Behavioral/Cognitive

Switching between Newly Learned Motor Skills

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Studies of cognitive flexibility suggest that switching between different tasks can entail a transient switch cost. Here, we asked whether analogous switch costs exist in the context of switching between different motor skills. We tested whether participants (23 males and 12 females) could switch between a newly learned skill associated with a novel visuomotor mapping and an existing skill associated with an intuitive mapping. Participants showed increased errors in trials immediately following a switch between mappings. These errors were attributable to persisting with the preswitch policy rather than imperfect implementation or retrieval of the postswitch policy. A subset of our participants further learned a second new skill. Switching between these two novel skills was initially very challenging but improved with further training. Our findings suggest that switching between newly learned motor skills can be challenging and that errors in the context of switching between skills are primarily attributable to perseveration with the wrong control policy.

Key words: de novo **learning; motor control; motor skill; switch cost; task switching**

Significance Statement

A large body of work in cognitive science has established small but consistent costs when switching between different cognitive tasks, but it is unknown whether similar switch costs apply when switching between motor skills. We tested people's ability to switch between a newly learned motor skill and an existing, well-learned one and found a transient increase in errors on trials that immediately followed a switch. These errors were primarily due to participants persisting with their preswitch behavior. Switching between two different newly learned skills was significantly more challenging, but switching ability improved with practice over days. These findings highlight the complexities of switching between novel motor skills and highlight perseveration as a primary cause of errors when switching between skills.

Introduction

In everyday life, we frequently need to switch between different skills. For instance, when picking up and using different tools, when getting on or off a bike, or when driving a car forward versus in reverse. In cognitive science, it is widely recognized that switching between different tasks entails a transient cost in the form of temporarily worse performance immediately after the switch. Here, we examined whether similar switch costs apply in the context of switching between different learned motor skills.

The phenomenon of task switching has been extensively studied in cognitive science (Rogers and Monsell, 1995; Meiran, 1996; Vandierendonck et al., 2010; Hazeltine, 2024). In a typical experiment, participants might learn to perform two or more different tasks that require them to respond to the same stimuli according to different rules. For example, participants might be asked to switch between classifying a digit as odd or even and classifying it as high or low (Sudevan and Taylor, 1987; Rogers and Monsell, 1995; Logan and Bundesen, 2003). Participants generally exhibit longer reaction times and/or are more prone to errors immediately after switching between tasks. Two different explanations for such switch costs have emerged. One theory suggests that switch costs arise from the need to retrieve a new task rule or policy from long-term memory (Mayr and Kliegl, 2000; Rubinstein et al., 2001; Sohn and Anderson, 2001; Schneider and Logan, 2009) and/or performing necessary reconfiguration of neural circuits to implement the new policy (Rogers and Monsell, 1995; Logan and Gordon, 2001; Monsell and Mizon, 2006). An alternative view posits that switch costs may primarily arise from difficulty in suppressing the existing task policy (Allport et al., 1994; Wylie and Allport, 2000; Monsell, 2003; Kiesel et al., 2010). Either or both of these explanations might apply in the context of switching between motor skills.

The need to switch between motor skills should be equally important as for cognitive skills but has not been examined as closely. Task switching in the cognitive domain is typically

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studied by switching task rules that require different responses to the same stimuli. A direct analog of this in the motor domain is to switch between different visuomotor mappings that require different motor commands to move a cursor to the same target location. Along these lines, numerous studies have examined people's ability to switch between two opposing perturbations, such as clockwise versus counterclockwise rotations of visual feedback (Tong et al., 2002; Osu et al., 2004; Krakauer et al., 2005; Addou et al., 2011; Forano et al., 2021), but, in these cases, it appears to be impossible to switch behavior based on a contextual cue [though see Cunningham and Welch (1994) and Huberdeau et al. (2019)], which appears to be an inherent limitation of the implicit adaptation mechanism which learns to counter the perturbation (Huberdeau et al., 2015; Morehead and de Xivry, 2021).

It is increasingly appreciated that, in more challenging tasks, motor learning is qualitatively different than in adaptation tasks where switching between motor skills has so far been studied. An emerging literature has examined motor learning that appears to require learning of a brand new controller (rather than adapting an existing controller). Critically, learning of this kind—referred to as "*de novo*" learning—leads to minimal aftereffects (Yang et al., 2021; Haith et al., 2022; Gastrock et al., 2023). Therefore, although participants cannot switch between different motor behaviors learned through adaptation, they may be able to switch between behaviors learned through de novo learning.

Here, we investigate people's ability to switch between motor skills using a recently introduced de novo motor learning task (Haith et al., 2022; Yang et al., 2022). Participants use both hands to control the position of an on-screen cursor through a highly nonintuitive mapping. Across three experiments, we examined whether participants could switch between this newly learned skill and either a preexisting baseline controller or a second such skill associated with a different mapping.

Materials and Methods

Participants

A total of 35 participants took part in this study (25.77 ± 7.22 years old; 12 female). 25 participants took part in Experiment 1 and seven also took part in Experiment 3. For Experiment 2, we recruited 10 participants who had participated in a separate study in which they practiced the De Novo mapping for 5 d under almost identical conditions. All participants were right-handed and naive to the purposes of the study, had no known neurological disorder, and provided written consent before participation. All procedures were approved by the Johns Hopkins University School of Medicine Institutional Review Board. All participants gave written informed consent and received $15 per hour for their participation.

Experimental setup

Participants sat on a chair in front of a glass-surfaced table with both arms resting on a plastic cuff mounted on an air sled which enabled frictionless planar movement of their arms across the surface of the table (Fig. 1*A*). Participants could not directly see their arms. Instead, they viewed visual cues (cursor and targets) which were displayed in the plane of the hand through a mirror positioned horizontally above their arms. The position of both the left and right hands was tracked at 130 Hz using a magnetic tracking device (Flock of Birds; Ascension Technologies).

