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Task Switch Costs Scale With Dissimilarity Between Task Rules

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Cognitive flexibility enables humans to voluntarily switch tasks. Task switching requires replacing the previously active task representation with a new one, an operation that typically results in a switch cost. Thus, understanding cognitive flexibility requires understanding how tasks are represented in the brain. We hypothesize that task representations are cognitive map-like, such that the magnitude of the difference between task representations reflects their conceptual differences: The greater the distinction between the two task representations, the more updating is required. This hypothesis predicts that switch costs should increase with between task dissimilarity. To test this hypothesis, we use an experimental design that parametrically manipulates the similarity between task rules. We observe that response time scales with the dissimilarity between the task rules. The findings shed light on the organizational principles of task representations and extend the conventional binary task-switch effect (task repeat vs. switch) to a theoretical framework with parametric task switches.

Public Significance Statement

Understanding how humans flexibly switch between tasks requires understanding how tasks are represented in the brain. Based on recent advances showing that cognitive maps can represent abstract relationships, we hypothesize that task representations are like cognitive maps, such that conceptual differences between tasks are encoded as the distance between task representations: The greater the distinction between the two task representations, the greater the updating required when switching between the two tasks, leading to larger switch costs in performance. To test this hypothesis, we use a new experimental design to parametrically manipulate task dissimilarity. Supporting the hypothesis, we observe that the task rule switch costs scale with the dissimilarity between the task rules in the two experiments. The findings shed light on the organizational principles of task representations and extend the conventional binary task-switch effect (task repeat vs. switch) to parametric task switches.

Keywords: task switch, task representation, cognitive control, cognitive map

Humans possess knowledge of many tasks and can flexibly switch between them. Theories and empirical evidence suggest that task knowledge, including stimuli, responses, contexts, and rules specifying how input is transformed into output, is encapsulated in a conjunctive task representation (Hommel, 2004; Kikumoto & Mayr, 2020; Kikumoto, Mayr, & Badre, 2022; Kikumoto, Sameshima, & Mayr, 2022; Rangel et al., 2022; Schumacher & Hazeltine, 2016). Switching between task representations is a key component of cognitive flexibility. For example, successful switching from making coffee to making cereal causes one to pour the cereal into the bowl rather than into the coffee cup. To successfully switch between tasks, interference from the old task must be resolved and the representation of the new task, including the input and output features and the processes that convert inputs into outputs, must be reconfigured (Monsell, 2003). This process will depend critically on the underlying format of the two task representations. On the one hand, tasks might be encoded in orthogonal neural codes such as sparse coding (e.g., Wixted et al., 2014). This would minimize interference but maximize reconfiguration

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Bettina Bustos served as lead for data curation, software, and visualization. J. Toby Mordkoff served in a supporting role for conceptualization and supervision. Eliot Hazeltine served in a supporting role for conceptualization and supervision. Jiefeng Jiang served as lead for conceptualization, funding acquisition, and supervision. Bettina Bustos, J. Toby Mordkoff, Eliot Hazeltine, and Jiefeng Jiang contributed equally to formal analysis and methodology. Bettina Bustos and Jiefeng Jiang contributed equally to writing–original draft and investigation. J. Toby Mordkoff and Eliot Hazeltine contributed equally to writing–review and editing.

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costs since task switches would require complete updating of the active task representation. On the other hand, two tasks might be encoded in a common reference frame, such that interference and reconfiguration costs of task switches are balanced by tuning the similarity between task representations. Such common reference frames can efficiently represent physical properties. For example, colors can be coded by a reference frame of three dimensions—brightness, hue, and saturation. In the human mind, the theory of psychological space, which provides a reference frame to represent multiple stimuli while capturing their perceptual similarity, has been successfully applied to account for generalization in perception (Shepard, 1987). Recently, it has been proposed that common reference frames, such as cognitive space (Bellmund et al., 2018) can be used to organize nonperceptual abstract information such as (Park et al., 2020; Tavares et al., 2015) and ratios (Constantinescu et al., 2016). Thus, cognitive spaces may also be applied to organize task representations by encoding task features (e.g., task rules) as parameters and using them like coordinates in a space. For example, in a Stroop task, the relevant stimulus feature can be parameterized so that changing its value from "word" to "ink color" will change the task from reading the presented word to reporting the ink color.

To capture perceptual similarity in the psychological space, Shepard (1987) defined metrics to quantify the distance in the psychological space between two stimuli such more perceptually similar stimuli will be closer in the psychological space. Similarly, we hypothesized that task information is organized such that similar tasks have similar mental representations. Specifically, we focused on task rules that determine how input should be processed to produce the goal-directed output. Importantly, in each task representation, the task rule is constant and thus differentiates the task from others. We designed an experimental paradigm in which rules were parameterized by orientations on a plane. A parametric switch effect (i.e., performance worsens as a function of the difference in rules) would support our hypothesis, whereas a null or nonmonotonic effect would support an orthogonal organization. Data from Experiments 1 and 2 revealed a parametric switch effect. We further ruled out other alternative explanations that the parametric switch effect was driven by a metatask representation, attention, saccades, other stimulus-based features, and mental rotation in Experiments 3 and 4.

Experiment 1

The hypothesis that similar tasks have similar representations predicts that switching between more similar tasks requires less reconfiguration of the active task representation, thus reducing the switching cost (see General Discussion on the effect of potential interference effects). In this experiment, we tested the hypothesis using five perceptual decision-making tasks (Figure 1A and 1B). Crucially, we manipulated the task rules such that (a) the task rules can be parameterized as orientations and (b) the difference in task rules between consecutive trials ranged from 0° to 160°, allowing for fine-grained tests of the similarity prediction. We also validated our operationalization of tasks using control analysis and independent experiments (see below).

Method

Participants

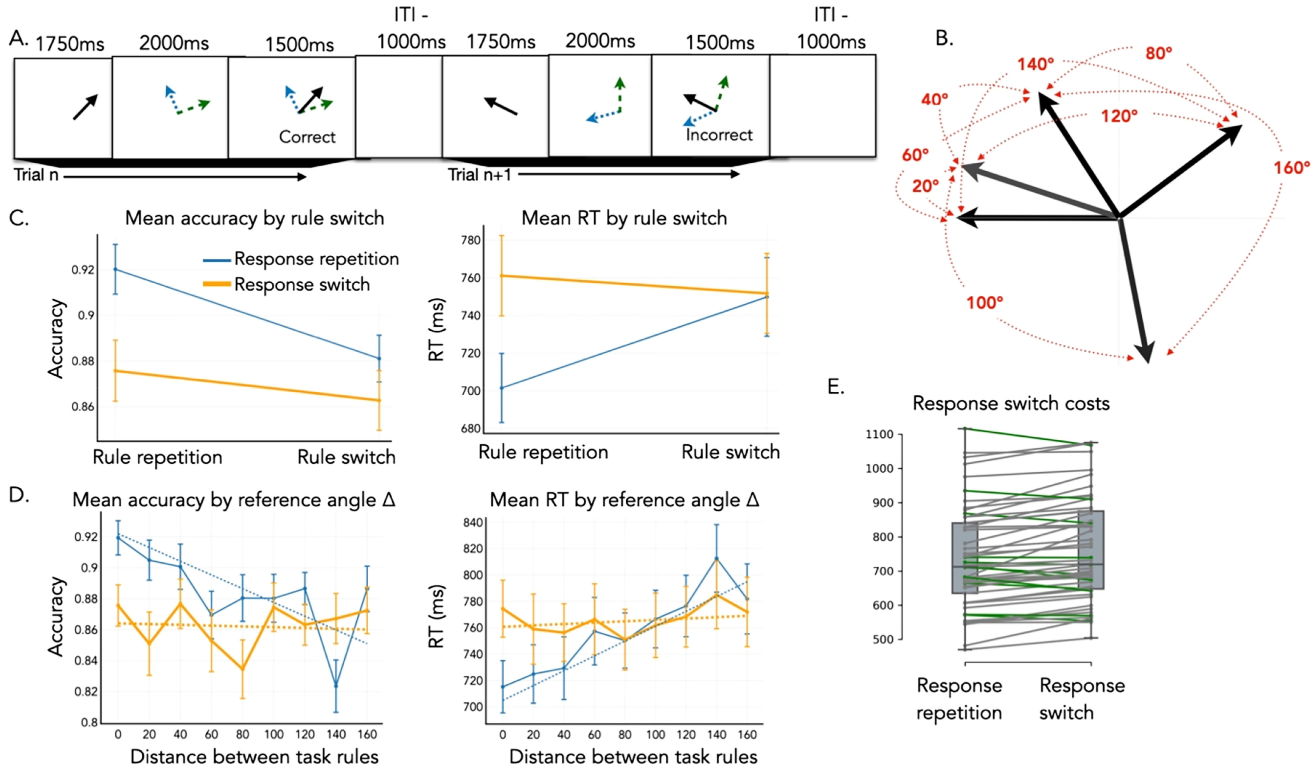
Seventy-three participants from the university provided informed consent and earned class credit for participation. Eighteen participants were removed for not meeting the accuracy threshold of 65% and two participants were further removed because of slow overall response time (RT), resulting in a final sample of 53 participants ($M_{age} = 19$ years, $SD = 1.15$, age not applicable for one participant, 33 female, 20 male). To acquire demographic information for all experiments in this study, participants were given an online survey to report their sex (three options: male, female, or do not wish to answer) and age (a text box that can be left empty if they do not wish to answer this question). All procedures were approved by the university Institutional Review Board. As all participants in this study were college students of both sexes, we expect that the findings can be directly generalized to healthy young adults.

