038

Mayr, U., & Bell, T. (2006). On how to be unpredictable: Evidence from the voluntary task-switching paradigm. *Psychological Science, 17,* 774–780. http://dx.doi.org/10.1111/j.1467-9280.2006.01781.x

Mayr, U., & Keele, S. W. (2000). Changing internal constraints on action: The role of backward inhibition. *Journal of Experimental Psychology: General, 129,* 4–26. http://dx.doi.org/10.1037/0096-3445.129.1.4

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

Meiran, N. (1996). Reconfiguration of processing mode prior to task performance. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 22,* 1423–1442. http://dx.doi.org/10.1037/0278-7393.22.6.1423

Mitchell, C. J., De Houwer, J., & Lovibond, P. F. (2009). The propositional nature of human associative learning. *Behavioral and Brain Sciences, 32,* 183–198. http://dx.doi.org/10.1017/S0140525X09000855

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,* 493–516. http://dx.doi.org/10.1037/0096-1523.32.3.493

Monsell, S., Sumner, P., & Waters, H. (2003). Task-set reconfiguration with predictable and unpredictable task switches. *Memory & Cognition, 31,* 327–342. http://dx.doi.org/10.3758/BF03194391

Muhle-Karbe, P. S., Andres, M., & Brass, M. (2014). Transcranial magnetic stimulation dissociates prefrontal and parietal contributions to task preparation. *Journal of Neuroscience, 34,* 12481–12489. http://dx.doi.org/10.1523/JNEUROSCI.4931-13.2014

Nieuwenhuis, S., Heslenfeld, D. J., von Geusau, N. J., Mars, R. B., Holroyd, C. B., & Yeung, N. (2005). Activity in human reward-sensitive brain areas is strongly context dependent. *NeuroImage, 25,* 1302–1309. http://dx.doi.org/10.1016/j.neuroimage.2004.12.043

Norman, D. A. (1981). Categorization of action slips. *Psychological Review, 88,* 1–15. http://dx.doi.org/10.1037/0033-295X.88.1.1

Poljac, E., & Yeung, N. (2014). Dissociable neural correlates of intention and action preparation in voluntary task switching. *Cerebral Cortex, 24,* 465–478. http://dx.doi.org/10.1093/cercor/bhs326

Richter, F. R., & Yeung, N. (2014). Neuroimaging studies of task switching. In J. A. Grange & G. Houghton (Eds.), *Task switching and cognitive control* (pp. 237–271). New York, NY: Oxford University Press. http://dx.doi.org/10.1093/acprof:osobl/9780199921959.003.0010

Rogers, R. D., & Monsell, S. (1995). Costs of a Predictable Switch Between Simple Cognitive Tasks. *Journal of Experimental Psychology: General, 124,* 207–231. http://dx.doi.org/10.1037/0096-3445.124.2.207

Sakai, K. (2008). Task set and prefrontal cortex. *Annual Review of Neuroscience, 31,* 219–245. http://dx.doi.org/10.1146/annurev.neuro.31.060407.125642

Schmitz, F., & Voss, A. (2012). Decomposing task-switching costs with the diffusion model. *Journal of Experimental Psychology: Human Perception and Performance, 38,* 222–250. http://dx.doi.org/10.1037/a0026003

Schneider, D. W., & Logan, G. D. (2011). Task-switching performance with 1:1 and 2:1 cue-task mappings: Not so different after all. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 37,* 405–415. http://dx.doi.org/10.1037/a0021967

Semlitsch, H. V., Anderer, P., Schuster, P., & Presslich, O. (1986). A solution for reliable and valid reduction of ocular artifacts, applied to the P300 ERP. *Psychophysiology, 23,* 695–703. http://dx.doi.org/10.1111/j.1469-8986.1986.tb00696.x

Shenhav, A., Botvinick, M. M., & Cohen, J. D. (2013). The expected value of control: An integrative theory of anterior cingulate cortex function. *Neuron, 79,* 217–240. http://dx.doi.org/10.1016/j.neuron.2013.07.007

Vallacher, R. R., & Wegner, D. M. (1987). What do people think they're doing? Action identification and human behavior. *Psychological Review, 94,* 3–15. http://dx.doi.org/10.1037/0033-295X.94.1.3

Vandierendonck, A., Liefooghe, B., & Verbruggen, F. (2010). Task switching: Interplay of reconfiguration and interference control. *Psychological Bulletin, 136,* 601–626. http://dx.doi.org/10.1037/a0019791

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,* 361–413. http://dx.doi.org/10.1016/S0010-0285(02)00520-0

Yeung, N. (2010). Bottom-up influences on voluntary task switching: The elusive homunculus escapes. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 36,* 348–362. http://dx.doi.org/10.1037/a0017894

Yeung, N., Nystrom, L. E., Aronson, J. A., & Cohen, J. D. (2006). Between-task competition and cognitive control in task switching. *The Journal of Neuroscience, 26,* 1429–1438. http://dx.doi.org/10.1523/JNEUROSCI.3109-05.2006

Zaghloul, K. A., Blanco, J. A., Weidemann, C. T., McGill, K., Jaggi, J. L., Baltuch, G. H., & Kahana, M. J. (2009). Human substantia nigra neurons encode unexpected financial rewards. *Science, 323,* 1496–1499. http://dx.doi.org/10.1126/science.1167342

Received April 23, 2019
Revision received September 3, 2019
Accepted September 17, 2019 ■