Experiment 1

Training for the De Novo mapping. In Experiment 1, 25 participants completed five sessions, each on separate days. In the first 4 d, participants learned to control the cursor under the De Novo mapping by making a series of point-to-point movements around the workspace (Fig. 1*B*, pursuit task). On each block, participants were required to move their hands to guide an on-screen cursor (5 mm diameter) to a fixed start circle (10 mm diameter) appearing in the center of the workspace. Once participants held the cursor stationary inside the start circle, a target appeared at a location 12 cm from the start position. After participants reaching this target, a new target appeared at different location. The distance between targets was always 12 cm, but the direction was determined pesudorandomly within a 20×20 cm workspace centered on the start location. We used two mappings (Fig. 1*C*): the Baseline mapping, in which the cursor appeared at the average location of the two hands and was therefore intuitive to use and the De Novo mapping which involved a nonintuitive mapping between hands and cursor that had to be learned. In the De Novo mapping, forward–backward movement of the left hand controlled left–right movement of the cursor, and left–right movement of the right hand controlled forward–backward movement of the cursor (Haith et al., 2022). Both mappings were explicitly explained to participants at the start of the experiment. On the first day, participants were not given any specific instruction when they practiced the De Novo mapping, but from the second day, they were asked to move the cursor in a straight line between targets as best as they could and to maintain their peak movement speed within a particular range (0.39–0.52 m/s). Feedback about movement speed was given by changing the color of the target at the end of the movement. If the peak speed was within the required range, the target changed color from gray to yellow and a pleasant sound played. If the movement speed was too fast, the target changed color from gray to magenta and, if the movement was too slow, it changed color to blue. Participants performed the task in a series of blocks, each of which consisted of 60 point-to-point movements. On the first day, participants performed three blocks of the pursuit task under the Baseline mapping to become familiar with the task and experimental setup and then practiced the De Novo mapping for 10 blocks. From the second to fourth day, participants performed one block with the Baseline mapping at the start of the session and then continued practicing the De Novo mapping for 10 blocks (Fig. 1*D*, training).

Assessment of switching between mappings. On the fifth day, we examined participants' ability to switch between the learned De Novo mapping and the Baseline mapping (Fig. 1*D*, testing). To facilitate switching between mappings and to ensure that initial conditions could be easily matched across mappings, participants made center-out movements from a fixed starting position in each trial (Fig. 1*B*, center-out task). Participants returned their hands to the same starting positions after each movement. We positioned air nozzles above the starting position for each hand to help guide participants back to the appropriate starting posture. If both the left and right hand were within 50 mm from the starting position for each hand, a trial started. During the center-out task, the background color of the screen turned either blue or magenta to indicate which mapping should be used in the upcoming trial, visible 500 ms before the target location was presented. The background color-mapping association did not randomize across participants; light blue and magenta indicated the Baseline and the De Novo mapping, respectively.

To ensure participants reacted rapidly to the appearance of each target, we applied time pressure through the threat of the target disappearing. After the target appeared, which served as the cue to begin moving, the target disappeared at a random, exponentially distributed time (0.5–2 s) within each trial, after which they were unable to successfully acquire the target. Participants first practiced this center-out task under either the Baseline mapping (one block of 60 trials) or the De Novo mapping (three blocks of 60 trials).

We then assessed participants' ability to switch between the Baseline mapping and the De Novo mapping. On each trial, the cursor was controlled either through the newly learned De Novo mapping or through the Baseline mapping, and the mapping for the upcoming trial was indicated by the color cue (Fig. 1*E*). The mapping switched randomly every 2–10 trials. Participants completed 10 blocks. Each block consisted of >63 trials, during which time the mapping switched five times in each direction (i.e., five times from Baseline to De Novo and five times from De Novo to Baseline).

Experiment 2

Experiment 2 exactly paralleled the final day of Experiment 1, except that, in the switching assessment, participants were provided with a push-button switch, held in their left hand (Fig. 4A). Participants were instructed to press the button when the background color changed to a color that was different from the previous trial. For this experiment, we recruited 10 participants who had recently participated in another study in which they had practiced the De Novo mapping for 5 d.

Experiment 3

In Experiments 1 and 2, we examined participants' ability to switch between a newly learned mapping (De Novo mapping) and a highly overlearned mapping (Baseline mapping). In Experiment 3, we tested whether participants could learn two De Novo mappings and be able to switch between them.

Practice for the second De Novo mapping. After Experiment 1, 7 of the 25 participants from Experiment 1 joined Experiment 3. In addition to the De Novo mapping that participants learned in Experiment 1 (which we will refer to as Mapping A), participants practiced a second De Novo mapping (Fig. 5, Mapping B). In this mapping, the contingencies between hand movement and cursor movement were transposed compared with Mapping A; forward–backward movement of the right hand controlled left–right movement of the cursor, and left–right movement of the left hand controlled forward–backward movement of the cursor. The structure of Mapping B was explicitly explained to participants at the start of Day 6. Days 6–10 of Experiment 3 were structured exactly the same as Days 1–5 in Experiment 1 (Figs. 1D, 5, Days 6–10).

Assessment of switching between two De Novo mappings. Before testing whether participants could switch between Mapping A and Mapping B, we first confirmed that participants could still successfully perform under Mapping A. After a warmup block for each mapping under by pursuit task, participants performed center-out task under either Mapping A or Mapping B (three blocks of 60 trials for each mapping, Fig. 5, Day 11).

We then assessed whether participants could switch between Mapping A and Mapping B (Fig. 5, Day 11), following exactly the same approach as in Experiment 1. Since we found that participants struggled to switch immediately after learning both mappings, we gave participants an opportunity to practice switching between mappings. Participants practiced switching between Mapping A and Mapping B over 5 d, with the frequency of switching steadily increasing over days (Fig. 5, Days 12–16). Participants switched between mappings every three blocks with pursuit task on Day 12, every block with pursuit task on Day 13, every three blocks with center-out task on Day 14, every block with center-out task on Day 15, and every 5–25 trials with center-out task (10 blocks of at least 63 trials) on Day 16. Participants performed six blocks of 60 trials for each mapping in total on Days 12–15. Then we repeated the same switching assessment from Day 11 which matched that in Experiment 1 (Fig. 5, Day 17). Two of the seven participants did not complete the initial switching assessment on Day 11 and instead directly started switching training (Days 12–16).