Stimuli and Procedure

The stimuli consisted of black, blue, and green arrows (200 × 10 px) all originating from the center of the screen. On each trial, a black reference arrow cue appeared in one of five orientations that differed by either 0°, 20°, 40°, 60°, 80°, 100°, 120°, 140°, or 160° (Figure 1B). An angle jitter was randomly chosen between 0° and 71° for each participant and applied to each of the reference angles. Specifically, for each subject, all the reference arrows will rotate by the same random angle in the same random direction (clockwise or counterclockwise) in relation to the design shown in Figure 1B. Figure 2 shows four examples of reference arrow configurations after jittering. The angular distance among reference arrows did not change as a result of jittering. The jittering procedure aimed to counterbalance the potential heterogeneity of performance to different reference arrow orientations (e.g., a horizontal orientation may be easier/harder than a diagonal orientation). The black reference arrow cue was presented for 1,750 ms and then disappeared, followed by a green and blue arrow until a valid response was made or until the response deadline of 4,000 ms (Figure 1A). All arrows originated from the center of the screen. Participants were instructed to indicate whether the blue or green arrow was closer to the black reference arrow. They then received feedback (the word "correct," "incorrect," or "no response" and the presentation of the reference arrow and option arrows) based on their accuracy for 1,500 ms at the time of the response or the response deadline. Stimulus-response mappings (e.g., the correspondence between response keys [F or J] and arrow color [blue or green]) were randomized across participants. Potential variations in Simon congruence (i.e., the match between the side of the response and the side of the chosen arrow) were controlled by making the left key always correspond to the leftmost arrow. For example, for a participant using the response mapping of F = blue and J = green, the horizontal coordinate of the blue arrow was always to the left of that of the green arrow when the vertical directions of both arrows were the same (i.e., both upwards or both downwards). When the vertical directions were different (e.g., one arrow pointed to the top right and one pointed to the bottom right), the colors were assigned based on their vertical coordinates. This design addressed the confound that, when a reference arrow is horizontal, the more horizontal test arrow (i.e., the correct response) was always the same color. Overall, this design mitigates the potential Simon conflict. This spatial congruency may also help the participants establish a direct mapping between arrow location and response (i.e., left arrow = left button, right arrow = right button). Trials were separated by an intertrial interval of 1,000 ms. The angular distance between the blue and

Figure 1

Task Design and Results of Experiment 1



Note. (A) Trial structure. Note that the different dash types are used to distinguish different option arrows. In the experiment, all arrows are in solid lines. (B) Reference arrow orientations and their differences. (C) Accuracy and RT measures (group $M \pm SEM$), plotted as a function of rule switch/repeat and response switch/repeat. The rule switch condition collapsed across all positive degrees of the rule switch to resemble the conventional task-switch effect. (D) Accuracy and RT measures (group $M \pm SEM$), plotted as a function of the degree of rule switch as illustrated in Panel B and response switch/repeat. (E) RT measures for response repetition and response switch, relative to the last trial using the same task rule. Rule repeat trials were excluded to test whether the task rules were encoded in separate representations. The box plot shows the group-level distribution. Each line represents a single participant. Error bars indicate *SEM*. ITI = inter-trial interval; RT = response time; *SEM* = standard error of the mean. See the online article for the color version of this figure.

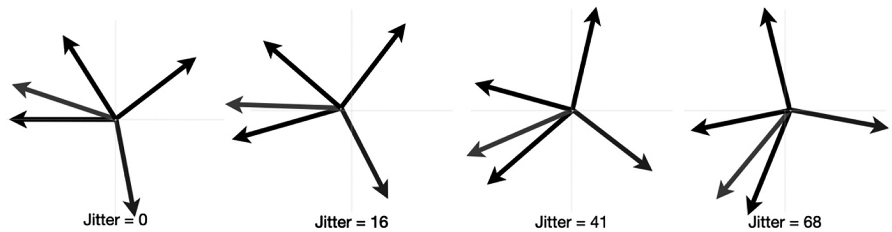
green arrows was constrained between 40° and 120°. Each arrow was at least 20° away from the reference arrow. Participants first completed 10 practice trials followed by the main task consisting of four blocks of 125 trials each.

Statistical Analysis

The dissimilarity between tasks on consecutive trials was quantified as the difference between the reference arrows (i.e., task rules). We performed three statistical tests. First, to replicate the classic task switch and response switch effects, we collapsed across all nonzero rule switches and conducted a 2 × 2 (rule switch × response switch) repeated measures analysis of variance (rmANOVA) on RT and accuracy separately. Effect sizes were reported as adjusted partial eta squared (adjusted $\hat{\eta}_p^2$; Mordkoff, 2019). Second, for the main goal of this study, we tested whether behavioral rule switch costs parametrically increased with the degree of rule switch using a two-way rmANOVA. The rmANOVA consisted of a factor of the rule switch type (0°, 20°, 40°, 60°, 80°, 100°, 120°, 140°, or 160° as a categorical variable) and a factor of response repeat/switch and was performed on RT and accuracy data separately. Here, the rule switch was treated as a categorical variable to detect all possible patterns of a rule switch's effect on performance. Third, to directly test the hypothesis of switch cost scaling with the degree of rule switch, for each participant, we conducted a multiple linear regression predicting trial-level RT with regressors for the logarithm-transformed rule switch (i.e., change in reference arrows between trials in degrees, collapsing across response repeat and switch trials, Figure 1B). We also included nuisance regressors of whether an error was committed on the previous trial (to account for potential posterror slowing), response repeat/switch from the previous trial, and the difficulty of each trial (defined as $||O_{ref} - O_{green}| - |O_{ref} - O_{blue}||$, where O_{ref}, O_{green}, and O_{blue} denote the orientations of the reference, green and blue arrow, respectively). This quantity captures how biased the reference arrow is to the closer than the farther arrow. To avoid the confounding that the effect is driven by the classic task-switch effect, we only included rule-switch trials in this analysis. A positive regression coefficient for the rule switch regressor would indicate that RT scales with the degree of the rule switch. Individual regression coefficients for the rule switch regressor were then entered into a one-sample t test and compared against zero. Because of the high accuracy in performance and resulting highly unbalanced correct versus error trials, the trial-level analysis was not performed on the accuracy data.

Figure 2

Visualization of Four Sets of Possible Reference Arrow Orientations After Applying a Randomized Jitter Between 0° and 71°



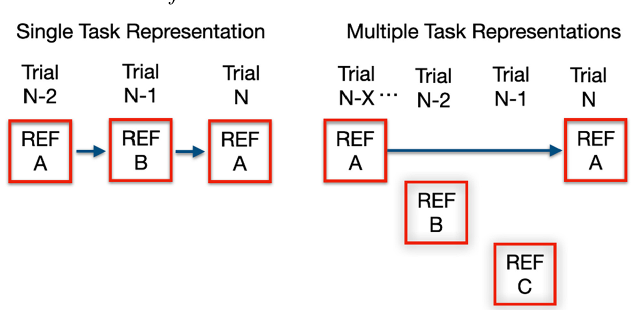
Note. The jittering was applied to Experiments 1, 2, and 4.

Additionally, we tested whether the task rules were encoded in separate task representations or under the same task representation by adopting the response switch test on nonconsecutive trials of the same type from Akçay and Hazeltine (2008) with a modification. Specifically, we first conceptualized a task as a holistic representation encompassing all information needed to achieve a given goal (Frings et al., 2020; Hommel, 2004; Schumacher & Hazeltine, 2016). For each task representation, the memory system automatically stores the most recent state (e.g., bindings of the reference arrow and the rule it represents, test arrows and response made), such that a change in response in the next encounter will incur a behavioral cost (e.g., Jiang et al., 2015; Mayr et al., 2003). This response switch effect was tested and confirmed (see below) in the 2×2 rmANOVA above.