Data analysis

Raw data of both hands' positions were smoothed using a Savitzky–Golay filter to eliminate high-frequency measurement noise, differentiated to obtain movement velocity and then smoothed again. Movement onset was determined based on the first time that the tangential velocity of the hand exceeded 0.026 m/s. Then the delays in our system (measured to be 100 ms) were subtracted from this time to obtain an estimate of the true time of movement initiation relative to the target appearing on the screen. The participant's reaction time in each trial was determined as the delay between the time of stimulus presentation and the time of movement initiation. Initial movement direction in each trial was defined based on the direction of the velocity vector of the hand 100 ms after movement onset.

To establish transient switch costs in initial movement directional errors and/or reaction times, we compared behavior in trials immediately following a switch (e.g., first trial post switch, second trial post switch) to performance at least six trials after a switch occurred (e.g., 6th–10th trials post switch).

We developed a probabilistic approach to estimate which policy participants attempted to use on each trial during the switching assessment, based on the initial movement direction of the right and left hands. We assumed that the distribution of left and right initial hand directions given the target direction comprised a mixture of three different possible policies: two associated with each mapping (Mapping A and either the Baseline mapping or Mapping B), plus a third, random policy that did not conform to either mapping:

$$p(\theta_L^i,\ \theta_R^i|\theta_T^i) = p(\theta_L^i,\ \theta_R^i|\pi_A,\ \theta_T^i)p(\pi_A) + p(\theta_L^i,\ \theta_R^i|\pi_B,\ \theta_T^i)p(\pi_B) + p(\theta_L^i,\ \theta_R^i|\pi_C,\ \theta_T^i)p(\pi_C).$$

Here π indicates the policy participants used [π_A, De Novo; π_B, Baseline; π_C, Other (uniform distribution) in Experiments 1 and 2; π_A, Mapping *A*; π_B, Mapping *B*; π_C, Other in Experiment 3], $\theta_R$and θ_L are the initial directions of the right and left hands, and θ_T is the direction of the target. $p(\theta_L,\ \theta_R|\pi,\ \theta_T)$ is the distribution of the left and right hand movements under each policy.

We estimated the distributions associated with Mapping A, the Baseline mapping, and Mapping B separately for each participant via kernel density estimation based on a set of reference trials in which participants showed steady-state behavior (the data used for this varied across Experiments). For simplicity, we assumed that the left and right hand movements were independent given the policy and target direction (i.e., $p(\theta_L,\ \theta_R|\pi,\ \theta_T) = p(\theta_L|\pi,\ \theta_T)p(\theta_R|\pi,\ \theta_T)$). The overall probability of a participant's behavior across multiples trials was therefore given as follows:

$$\log p(\theta_L^{1:N},\ \theta_R^{1:N}|\theta_T^{1:N}) = \sum_{i=1}^{N} \log p(\theta_L^i,\ \theta_R^i|\theta_T^i) = \sum_{i=1}^{N} \sum_{j=\{A,B,C\}} \log\left[\, p(\theta_L^i|\pi_j,\ \theta_T^i)p(\theta_R^i|\pi_j,\ \theta_T^i)p(\pi_j)\right].$$

We used this model to estimate the probabilities of each policy $p(\pi_A)$, $p(\pi_B)$, and $p(\pi_C)$ by maximum likelihood, constraining $p(\pi_A)$, $p(\pi_B)$, and $p(\pi_C)$ to be between 0 and 1 and requiring that $p(\pi_A) + p(\pi_B) + p(\pi_C) = 1$. We separately estimated these policy probabilities at different numbers of trials postswitch, pooling data from all trials at a given trial number after a switch (1st through 10th trials postswitching for Experiments 1 and 2 and at 1st through 10th or 15th trials post switching for Experiment 3).

Our approach is illustrated through example trials in Figure 3B, which shows the following: (1) Trial *i* is located on the distribution of the De Novo mapping and is therefore highly likely to have been generated by the De Novo policy. (2) Trial *j* is located on the distribution of the Baseline behavior and is therefore likely to have been generated under the Baseline policy. (3) Trial *k* does not overlap with either the De Novo or Baseline distributions. This trial is better explained by a third, uniform distribution. This analysis therefore allowed us to quantify the probability of using different policies and therefore determine the nature of errors.

To obtain a baseline measure of the rate at which our approach would misclassify behavior, we applied this analysis to the reference dataset itself (i.e., the dataset which was used to establish the policy distribution) but held out 10 randomly selected trials and classified the policy based on the remaining trials. We repeated this 1,000 times to estimate the extent of classification errors arising from limitations of our method.

For Experiment 1, we took as our reference behavior the center-out trials at the start of Day 5 in which no switching occurred. For Experiment 3, since participants' policies seemed to change between initial learning and the much later switching test (particularly for Mapping A), we took behavior on Day 16 as the reference, using trials at least six trials after a switch, at which point behavior appeared to be stable. To avoid the issue of circularity in our analysis, where the trial we were analyzing was also part of the reference data, we analyzed each trial from Day 16 by repeating the full analysis but with that trial withheld from the reference dataset.

Analysis was performed using MATLAB R2022a (MathWorks).

Statistics

Unless otherwise specified, two-tailed paired t tests were used to assess differences in behavior across conditions (e.g., the Baseline mapping vs the De Novo mapping), and two sample t tests were used to assess differences between steady-state behavior and behavior post switching (e.g., reaction time at 6–10 trials postswitch vs reaction time at first trial postswitch). All statistical tests were conducted in MATLAB R2022a and JASP (Version 0.95.1).

Results

Participants learned the De Novo mapping over multiple days of practice

Twenty-five healthy participants practiced maneuvering an on-screen cursor to reach to a series of visual targets using a novel and nonintuitive mapping between their hands and the cursor ("De Novo mapping"; Fig. 1*A–D*). As in our previous studies (Yang et al., 2021; Haith et al., 2022), participants initially found this task very challenging, but their performance gradually improved with practice across multiple sessions. Both the reaction time [reaction time of the first five blocks on Day 1, 570.55 ± 34.87 ms (mean ± SEM); the last five blocks on Day 4, 289.14 ± 7.58 ms; paired t test; $t_{(24)} = 8.57$; $p < 0.001$; not shown as a figure] and the initial direction error of the cursor movement (Day 1, 51.63 ± 1.74°; Day 4, 21.73 ± 1.22°; paired t test; $t_{(24)} = 18.73$; $p < 0.001$; Fig. 1*F*) significantly decreased between the beginning and end of practice. By the end of Day 4, performance under the De Novo mapping was almost as good as performance under an intuitive mapping in which the cursor appeared at the average location of the two hands ("Baseline mapping"), though reaction times under the De Novo mapping remained slightly longer (Baseline mapping, 275.09 ± 6.98 ms; paired t test; $t_{(24)} = -2.69$; $p = 0.013$) and initial direction error was slightly greater (Baseline mapping, 8.42 ± 0.56°; paired t test; $t_{(24)} = -10.57$; $p < 0.001$) than under the Baseline mapping. By the end of learning, participants had developed a novel movement policy associating the direction of the target to movement of the right and left hands (Fig. 1*G*, example participant). Note that, since the De Novo mapping was redundant (e.g., left/right movement of the left hand had no effect on the cursor), participants did not always move their hands exactly along the cardinal directions indicated in Figure 1*C* and, in some cases, even moved their hands in parallel directions. Nevertheless, as in our previous work (Haith et al., 2022), all participants settled on consistent direction in which they moved each hand.

Participants could easily switch between the Baseline and De Novo mappings

On the fifth day, we examined participants' ability to switch between the learned De Novo mapping and the Baseline mapping (Fig. 1*D*, testing). We used center-out reaches from a common starting cursor position and arm posture so that the mapping could be switched between trials without providing any additional cues to the participant. We first measured participants' performance in the center-out task when the mapping was fixed throughout a 60-trial block, and we used this to establish a steady-state level of performance under each mapping. We then tested participants' ability to switch between mappings within a block. The background color of the screen at the start of each trial indicated which mapping would be applied in that trial and this switched randomly every 2–10 trials.

Figure 2*A* shows data from a representative participant (Participant 1). This participant showed an increased directional error in trials immediately following a switch from the Baseline to the De Novo mapping [6th–10th trials postswitch, 15.05 ± 17.57° (mean ± SD); 1st trial postswitch, 29.74 ± 23.07°; Welch's $t_{(84.14)} = 3.78$; $p < 0.001$] as well as following switches from the De Novo mapping to the Baseline mapping (6th–10th trials postswitch, 10.46 ± 8.39°; 1st trial post switch, 28.84 ± 22.91°; Welch's $t_{(55.44)} = 4.24$; $p < 0.001$; 2nd trial postswitch, 16.08 ± 10.30°; Welch's $t_{(86.66)} = 3.28$; $p = 0.002$). Within 2–3 trials, however, their directional errors returned to the same steady-state level as that seen in blocks with no task switching at all (horizontal light blue line). Reaction times—the measure more conventionally used to establish switch costs in cognitive tasks—did not exhibit this transient switch cost (Fig. 2*A*, inserted panel), likely because we deliberately pressured participants' reaction times in order to focus on the pattern of directional errors following a task switch. These transient but consistent increases in directional error following a switch suggest a cost associated with switching between mappings, analogous to the task switch costs identified in more cognitive tasks.

Not all participants exhibited a switch cost when the mapping changed. Figure 2*B* shows performance of another participant (Participant 2) who showed no increase in directional errors following switches from the Baseline mapping to the De Novo mapping [6th–10th trials, 12.88 ± 9.57° (mean ± SD); 1st trial, 13.36 ± 14.48°; Welch's $t_{(53.10)} = 1.61$; $p = 0.113$] as well as following switches from the De Novo mapping to the Baseline mapping (6–10 trials, 10.47 ± 20.07°; 1st trial, 20.49 ± 32.76°; Welch's $t_{(81.14)} = 1.85$; $p = 0.068$), and thus it was possible for this participant to switch immediately both ways based on the color cue. Furthermore, Participant 2 had negligible changes in reaction time in the first trial after a switch either way (Fig. 2*B*, inserted panel).

At an overall group level, however, we found clear increased directional errors in trials immediately following a switch, both when switching from the Baseline to the De Novo mapping and vice versa; however, the switch cost was short-lived [Fig. 2*C*; Baseline to De Novo, 6th–10th trials, 26.83 ± 2.71° (mean ± SEM); 1st trial, 37.74 ± 3.12°; paired t test; $t_{(24)} = 7.63$; $p < 0.001$; 2nd trial, 30.46 ± 2.73°; $t_{(24)} = 3.13$; $p = 0.005$; 3rd trial, 29.30 ± 2.66°; $t_{(24)} = 2.64$; $p = 0.014$; De Novo to Baseline, 6th–10th trials, 16.43 ± 2.29°; 1st trial, 28.97 ± 15.40°; $t_{(24)} = 5.83$; $p < 0.001$; 2nd trial, 20.39 ± 2.73°; $t_{(24)} = 2.86$; $p < 0.009$; all comparisons are uncorrected]. Participants at a group level also showed no transient increases in reaction time postswitch, with the exception of first trial switching from the De Novo mapping to the Baseline mapping, which showed a marginal increase (Fig. 2*C*, inserted panel; Baseline to De Novo, 6th–10th trials, 420.83 ± 14.94 ms; 1st trial, 423.39 ± 16.72 ms; paired t test; $t_{(24)} = 0.48$; $p = 0.634$; De Novo to Baseline, 6th–10th trials, 380.94 ± 17.46 ms; 1st trial, 395.99 ± 17.39 ms; paired t test, $t_{(24)} = 2.58$; $p = 0.016$; 2nd trial, 372.96 ± 15.20 ms; paired t test; $t_{(24)} = -1.42$; $p = 0.167$; all comparisons are uncorrected).