We then leveraged the response switch effect to assess how the rules were represented (Figure 3). Consider a trial sequence ABA, with A and B being different reference arrows. If the reference arrows are represented using the same task representation, there will be two reference arrow switches (A to B then B to A) within the same task representation. As a result, the state of the first A trial would be replaced by the state of the B trial and should not influence the performance of the second A trial. On the other hand, if each reference arrow has its own task representation, by the second A trial there will be both the recent states, A and B. Thus, the state of the first A trial would still cause a response switch effect on the second A trial. Following this logic, within each subject, we identified trials whose most recent trial with the same rule was at least two trials ago (i.e., there were rule switches between the two trials) and computed the average RT as a function of response repeat/switch of the second trial with respect to the response of the first trial. Then, a paired *t* test was conducted between the response switch and repeat conditions at the group level. Note that Akçay and Hazeltine (2008) selectively analyzed trials where the last occurrence of the same task was two trials ago. To increase the trial counts in our analysis, we tested all trials where the last occurrence of the same task rule was at least two trials ago, similar to Xu and Mordkoff (2020).

Figure 3

Visualization of the Response Switch Test on Nonconsecutive Trials With the Same Reference Arrow



Note. The null hypothesis (i.e., a single task representation for all reference arrows) predicts that in a trial sequence ABA, switching from the first trial A to trial B would overwrite the state of the first trial. As a result, the response on the first trial A, which was overwritten, cannot interact with a response on trial *n*. On the other hand, the alternative hypothesis (i.e., each reference arrow has its own task representation) predicts that switching from trial A to another reference arrow (e.g., B or C) will not overwrite the state for A, as the state of the new trial will be stored in a different task representation. As a result, the response on the first A trial can interact with the response on the second A trial. REF = reference arrow; N = current trial. See the online article for the color version of this figure.

Transparency and Openness

This study was not preregistered. All data and analysis scripts related to this article are available in Open Science Framework at https://osf.io/29feh/ (Bustos et al., 2023).

Results and Discussion

An RT analysis examining the classic task-switch effect was performed by collapsing across all nonzero rule switch trials revealed a significant main effect of a task switch, $F(1, 52) = 11.33$, $p = .001$, adjusted $\hat{\eta}_p^2 = .16$, a significant main effect of response switch, $F(1, 52) = 25.15$, $p < .001$, adjusted $\hat{\eta}_p^2 = .31$, and a significant interaction that was driven by reduced response switch effect in task switch condition, $F(1, 52) = 31.03$, $p < .001$, adjusted $\hat{\eta}_p^2 = .36$ (Figure 1C). When the same analysis was performed on accuracy data (Figure 1C), we observed a significant main effect of a task switch, $F(1, 52) = 22.9$, $p < .001$, adjusted $\hat{\eta}_p^2 = .29$, and a significant main effect of response switch, $F(1, 52) = 9.15$, $p = .004$, adjusted $\hat{\eta}_p^2 = 13$. In this case, no interaction was found, $F(1, 52) = .90$, $p = .35$, adjusted $\hat{\eta}_p^2 = -.002$. Overall, the results are consistent with classic task switching, response switch, and reduced response switch cost following task switch (Kiesel et al., 2010).

We next turned to the main analysis of whether behavioral performance changes parametrically with change in the reference arrows

(Figure 1D). A significant main effect of the rule switch on RT was found, $F(8, 416) = 5.32$, $p < .001$, adjusted $\hat{\eta}_p^2 = .06$, but was not observed for response switch, $F(1, 52) = 2.33$, $p = .13$, adjusted $\hat{\eta}_p^2 = .03$. This difference was supported by a significant interaction, $F(8, 416) = 3.58$, $p < .001$, adjusted $\hat{\eta}_p^2 = .05$. A significant main effect of the parametric rule switch on accuracy was found, $F(8, 416) = 3.12$, $p = .002$, adjusted $\hat{\eta}_p^2 = .04$, but was not observed for response switch, $F(1, 52) = 3.21$, $p = .08$, adjusted $\hat{\eta}_p^2 = .04$. Again, a significant interaction was found, $F(8, 416) = 4.18$, $p < .001$, adjusted $\hat{\eta}_p^2 = .06$.

We then focused on rule switch trials only and tested whether performance varies as a function of the magnitude of the parametric rule change. At the group level, RT slows as a function of the logarithm of task-rule difference between consecutive trials, $t(52) = 6.39$, $p < .001$, 95% confidence interval, CI = [13.17, 25.23], $d_z = 0.88$. As some transitions (e.g., 20°) are tied to specific reference arrows, it is possible that the effect of task-rule difference is confounded by reference arrows-specific effects. To address this issue, we re-ran the linear model by replacing the grand constant regressor with reference arrow-specific regressors. The effect of task-rule difference remained statistically significant, $t(52) = 3.83$, $p < .001$, 95% CI = [4.61, 18.6], $d_z = 0.53$. Together, these results indicate that RT scales with the magnitude of the difference in reference arrows (i.e., rules), thus supporting the hypothesis of cognitive map-like organization of task rules.

Finally, relative to a given trial's most recent task rule repetition (excluding rule repeat trials), RTs were significantly slower for response switch than response-repeat trials, $t(52) = -5.17$, $p < .001$, 95% CI = [−37.57, −17.26], $d_z = 0.72$ (Figure 1E). This finding supports separate representations for different rules. In other words, participants demonstrated a response switch cost between the current trial and the last trial using the same task rule, despite there being other trials with different task rules between the two trials. We further tested whether the response switch effect changes as a function of the difference between A and B trials. To this end, we limited our analysis to ABA sequences in which B is a single trial. We then tested the interaction of the degree of reference arrow switch between trial $n - 1$ and trial n with the response switch between trial $n - 2$ and trial n using trial-level linear regression for each participant. Individual interaction effects were grouped and tested against 0 using a one-sample t test. The interaction did not reach statistical significance, $t(52) = 0.566$, $p > .57$, 95% CI = [−18.29, 32.65], $d_z = 0.17$, indicating that the response switch effect between the two A trials was not modulated by the difference between reference arrows A and B.

Experiment 2

Experiment 2 aimed to replicate the findings in Experiment 1 and address whether the observed rule-switch cost in Experiment 1 was because of the perceptual similarity of the reference arrows (i.e., similarity in visual input) on consecutive trials. To this end, we changed the experimental paradigm such that the reference arrow was not perceptually available and the rule must be retrieved from memory based on previously learned associations.

Method

Participants

Eighty participants from the university provided informed consent and earned class credit for participation. Twenty-nine participants were removed for not meeting the accuracy threshold of 65%, resulting in a final sample of 51 participants ($M_{age} = 19$ years, $SD = 1.96$, 27 female, 24 male). The target sample size was determined using the effect size of the trial-level parametric switch effect from Experiment 1, with an α level of .05 and a power level of .90. All procedures were approved by the university Institutional Review Board.

Stimuli and Procedure

The procedure for Experiment 2 was identical to Experiment 1 (Figure 4A and 4B), with one key change. To address the confound that the rule-switch effect captures the perceptual difference in reference arrow orientations rather than the task rules, each reference arrow was first associated with one of five unique fractal images. The associations between fractal and arrow were randomized at the participant level. Prior to the main task, participants completed at least one learning phase and one test phase to ensure participants appropriately learned the associations between the reference arrows and fractal stimuli. The learning phase was self-paced. Participants were shown each of the five reference arrows and their paired fractals. They were instructed to memorize the pairings. On each trial of the test phase, participants were presented with a fractal image and were asked to recall its paired reference arrow by adjusting a presented arrow to the orientation of the reference arrow. A trial was considered correct if the error between the response and the true reference arrow was within 25°. Participants repeated the learning and test phases if they did not achieve 100% accuracy. Additionally, for the present experimental design response deadlines were increased by 1,500 ms to account for the increased difficulty of the task (Figure 4A). After successfully passing the fractal cue test phase, participants completed five practice trials followed by the main task consisting of two blocks of 125 trials. All other task specifics were the same as in Experiment 1.