Although we did not observe transient increases in reaction time following a switch, we did find that many participants did exhibit a small but consistent increase in reaction time throughout the task-switching assessment, compared with their reaction times in blocks with the same mapping but without any task switching (Fig. 2*C*, inserted panels). We wondered whether this increase in reaction times might be related to task errors, perhaps if increasing reaction times enabled participants to reduce their directional errors. We examined the relationship between the magnitude of these elevated reaction times and increases in directional error of the cursor, potentially to see if participants who avoided making errors did so by having overall increased reaction times. However, we found that this was not the case and

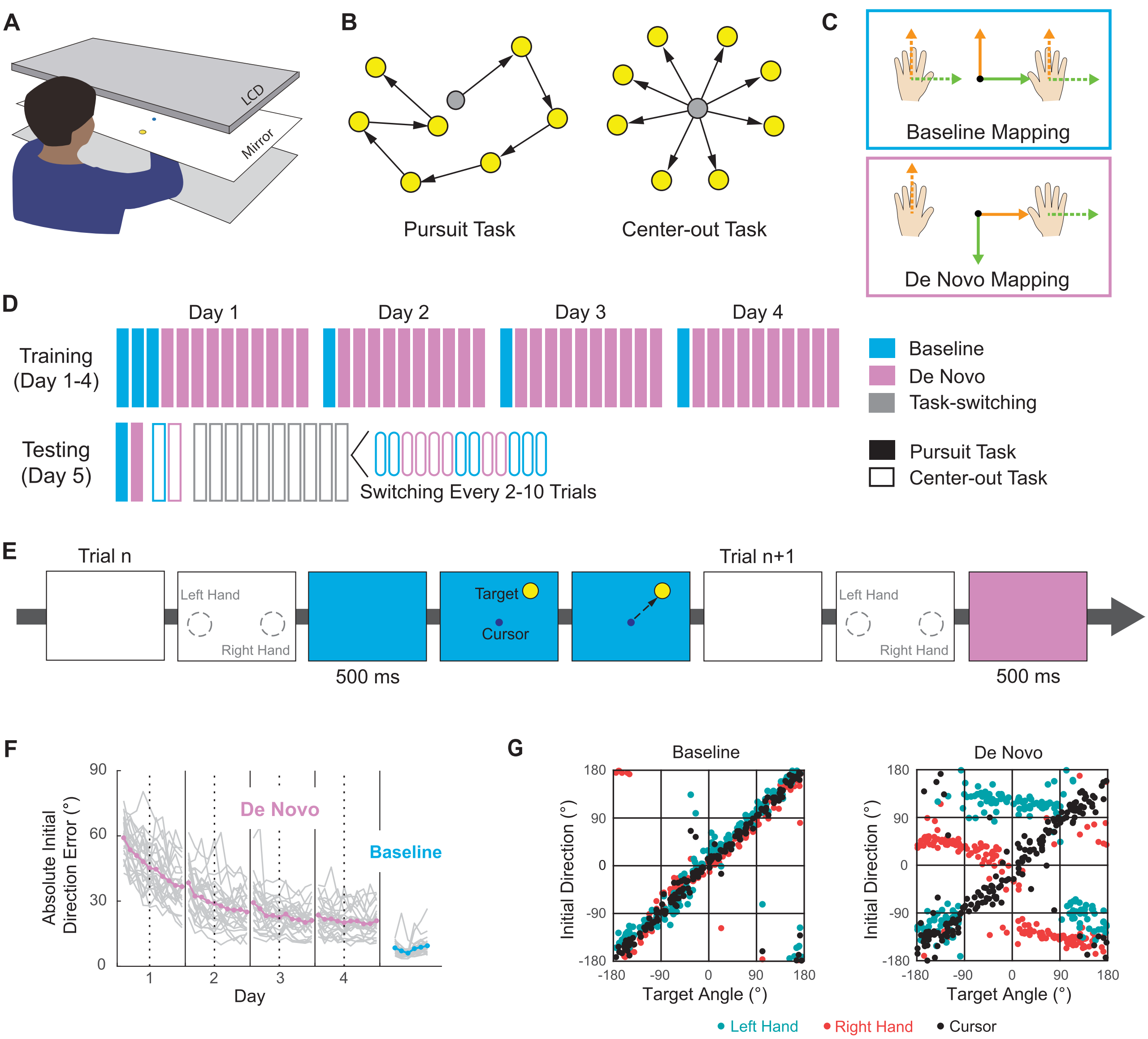

Figure 1. Experiment 1, switching between the De Novo and the Baseline mapping. ***A***, Participants performed reaching movements to move a cursor toward targets presented via mirrored display. ***B***, Participants were trained on the De Novo mapping by making a series of point-to-point movements around the workspace (pursuit task). Participants' ability to switching between mappings was assessed in a center-out task. ***C***, Two mappings: the Baseline mapping, in which the cursor appeared at the average location of the two hands, and the De Novo mapping, in which each hand controls one degree of freedom of the cursor but orthogonal to its own movement. In both panels, dashed orange and dashed green lines indicate hand movements required to move the cursor in the corresponding direction indicated by the solid lines. ***D***, Participants first performed the Baseline mapping to measure their baseline performance, followed by 4 d of practice on the De Novo mapping (600 trials per day). On the fifth day, participants were tested on their ability to switch between the Baseline and De Novo mappings on a trial-by-trial basis based on a color. Each rectangle indicates a single block of 60 trials. Light blue rectangles indicate blocks using the Baseline mapping, while magenta rectangles indicate blocks using the De novo mapping. Filled rectangles indicate blocks of the pursuit task and unfilled rectangles indicate blocks using the center-out task. ***E***, During the task-switching assessment, the background color of the screen turned either light blue or magenta to indicate which mapping should be used in the upcoming trial. The target appeared on the screen 500 ms later at which point participants had to rapidly initiate a movement of the cursor toward it. ***F***, Performance during initial learning of the De Novo mapping. Thick lines indicate average across participants (magenta, De Novo mapping; light blue, Baseline mapping). Thin gray lines indicate individual participants. ***G***, Behavior of a representative participant at the center-out task on Day 5. Initial direction of the left hand (blue gray dots) and right hand (red dots) using either the Baseline or De Novo mapping, showing that the participant adopted a very different coordination pattern for the De Novo mapping compared with their behavior in the Baseline mapping. Black dots indicate initial direction of the cursor.