Statistical Analysis

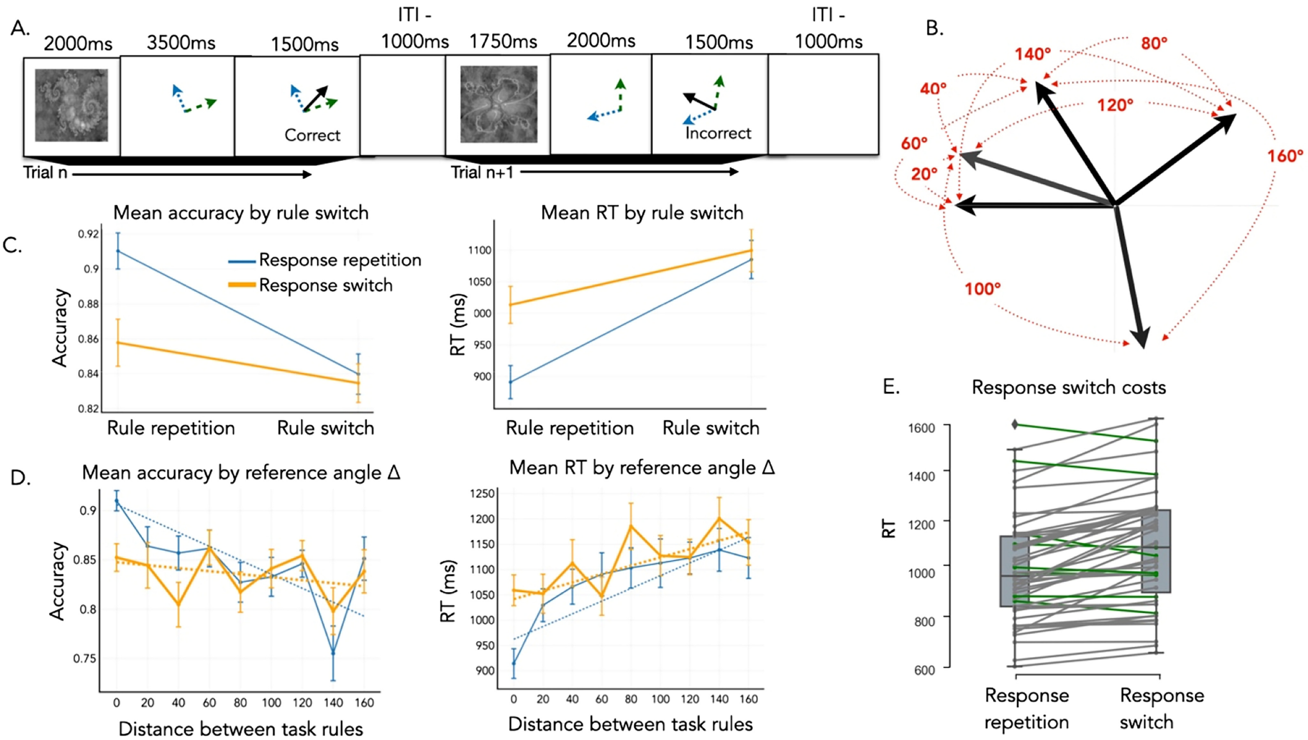
Statistical analysis was identical to Experiment 1.

Results and Discussion

An RT analysis examining the classic task-switch effect by collapsing across all nonzero rule switch trials (Figure 4C) revealed a significant main effect of a task switch, $F(1, 50) = 75.43$, $p < .001$, adjusted $\hat{\eta}_p^2 = .60$, a significant main effect of response switch, $F(1, 50) = 22.50$, $p < .001$, adjusted $\hat{\eta}_p^2 = .30$, and a significant interaction that was driven by reduced response switch effect in task switch condition, $F(1, 50) = 18.76$, $p < .001$, adjusted $\hat{\eta}_p^2 = .26$. When the same analysis was performed on the accuracy data (Figure 4C), we found a significant main effect of a task switch on the accuracy, $F(1, 50) = 40.24$, $p < .001$, adjusted $\hat{\eta}_p^2 = .44$, a significant main effect of response switch, $F(1, 50) = 15.70$, $p < .001$, adjusted $\hat{\eta}_p^2 = .22$, and a significant interaction, $F(1, 50) = 11.98$, $p = .001$, adjusted $\hat{\eta}_p^2 = .18$, driven by a reduced response switch effect in the rule-switch than the rule-repeat condition. Worse performance in the response repeat condition than the response switch condition when the rule switched is commonly observed in task-switching literature (Gade et al., 2014; Koch et al., 2023), but this was not the case in our results. We speculate that this pattern may be attributed to the fact that the stimulus-response mapping remains constant across tasks (e.g., green arrow = left button, blue arrow = right button)

Figure 4

Task Design and Results of Experiment 2



Note. (A) Trial structure. Note that the different dash types are used to distinguish different option arrows. In the experiment, all arrows are in solid lines. (B) Reference arrow orientations and their differences. (C) Accuracy and RT measures (group $M \pm SEM$), plotted as a function of rule switch/repeat and response switch/repeat. The rule switch condition collapsed across all positive degrees of the rule switch to resemble the conventional task-switch effect. (D) Accuracy and RT measures (group $M \pm SEM$), plotted as a function of the degree of rule switch as illustrated in Panel B and response switch/repeat. (E) RT measures for response repetition and response switch, relative to the last trial using the same task rule. Rule repeat trials were excluded to test whether the task rules were encoded in separate representations. The box plot shows the group-level distribution. Each line represents a single participant. Error bars indicate *SEM*. ITI = inter-trial interval; RT = response time; *SEM* = standard error of the mean. See the online article for the color version of this figure.

across tasks for each participant, whereas most task switch studies use different stimulus-response mappings for different tasks. Overall, the results are consistent with classic findings of task switch, response switch, and reduced response switch cost following task switch and replicated the findings from Experiment 1.

We then tested whether performance changes with the degree of rule switch. A significant main effect of the rule switch on RT was found, $F(8, 400) = 8.11, p < .001$, adjusted $\hat{\eta}_p^2 = .12$, along with a significant interaction, $F(8, 400) = 2.21, p = .03$, adjusted $\hat{\eta}_p^2 = .02$. The effect of response switch was *ns*, $F(1, 50) = 2.10$, $p = .15$, adjusted $\hat{\eta}_p^2 = .02$. For accuracy data, we observed a significant main effect of the rule switch, $F(8, 400) = 5.18$, $p < .001$, adjusted $\hat{\eta}_p^2 = .08$. The main effect of response switch was not observed, $F(1, 50) = 1.90$, $p = .17$, adjusted $\hat{\eta}_p^2 = .02$. The interaction effect was marginally significant, $F(8, 400) = 2.00$, $p = .05$, adjusted $\hat{\eta}_p^2 = .02$. Overall, the findings indicate that performance varied across different rule-switch conditions.

Next, we focused on rule-switch trials only and tested whether there was a linear change in RT as a function of the logarithm of the magnitude of the rule change. At the group level, we found that the regression coefficient of the rule switch in predicting RT was significantly above 0, $t(50) = 3.28$, $p = .002$, 95% CI = [15.65, 65.26], $d_z = 0.46$ (Figure 4D). When using reference arrow-specific intercepts, the effect remained statistically significant, $t(50) = 2.32$, $p = .02$, 95% CI = [4.55, 48.08], $d = 0.33$. This finding suggests that RT scales with the magnitude of the rule switch, thus providing additional support for the hypothesis of cognitive map-like organization of task rules. The parametric switch effects did not significantly differ between Experiments 1 and 2, $t(55.9) = 1.67$, $p > .10$, 95% CI = [−4.21, 46.71], $d = 0.33$.

Finally, relative to a given trial's most recent reference arrow repetition (excluding rule repeat trials), RTs were significantly slower for response switch than response repeat trials, $t(50) = -6.52$, $p < .001$, 95% CI = [−112.6, −59.54], $d_z = 0.37$ (Figure 4E). This finding replicated the result in Experiment 1 and supported separate representations for different task rules in this experiment. Finally, for ABA sequences of three trials, the degree of reference arrow switch from trial $n - 1$ to trial n did not interact with the response switch between trial $n - 2$ and trial n, $t(50) = -0.363$, $p > .71$, 95% CI = [−93.88, 65.2], $d_z = 0.05$, a finding consistent with Experiment 1.

In summary, in both Experiments 1 and 2 we found that in rule switch trials, RT scaled with the degree of rule switch. We further argued that each rule is represented as a single task. This argument received initial support from the response switch effect between two nonconsecutive trials with the same reference arrow (Figures 1E, 3, and 4E). In Experiment 3, we conducted an independent experiment to test this argument using a different analysis.

Experiment 3

It remains possible that the parametric rule switch effect can be observed even when there is only one task, that is, all five reference arrows were represented in the same task (i.e., the metarule view). Changing the value of the reference arrow may still cause a reconfiguration cost, although this cost may be smaller than the cost of switching the task representation. This alternative view assumes a compositional task representation (Cole et al., 2011; Collins & Frank, 2013; Reverberi et al., 2012) that allows task features to be reconfigured without affecting other components of the active task representation. However, as the rule changes, the brain must reconstruct the mental procedures specifying how the new rule applies to the input and output features, a process termed proceduralization (Brass et al., 2017; Oberauer, 2010). On the other hand, if each reference arrow is represented in a separate task representation (i.e., each task has a constant rule), the procedural memories of executing each task should be included in their respective task representations to form a conjunctive task representation (Hommel, 2004; Kikumoto & Mayr, 2020; Kikumoto, Mayr, & Badre, 2022; Kikumoto, Sameshima, & Mayr, 2022; Rangel et al., 2022; Schumacher & Hazeltine, 2016). In other words, compared to the compositional task representation view (i.e., one task that includes all reference arrows), the conjunctive task representation view (i.e., one task for each rule) will have better overall performance (as proceduralization is not necessary on each trial) and stronger parametric switch costs (as conjunctive task representation requires reconfiguring the whole task presentation rather than only the rule). It has been shown that practice produces a shift from a compositional task representation to a conjunctive one (Mill & Cole, 2023). To formally adjudicate between the two possibilities, we conducted another control experiment identical to Experiment 1 except that now we ensured that there was only one task representation. If only one task was executed in Experiment 1, then Experiment 3 should produce the same effect. Conversely, if multiple rules were used in Experiment 1, then Experiment 3 should produce a smaller parametric switch effect.

In addition, the effect of changing the values of the reference parameters might be seen as coming from a process of mental rotation (Shepard & Metzler, 1971). In other words, a single task representation for all rules has a proceduralization of a generic "metarule" that treats the reference arrow as a variable. As the execution of the task requires the comparison to the presented reference arrow, additional procedualization that replaces the variable of reference arrow with the presented value (i.e., mentally rotating the rule from the previous reference arrow to the current one) must take place and may underlie the observed parametric switch cost. The observed parametric task rule switch cost may also be because of shifts of spatial attention and/or saccades. For example, if the rule switch is small, the previous and current reference arrows are close in space. Therefore, any shift of attention and/or eye movement will be less than it would be for a larger rule switch. As the physical presentation remained identical between Experiments 1 and 3, contrasting data between the two experiments will also help control for these alternative explanations. That is, if Experiments 1 and 3 have similar parametric switch effects, the effect may be driven by a metarule or mental rotation. Conversely, if the parametric switch effects were different between the two experiments, the effects must be driven by more than just mental rotation and not by metarule.

Method

Participants

Eighty-two participants from the university provided informed consent and earned class credit for participation. Eleven participants were removed for not meeting the accuracy threshold of 65%, resulting in a final sample of 71 participants ($M_{\text{age}} = 19$ years, $SD = 1.02$, 54 female, 15 male, two preferred not to answer). The target sample size was determined using the effect size of the trial-level parametric switch effect from Experiment 1, with an α level of .05 and a high power level of .99 to reduce the false negative rate. All procedures were approved by the university Institutional Review Board.

Stimuli and Procedure

The stimuli and procedure were identical to Experiment 1 with one difference: The reference arrow was randomly chosen and sampled from all orientations (i.e., uniformly from 0° to 359°, Figure 5B). Due to the high number of possible reference arrows, it is impossible to represent each task rule as a separate task. Therefore, we reasoned that all reference arrows are represented as a task feature within the same task representation, which has a more abstract task rule (e.g., "finding the test arrow closer to the reference arrow") than task representations in Experiments 1 and 2 (e.g., "finding the test arrow closer to the reference arrow at 60°"). Participants first completed 10 practice trials followed by the main task consisting of five blocks of 125 trials each.

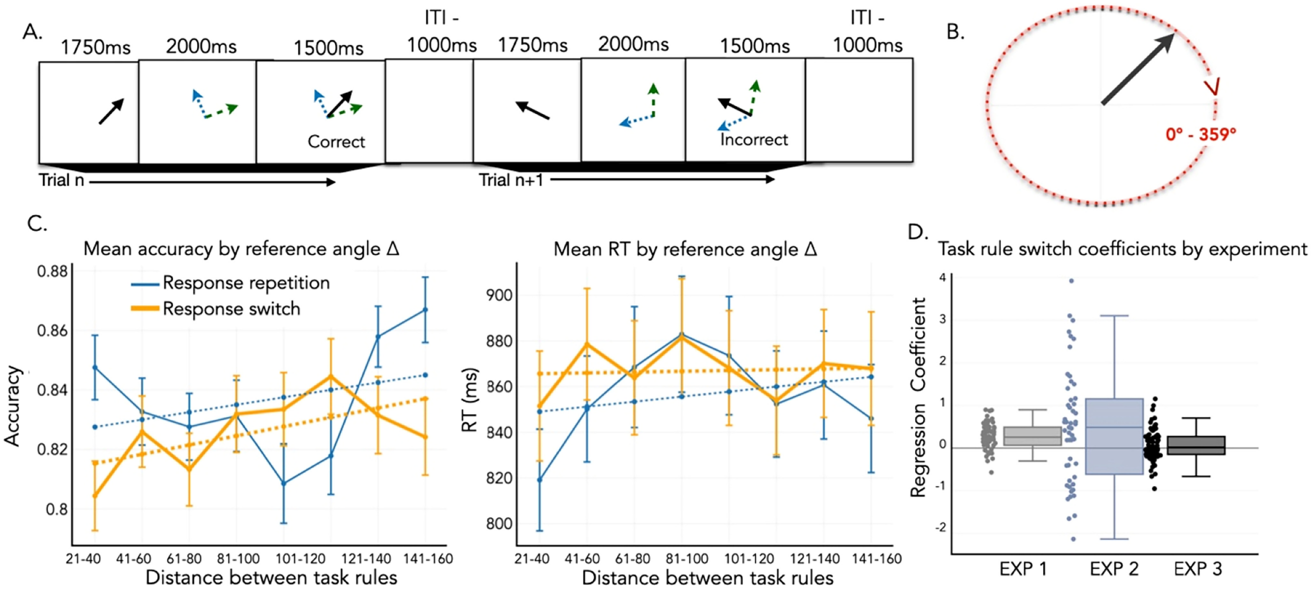
Statistical Analysis

As the reference arrow was a continuous variable in this experiment, only trial-level regression analysis was performed. Similar to Experiment 1, we constructed a linear model consisting of each trial's logarithm-transformed rule switch and nuisance regressors of whether an error was committed on the previous trial, response repeat/switch from the previous trial, and the difficulty of each trial. To be consistent with Experiment 1, only trials with reference arrow switch between 20° and 160° were included in the analysis. Due to the binary nature of accuracy, trial-wise accuracy was regressed against this model using logistic regression. For RT analysis, trial-wise RT (excluding error trials) was regressed again in this model using linear regression. The analysis was conducted on each participant separately. The resulting individual regression coefficients for the task rule switch were submitted to a group-level one-sample *t* test. To compare the rule switch cost to Experiment 1, the regression coefficients from the RT analyses of both experiments were tested using an independent sample *t* test. The same linear model was applied to both experiments to ensure unbiased comparison. Because the relationship between RT and degree of change appears to be linear in the mental rotation effect (Shepard & Metzler, 1971), we also repeated the same RT analysis using a raw degree of rule switch for both experiments.

Results and Discussion

The accuracy analysis showed no significant difference from zero, $t(70) = 0.24$, $p = .81$, 95% CI = [−0.03, 0.03], $d_z = 0.03$,

Figure 5
Task Design and Results of Experiment 3



Note. (A) Trial structure. Note that the different dash types are used to distinguish different option arrows. In the experiment, all arrows are in solid lines. (B) Possible reference arrow orientations ranging from 0° to 359°. (C) Accuracy and RT measures (group $M \pm SEM$), binned and plotted as a function of the degree of rule switch and response switch/repeat. Note that this analysis was conducted at the trial level. (D) Difference in regression coefficients for rule switch effect for each of the first three experiments. Boxplots showed group-level data. Individual data were shown in dots. Error bars indicate *SEM*. ITI = inter-trial interval; RT = response time; Exp = experiment; *SEM* = standard error of the mean. See the online article for the color version of this figure.

suggesting that there was no rule switch cost in accuracy (Figure 5C). RT regression coefficients of the rule switch were significantly above zero, $t(70) = 2.47$, $p = .02$, 95% CI = [1.67, 15.71], $d_z = 0.29$, thus supporting the presence of a rule switch cost in this experiment (Figure 5C). Crucially, the regression coefficients in this experiment were significantly lower than those from Experiment 1, $t(122) = -2.27$, $p = .025$, 95% CI = [−19.64, −1.32], $d_z = 0.40$. When using the raw degree of the rule switch as a predictor, the RT regression coefficients of the rule switch in this experiment were not significantly different from zero, $t(70) = 1.70$, $p = .094$, 95% CI = [−0.01, 0.16], $d_z = 0.20$, and were significantly lower than those from Experiment 1, $t(122) = -3.13$, $p = .002$, 95% CI = [−0.32, −0.07], $d_z = 0.56$. Considering that the key difference from Experiment 1 is that task rules can only be represented in a single task representation in this experiment, this finding provides strong evidence that the rule switch cost in Experiment 1 cannot be fully explained by a mental rotation effect, saccades and/or rule switch cost within the same task. In other words, it is likely that the rule switch cost observed in Experiment 1 was (at least partly) driven by a switch of the task representation.