in fact found the opposite relationship (Fig. 2*D*,*E*). During switches from the Baseline to the De Novo mapping, we observed a weak, nonsignificant positive correlation between increases in reaction time over steady state and increases in initial direction error in trials immediately following a switch of mapping (Fig. 2*D*, filled circles; $r_{(23)} = 0.30$; 95% CI [−0.11, 0.62]; $p = 0.15$). When switching from the De Novo mapping to the Baseline mapping, increases in reaction time were actually positively correlated with initial direction error (Fig. 2*E*, filled circles; $r_{(23)} = 0.77$; 95% CI [0.53, 0.89]; $p < 0.001$), such that participants who increased their reaction times during the task-switching blocks actually performed worse. Both of these patterns were similar 6th–10th trials after a switch (Fig. 2*D*,*E*, open circles; Baseline to De Novo, $r_{(23)} = 0.38$; 95% CI [−0.02, 0.67]; $p = 0.06$; De Novo to Baseline, $r_{(23)} = 0.70$; 95% CI [0.41, 0.86]; $p < 0.001$), suggesting that the overall increases in reaction time were unrelated to transient increases in directional error following a switch.

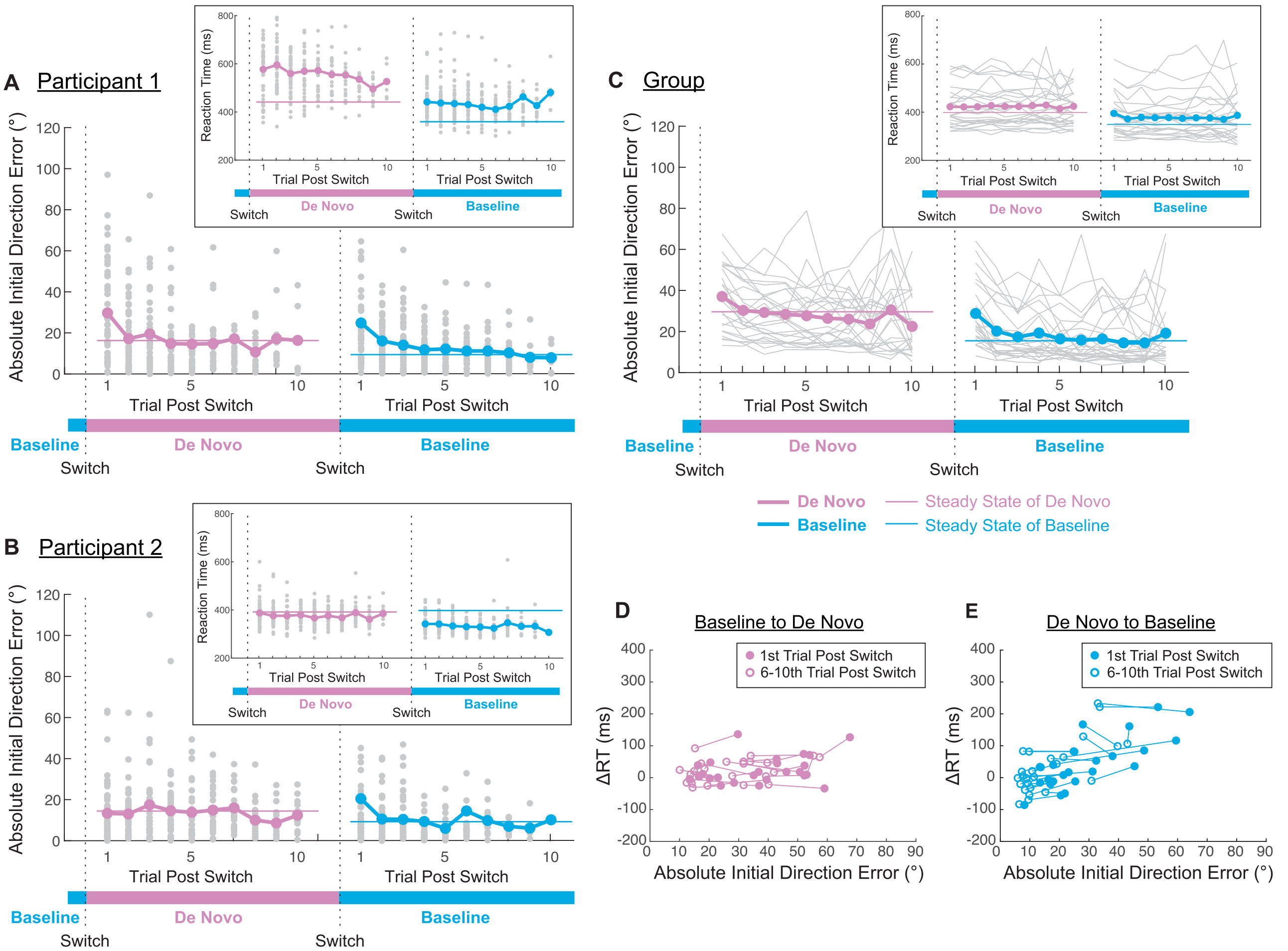

Figure 2. Performance when switching between the Baseline and De Novo mappings. Panels ***A–C*** show performance (absolute initial direction error and reaction time) in the first 10 trials postswitch either from the Baseline to the De Novo mapping or from the De Novo to the Baseline mapping, during the switching assessment on Day 5. ***A***, ***B***, Performance of two representative participants (***A***, Participant 1; ***B***, Participant 2). Thick lines indicate average initial direction error for each participant, and thin lines indicate steady-state performance for each participant, assessed in blocks without any task switching at the start of Day 5 (magenta, De Novo mapping; light blue, Baseline mapping). Gray dots indicate performance in individual trials. ***C***, Performance across all participants. Thick colored lines indicate mean performance across all participants. Thin gray lines indicate averaged behavior across trials for each individual participant. Thin magenta and light blue lines indicate steady-state performance of under the De Novo and the Baseline mappings on Day 5. ***D***, ***E***, Relationship between absolute initial direction error and reaction time in postswitch trials when switch from the Baseline to the De Novo (***D***) and from the De Novo to the Baseline mapping (***E***). ΔRT indicates different between reaction time postswitch trials and steady-state performance under that mapping in nonswitching blocks (thin horizontal lines in ***A–C***). Filled circles indicate first trials postswitch and open circles represent the average across the 6–10th trials post switch. Each circle indicates one participant.