Experiment 4

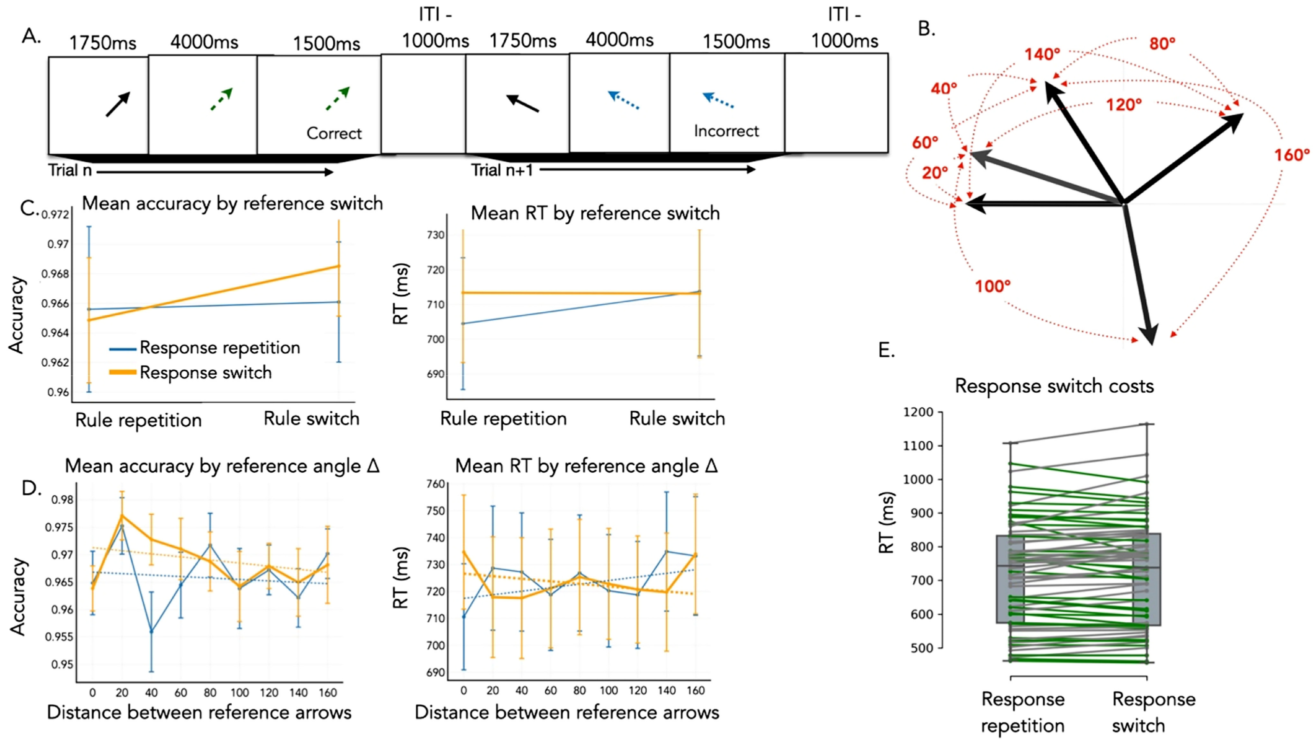
The effect of the observed parametric task rule switch cost may be because of shifts of spatial attention and/or saccades, instead of task reconfiguration. For example, if the rule switch is small, the previous and current reference arrows are close in space. Therefore, any shift of attention and/or eye movement will be less than it would be for a larger rule switch. Experiment 4 is an additional control experiment to address this confound. To this end, we changed the design from Experiment 1 such that the reference arrows still served as a cue of spatial attention and/or the target of an eye movement. However, the reference arrows no longer indicated task rules (Figure 6A). As in Experiment 1, the reference arrow in Experiment 4 was presented following a blank screen. Thus, we expected that the bottom-up spatial attention would be directed to the orientation of the arrow in both experiments. Additionally, as the reference arrow also contains task-relevant information, top-down spatial attention may also be directed to the reference arrow. Note that there was a 1,750 ms interval between the onset of the reference arrow and the onset of its color, this allows spatial attention to engage prior to feature-based attention. A saccade may be made towards the arrow as a result of spatial attention. As these processes are shared by both Experiments 1 and 4, if the parametric switch effect in Experiment 1 was because of spatial attention and/or saccade, it is expected that the parametric switch effect should also be observed in Experiment 4. On the other hand, since the rule did not change in Experiment 4, a null finding of the parametric switch effect would indicate that the parametric switch effect in Experiment 1 can be attributed to the rule and/or task switch, which was tested in Experiment 3.

Method

Participants

Seventy-two participants from the university provided informed consent and earned class credit for participation. Three participants were removed for not meeting the accuracy threshold of 65%, and one participant was further removed because of slow overall RT,

Figure 6
Task Design and Results of Experiment 4



Note. (A) Trial structure. Note that the different dash types are used to distinguish different colors. In the experiment, all arrows are in solid lines. (B) Reference arrow orientations and their differences. (C) Accuracy and RT measures (group $M \pm SEM$), plotted as a function of rule switch/repeat and response switch/repeat. The rule switch condition collapsed across all positive degrees of the rule switch to resemble the conventional task-switch effect. (D) Accuracy and RT measures (group $M \pm SEM$), plotted as a function of the degree of rule switch as illustrated in Panel B and response switch/repeat. (E) RT measures for response repetition and response switch, relative to the last trial using the same task rule. Rule repeat trials were excluded to test whether the task rules were encoded in separate representations. The box plot shows the group-level distribution. Each line represents a single participant. Error bars indicate *SEM*. ITI = inter-trial interval; RT = response time; *SEM* = standard error of the mean. See the online article for the color version of this figure.

resulting in a final sample of 68 participants ($M_{age} = 19$ years, $SD = 1.5$, 43 female, 24 male, one preferred not to answer). The target sample size was determined using the effect size of the trial-level parametric switch effect from Experiment 1, with an α level of .05 and power level of .99 (given that this experiment aimed to test a null effect). All procedures were approved by the university Institutional Review Board.

Stimuli and Procedure

Experiment 4 retained most of the components from Experiment 1 but did not require the use of the different task rules. In each trial, participants were presented with one of five reference arrows for 1,750 ms (Figure 6A). The reference arrows were arranged at the same distances as those in Experiments 1 and 2 (Figure 6B). Different from the previous experiments, the reference arrow changed to either blue or green color. Participants were asked to respond based on the color of the arrow using the [F or J] keys (Figure 6A). After a response was made or the 4,000 ms response deadline had passed, participants were given feedback on the accuracy of the trial for 1,500 ms, followed by an intertrial interval of 250 ms consisting of a blank screen. Crucially, the reference arrow still cued where task-relevant information would be presented. However, it no longer provided information to generate the correct response. Despite this, to maintain consistency throughout the experiments, we continued to refer to them as reference arrows, even though they were merely cues to the target's location. Participants first completed 10 practice trials followed by the main task consisting of four blocks of 125 trials.

Statistical Analysis

All analyses were identical to Experiment 1.

Results and Discussion

An RT analysis examining the classic task-switch effect (Figure 6C) by collapsing across all nonzero reference arrow switches revealed an absence of a significant main effect of a task switch, $F(1, 67) = 1.22$, $p = .27$, adjusted $\hat{\eta}_p^2 = .003$; main effect of response switch, $F(1, 67) = 0.68$, $p = .41$, adjusted $\hat{\eta}_p^2 = -.005$; and interaction, $F(1, 67) = 1.12$, $p = .29$, adjusted $\hat{\eta}_p^2 = .002$. When the same analysis was performed on accuracy data (Figure 6C), we did not observe a significant main effect of a task switch, $F(1, 67) = 0.86$, $p = .36$, adjusted $\hat{\eta}_p^2 = -.002$; main effect of response switch, $F(1, 67) = 0.10$, $p = .75$, adjusted $\hat{\eta}_p^2 = -.013$; or a significant interaction,

$F(1, 67) = 0.31$, $p = .58$, adjusted $\hat{\eta}_p^2 = -.01$. Together, these findings provide initial evidence of a null effect of the reference arrow switch on performance.

We then compared performance across different degrees of reference arrow switch (Figure 6D). The rmANOVA on RT revealed no significant main effect of the reference arrow switch, $F(8, 536) = 0.70$, $p = .70$ adjusted $\hat{\eta}_p^2 = -.004$; main effect of response switch, $F(1, 67) = .53$, $p = .47$, adjusted $\hat{\eta}_p^2 = -.007$; or interaction, $F(8, 536) = 1.28$, $p = .25$, adjusted $\hat{\eta}_p^2 = .004$. Similarly, no effect reached statistical significance in accuracy data, main effect of reference arrow switch, $F(8, 536) = 1.61$, $p = .12$, adjusted $\hat{\eta}_p^2 = .01$; main effect of response switch, $F(1, 67) = 0.98$, $p = .32$, adjusted $\hat{\eta}_p^2 < -.001$; and interaction, $F(8, 536) = 0.99$, $p = .44$, adjusted $\hat{\eta}_p^2 < -.001$.

We then focused on reference arrow switch trials and did not observe a statistically significant linear change of RT as a function of the logarithm of reference arrow change, $t(67) = 0.93$, $p = .36$, $d_z = 0.11$. The absence of the linear relation between the logarithm of reference arrow change and RT was different from the findings from Experiments 1 and 2.

Finally, relative to a given trial's most recent reference-arrow repetition (excluding reference arrow repeat trials), RTs were not significantly slower for response switch than response repeat trials, $t(67) = -1.41$, $p = .16$, $d_z = 0.17$ (Figure 6E). Unlike Experiments 1 and 2, this finding suggests that in Experiment 4 all reference arrows were likely represented as a single task defined by the color-response mapping.

Considering that the key difference between Experiments 1 and 2 versus 4 is that the reference arrows in Experiment 4 do not represent task rules, the results indicate that the relation between reference-arrow change and RT in Experiments 1 and 2 was likely attributable to task rules rather than shifts of spatial attention and/or saccades.

General Discussion

We investigated how tasks are represented in the human mind. To this end, we designed a perceptual decision-making paradigm with rules defined as orientations of reference arrows. Experiments 1 and 2 showed that RT scales with the difference in rule change across consecutive trials. The parametric switch costs in these two experiments supported the hypothesis that task representations are organized based on their conceptual similarity.

The current experimental design differs from conventional task-switch designs in that the rules are not qualitatively different (e.g., relying on different stimulus features). This raises the question of whether the different rules are represented as different tasks or as different values within a single task. To address this issue, we first examined whether rule switches between two trials with the same rule (e.g., a trial sequence of ABA) would eliminate the response switch cost between the two trials. In other words, we tested whether A and B shared the same task representation (i.e., whether they belong to the same task). If they share the same task representation, the representation of the first A trial will be overwritten by the B trial and will not affect the second A trial (i.e., no response switch effect). On the other hand, if A and B have their own task representations, switching to the B trial will not overwrite the representation of the first A trial. Thus, the response switch effect between the two A trials is expected.

Data from both Experiments 1 and 2 show this response switch effect between the first and last A trial in an ABA sequence, thus supporting separate representations. We further speculate that in this study the rules are represented separately because of the low number of rules. If more rules are available (e.g., when any orientation could be used as a rule), it may become more taxing to represent each rule separately. As a result, a more abstract task representation with a flexible rule might be formed. This was directly tested in Experiment 3, where we found a smaller parametric switch cost than observed in Experiment 1. This finding also rules out an alternative explanation that the parametric switch effect only captures the change in perceptual processing. This is because the visual presentation in Experiments 1 and 3 was identical and perceptual processing change in consecutive trials would be similar between the two experiments. Together, the findings support the proposal that each task rule is represented as a separate task in Experiments 1 and 2. Therefore, the parametric switch cost reflects the switching of tasks, rather than the switching of part of a task.

In the interpretation of the parametric switch effect, each rule is treated as being represented by a different task. Here, a task representation includes all task-relevant information, and the rule is a component of a task. It is also possible that different rules are represented in a single task. This view is equivalent to the idea that there is a "metarule" that is also invariant to the reference arrow (i.e., the metarule is defined at an abstract level such that the same processing applies to any reference arrow and option arrows). Note that the metarule is also a component of a task. To demonstrate the difference between a rule and a metarule, consider a reference arrow with the orientation of 20° and two random option arrows with orientations encoded as variables x and y, the rule can be coded as $\min(|x - 20|, |y - 20|)$. This rule treats the reference arrow as a constant. If the reference arrow changes to 40°, the current rule no longer applies, and a new rule of $\min(|x - 40|, |y - 40|)$ must be used. On the other hand, a metarule treats the reference arrow as a variable r and takes the form of $\min(|x - r|, |y - r|)$, which applies to any reference arrow. The metarule is more flexible than the rules tied to specific orientations. However, the flexibility also incurs a cost. For example, in motor control, fewer precued defining values for a movement (e.g., which arm to move, moving direction, and extent) are accompanied by slower response, suggesting additional online adjustments to specify the details of the movement (Rosenbaum, 1980). Similarly, the metarule requires online changes once the reference arrow is known, making it cognitively more demanding. We compared the single task representation view (i.e., metarule, or all rules in the same task) and multiple task representation view in Experiments 1 and 3. The finding that the parametric switch effect in Experiment 1 was larger than that in Experiment 3 (only one task representation) supports our argument that the five reference arrows were represented in different tasks.

Why would the brain segregate the task representations when the number of reference arrows is low? One possibility is that a more concrete task representation (i.e., with more fixed components such as a constant task rule) is more easily linked to specific cognitive control settings, which contain information that guides information processing (Miller & Cohen, 2001). That is, when a task has more concrete features (e.g., a reference arrow with a specific orientation), specific cognitive control settings (e.g., how the blue and green arrows should be processed in relation to the reference arrow) can be formed, and associated with (or be part of) the task representation. On the other hand, when a task has more abstract features (e.g., a reference arrow that could be in any orientation), the corresponding cognitive control settings would be more difficult to form. It has been shown that cognitive control settings can be associated with specific stimuli to guide behavior (e.g., Braem et al., 2019; Bugg, 2012; Chiu et al., 2017; Whitehead et al., 2020). In the context of this paradigm, each reference arrow can be linked to specific cognitive control settings. Because storing all the associations in the same task representation might cause interference, representing each reference arrow as a separate task may allow for more efficient and flexible control that links specific comparisons with optimal control settings (Egner, 2023). Furthermore, because the participants were required to switch between reference arrows, organizing task knowledge based on the similarity between task rules would incur lower reconfiguration costs compared to fully orthogonal task representations, thus balancing stability (i.e., reducing interference within each trial) and flexibility (i.e., switching rules between trials) of cognitive control (Musslick & Cohen, 2021).

As participants were not explicitly told the number of reference arrows in Experiment 1, we speculate that the task representations may be formed in a bottom-up manner, possibly along with the knowledge of a low number of reference arrows and the learning of each reference arrow's cognitive control settings. It remains to be seen how top-down mechanisms facilitate the formation of task representations. For example, how explicit knowledge of the number of task rules would shape the formation of shared versus separated task representations. Future research is needed to fully answer the question of how separate task representations are formed.

Our data supports the notion that the five reference rules in Experiments 1 and 2 were represented as discrete tasks. This appears to be at odds with the continuous nature of cognitive space. We argue that although cognitive space provides a coding scheme that can represent any point in the space, not all points need to be represented. For example, the longitude and latitude coordinate system encodes all points on a map. However, only some points (e.g., major cities) are marked. In the context of this study, the orientation of the reference arrow can be treated as an axis to organize different task representations, such that any reference arrow can be uniquely represented on a continuous feature. However, as only five reference arrows were used, each of them was encoded as a discrete representation, similar to five cities on a map. The idea is similar to representing a pentagon in a Cartesian coordinate system by the coordinates of its five vertices: on the one hand, there are discrete sets of coordinates; on the other hand, the coordinates are from a continuous space. Our findings provided support for both accounts. First, the parametric switch cost supports the notion that task representations are organized along a continuous dimension. Second, the stronger parametric switch cost in Experiment 1 than in Experiment 3 suggests that there is one task representation for each reference arrow.