Directional errors following a switch arose from inappropriately persisting with the preswitch policy

Overall, our data demonstrate that most participants had little difficulty switching between the De Novo and Baseline mappings. Nevertheless, most participants did exhibit temporary increased directional errors in trials immediately following a switch. We reasoned that these errors could have arisen because the new control policy had not yet been fully retrieved from long-term memory and prepared for use (Monsell, 2003). Alternatively, these postswitch errors might have been due to participants inappropriately persisting with the policy that had been appropriate for the preswitch mapping.

In order to dissociate between these two explanations, we closely examined the direction of movement of participants' left and right hands, rather than just the direction of movement of the cursor. The patterns of movement of the two hands exhibited a distinctive pattern under each mapping (Fig. 1G), and we exploited this structure to infer which policy (Baseline or De Novo) participants were applying in each trial or whether their movements were inconsistent with either policy (Fig. 3*A*).

We used a maximum likelihood approach to estimate, on a trial-by-trial basis, the probability that participants used each policy. Figure 3*C–F* shows the individual hand movement directions and inferred choice of policy for the two representative participants from Figure 2, when switching from the Baseline mapping to the De Novo mapping. Figure 3, *G* and *H*, shows the choice of policy across participants when switching in both directions. This analysis clearly revealed significant persistence with using the policy that had been appropriate preswitch but which was no longer appropriate. At a group level, the probability of using the correct postswitch policy was transiently reduced in trials immediately following a switch, both when switching from the Baseline mapping to the De Novo mapping and vice versa [Baseline to De Novo, 6th–10th trials, 0.86 ± 0.02 (mean ± SEM); 1st trial, 0.70 ± 0.03; paired *t* test; $t_{(24)} = -5.41$; $p < 0.001$; 2nd trial, 0.81 ± 0.02; $t_{(24)} = -2.70$; $p = 0.013$; De Novo to Baseline, 6th–10th trials, 0.80 ± 0.05; 1st trial, 0.66 ± 0.05; $t_{(24)} = -5.39$; $p < 0.001$; 2nd trial, 0.75 ± 0.05; $t_{(24)} = -2.54$; $p = 0.018$; all comparisons are uncorrected]. Across all trials, there was a small probability that behavior did not match either