While previous studies have reported parametric task-switch effects (Dreisbach et al., 2002; Jiang et al., 2018), these probabilistic task-switch paradigms do not manipulate similarity between the tasks involved, so they do not target the underlying representations of tasks or rules. As this study manipulated the task rule (i.e., how the task-relevant information should be processed to produce a response), it also complements previous research examining switch cost as a function of other aspects of the task such as task-relevant stimulus features and responses. For example, Arrington et al. (2003) use two types of task-relevant features (spatial and surface) and found that switching task-relevant features within a feature type is associated with better performance than switching features across feature types. They also manipulated response modality (motor and vocal) and again observed smaller switch costs when switching response types within the modality than across modalities. Dykstra et al. (2022) reported lower costs when responses are closer (e.g., faster response when switching from index to middle finger than from pinky to middle finger). For task rules, a larger switch costs for higher-level task rules in a hierarchy of task rules has been documented (Cellier et al., 2022; Collins et al., 2014). We further showed that within the same level of a rule hierarchy, a larger switch cost is associated with a larger shift in task rule. At the theoretical level, the present study is consistent with the theory of conjunctive representation of tasks (i.e., including the collection of all task information; Schumacher & Hazeltine, 2016).

Altmann (2011) used multiple task cues for the same task to show that response switch cost decreases in descending order of cue repeat, cue switch (task repeat), and task switch. This finding supports an episodic account, such that all task information (e.g., stimulus, rule, response mapping, and response) on a trial is bound together to form an episode or event file (Hommel, 2004). Repetition of more features (e.g., cue and task repeat) leads to stronger retrieval of the event file and subsequently greater facilitation if the response repeats and/or stronger interference if the response switches. This account also explains the congruency sequence effect (Jiang et al., 2015).

To investigate the nature of the bindings in the episodes, researchers have manipulated switching of multiple components of tasks, including rule and response (Kleinsorge & Heuer, 1999), compatibility (i.e., whether the stimulus leads to the same response for both tasks) and response (Kleinsorge & Heuer, 1999; Korb et al., 2017), and rule and stimulus feature/modality (Hübner et al., 2001; Philipp & Koch, 2010; Seibold et al., 2018; Vandierendonck et al., 2008). A common finding is that switching one component reduces the switching cost of the other component, similar to the response switch cost (i.e., the interaction between rule switch and response switch) reported in Experiments 1 and 2 of the present study.

These findings suggest that the episodes are conjunctive, such that components cannot be switched independently. When the rule changes in the present study, we speculate that the whole task representation associated with the rule is replaced because of the conjunctive nature of the task representation. This notion was supported by the larger parametric switch effect in Experiment 1 than in Experiment 3. As a result, the response from the previous trial, which was part of the replaced task representation, was also replaced and would not influence the current response. This is reflected in behavioral data as a reduced response switch effect when the rule changes.

It is possible that for two consecutive trials, the retrieval of the task rule (and its associated task representation) on the latter trial is a function of the similarity between the two trials' reference arrows. This process of retrieving a rule/task in the presence of competition from the episode of the previous trial is similar to episodic retrieval when competitor episodes are available (e.g., trying to remember where my car is parked today with the interference of the memory of where I parked my car yesterday). However, the general finding in the literature is that rather than producing a facilitation effect, this produces an interference effect that scales with the similarity between the target memory and the competitors (Anderson & Neely, 1996). When translated into this study, the interference effect should produce worse retrieval on the current trial if the reference arrows between the previous and the present trials are more similar. Consequently, the pattern of the predicted parametric switch effect would be expected to produce a negative correlation between the change in reference arrows and RT, which is opposite to the observed parametric switch effect.

Previous research demonstrates reconfiguration in reference switch in numeric judgment (whether a presented number is larger or smaller than a reference number) and spatial relation judgment (whether a presented point is to the left or right of a reference point), changing the reference point induces a reconfiguration cost as compared to repeating the reference point (Schneider & Logan, 2007). The parametric rule switch cost in the present study is consistent with the interpretation of reconfiguration and extends it to within rule switch conditions. Interference is another source of task-switch costs (Allport et al., 1994), so it was possible that a rule-switch effect would be larger for more similar tasks. However, we did not observe this in the present study. One possibility is that the smallest rule switch (i.e., 20°) is not enough to induce any interference. Another possibility is that the amount of interference from the old task is the same for all new tasks. Because our regression analyses testing the relation between the degree of rule switch and RT only included rule-switch trials, a constant interference effect would not be captured by the regression. Future research is encouraged to test the two accounts.

If the neural representations of rules reflect a cognitive space of parameterized rules (i.e., each rule is identified using its parameters as coordinates in space), switching between rules can be implemented as traversing the space from one point to another (cf. Bellmund et al., 2018). In the context of this study, larger changes in the rules would require a longer course to transverse on the cognitive space, resulting in a larger behavioral switch cost. This is consistent with a recent study demonstrating that within-task cognitive control settings are organized in a parametric space (Grahek et al., 2022). More generally, the findings suggest that rule/task switch may not be a "teleporting" process on the cognitive space that updates the active task representation with a fixed cost. Instead, a switch of rule/task may be a "traversing" process that requires time-resolved adjustments in mental states based on the amount of change needed. This account is similar to a theory that shifts of visuospatial attention are a continuous process traversing the path linking the old and the newly attended locations (Yantis, 1988).

The psychological space theory predicts that stimuli closer in space are more likely to generalize to each other (Shepard, 1987). Consistent with this prediction, computational simulations have shown that tasks with more similar representations (i.e., with more overlap in their representations) exhibit faster learning (i.e., requiring less iterations to train the neural network representing the tasks, Musslick et al., 2017). Empirically research is still needed to test whether there is a relation between similarity in task representations and performance generalization.

If task switching is conceptualized as navigating a task space, an open question is whether the task cognitive has an egocentric (i.e., centered on the current task) or allocentric (i.e., centered on an anchor task). Specifically, an egocentric representation encodes other tasks as relative changes from the current task. This appears to be consistent with the observed parametric switch effect such that the switch effect is larger when switching to a more dissimilar task rule. On the other hand, the allocentric representation is centered on a specific task regardless of the current task. It suggests a switch strategy that starts with shifting to the anchor task (i.e., the origin of the allocentric representation) and then to the new task. As the cost of shifting between the anchor task and a given task is constant, the cost of switching between two tasks should depend on both the previous and the current tasks, rather than their difference.

To test both egocentric and allocentric presentations in the same model, we conducted a linear regression analysis with task rule-specific intercepts. In other words, each trial had two intercepts encoding the identity of the previous and current task rules to account for the allocentric switch strategy. The parametric effect, which is consistent with the egocentric view, remained statistically significant in both Experiment 1, $t(52) = 4.83$, $p < .001$, 95% CI = [14.83, 36.09], $dz = 0.66$, and Experiment 2, $t(50) = 2.58$, $p = .013$, 95% CI = [9.31, 75.82], $dz = 0.38$, thus supporting egocentric representation.

Although the rule manipulation is one-dimensional in this study, we argue that the results can be generalized to a higher-dimensional task space for two reasons. First, this study focuses on the dissimilarity (e.g., distance) of task representations, which is a measure agnostic to dimensionality. In other words, distance in 1D space can be generalized to higher-dimensional spaces by pooling differences within each dimension (e.g., using Euclidean distance). As our analysis used distance as a predictor, it can be directly applied to tasks that differ in multiple dimensions. Second, even in a high-dimensional space, structure may be encoded in a lower-dimension subspace. For example, in a 2D space grid-like activation patterns in the human entorhinal cortex are represented in a 1D space (Constantinescu et al., 2016; Doeller et al., 2010). Other studies also show that representational geometry is better captured by projecting neural representations to a lower dimensional space (e.g., Flesch et al., 2022; Nelli et al., 2021).

To conclude, we found that behavioral switch costs scale with the conceptual difference between the old and new task rules, thus supporting the hypothesis that task representations are organized to reflect their conceptual similarity. This study also extends the conventional task-switch effect to a parametric fashion within the switch condition.

Constraints on Generality

The key to the experimental paradigm is the parametric manipulation of rules. Thus, the findings are expected to be generalized to designs in which the rules are defined on a continuous dimension (e.g., orientations, color wheel). As shown in Experiments 1 and 3, the parametric switch effect is more pronounced when there is a limited number of rules than when the rules are randomly sampled from the space. The parametric switch effect is thought to reflect cognitive flexibility and the organization of task information. Thus, we believe the findings are more generalizable to healthy adults than other populations, because of underdevelopment (e.g., children) or impaired mental functioning of cognitive flexibility and executive functions. We have no reason to believe that the results depend on other characteristics of the participants, materials, or context.

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