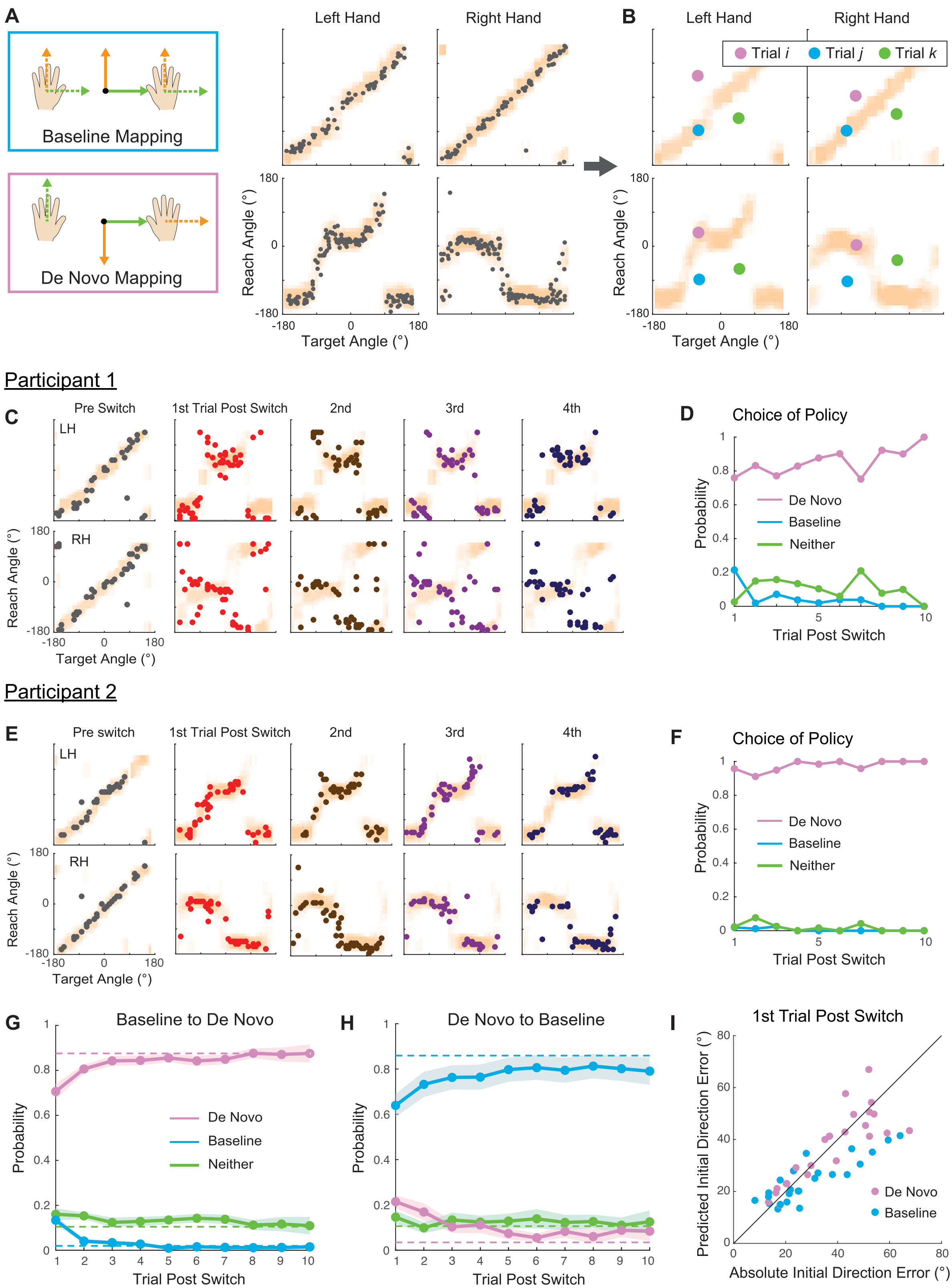

Figure 3. Inferring the policy used by participants on each trial post switching. ***A***, Initial direction of the left hand and right hand varied systematically as a function of target direction (gray dots; each dot = 1 trial, taken from nonswitching block at the start of Day 5). Based on this data, we estimated the conditional distribution of each hand's direction given the target direction (orange shaded region). We did this separately for the left and right hand (left/right column) and for the Baseline and the De Novo mapping (top/bottom row). ***B***, We used these distributions to infer, on subsequent trials, which policy participants employed. The colored circles represent potential observations (initial directions of the left and right hands given the target direction), with each trial (i, j, k) shown in a different color. Trial i (magenta) falls within the distribution of movements under the De Novo mapping (bottom row), but not the Baseline mapping (top row). We therefore infer a high likelihood that this trial was generated using the policy learned for the De Novo mapping. Trial j (blue) falls within the distribution of movements under the Baseline mapping (top row), but not the De Novo mapping (bottom row), so we infer a high likelihood that this trial was generated by the policy used for the Baseline mapping. Trial k (green) does not fall within either distribution, and we infer that this movement was not likely to have been generated under either policy. ***C–F***, Illustration of this analysis for the two representative participants

the Baseline or the De Novo policy (Fig. 3*G*,*H*, green lines). These errors did not seem to be associated with the switch, however. The incidence of such trials did not vary as a function of the number of trials postswitch (Baseline to De Novo, repeated-measure ANOVA, $F_{(2.71,\ 65.05)} = 0.47$; $p = 0.685$; De Novo to Baseline, $F_{(3.91,\ 72.32)} = 0.44$; $p = 0.725$) and matched that seen in blocks without any switching requirements. Therefore, trials in which behavior did not resemble policies for either the preswitch or postswitch mapping reflected variability in execution that was independent of the task-switching demands.

We further asked whether this persistence phenomenon fully accounted for the observed increase in directional errors following a switch or whether there could be some other, additional factor contributing to these switch costs. We predicted the magnitude of directional errors that would be expected due to persistence alone, based on our inferred probabilities of persisting with the preswitch policy, and the average errors expected when persisting with the preswitch policy or when applying the correct policy. Figure 3*I* directly compares these predicted directional errors to the actual observed errors for trials immediately following a switch. These predictions had no statistically significant difference from the observed values (Baseline to De Novo, paired *t* test, $t_{(24)} = 0.608$; $p = 0.608$; De Novo to Baseline, $t_{(24)} = 0.451$; $p = 0.656$). A Bayes factor analysis supported the hypothesis that the predictions matched the observed values (Baseline to De Novo, Bayesian paired-sample *t* test, Cauchy prior $r = 0.707$; BF = 0.238; error = 0.026%; De Novo to Baseline, Cauchy prior $r = 0.707$; BF = 0.231; error = 0.026%; BF < 1 indicates evidence in support of null hypothesis). This demonstrated that the observed errors were well accounted for by the persistence phenomenon. The correspondence between predicted and observed errors was similarly strong for all trials post switch (Figs. S1, S2). Therefore, the brief increase in directional errors following a switch (Fig. 2*C*) was mostly driven by a small probability of incorrectly persisting with the policy for the preswitch mapping rather than any difficulty in retrieving and successfully implementing the postswitch mapping.

Switch costs were not attributable to a failure to detect a change in context

In Experiment 1, we found that participants exhibited a cost for switching between mappings in the form of a small (∼20%) probability of persisting with the previously appropriate policy rather than switching to the new policy. While this might be construed as a cognitive phenomenon whereby participants fail to appropriately implement the novel policy, it could alternatively be explained by an occasional failure to notice the change in the color cue that prompted the switch. To test this "perceptual lapse" hypothesis, we conducted a second experiment, Experiment 2, which closely parallel Experiment 1, except that participants were provided with a push button in their left hand and instructed to press this button whenever the initially presented background color was different from that in the previous trial (Fig. 4*A*), during the 500 ms interval before the target appeared. We found that participants ($N = 10$; all of whom had practiced the De Novo mapping for 5 d in a separate study, under almost identical conditions) almost never failed to press the button at the appropriate time (Fig. 4*B*), indicating that there was no perceptual failure. Nevertheless, we still observed the exact same pattern of switch costs (Fig. 4*C*) and persistence of using the previous mapping (Fig. 4*D*,*E*), as before. We used the same policy-inference approach as before to determine the cause of these errors, focusing on trials after participants had accurately reported that a switch occurred ("Different Color" and "Push," Fig. 4*B*, right), and found a similar probability of persisting in using the previous mapping as in Experiment 1. The results from this experiment strongly refute the idea that the switch costs and persistence we identified in Experiment 1 were attributable to a perceptual failure and instead indicate a failure to appropriately switch to the new controller.

Participants could learn a second De Novo mapping with minimal interference

In the first two experiments, we found that people had little difficulty in switching between a newly learned skill (the De Novo mapping) and a well-established skill (the Baseline mapping). However, we suspected that it may be more challenging to switch between two newly learned skills. We therefore conducted a further experiment to test whether people could learn two De Novo mappings and switch between them in a similar manner to switching between the De Novo and the Baseline Mappings.

Seven participants who had already learned the De Novo mapping in Experiment 1 (which we will now refer to as Mapping A) went on to participate in Experiment 3, in which they learned another De Novo mapping (Mapping B). Mapping B was similar to Mapping A, except the roles of the left and right hand were transposed (Fig. 5). Participants practiced Mapping B over 5 d (Fig. 5, Days 6–9, switching test between the Baseline mapping and Mapping B on Day 10). Learning of Mapping B proceeded in a similar manner as initial learning of Mapping A in terms of initial direction error [Fig. 6*A*,*B*, the last five blocks of practice Day 4 under Mapping A, 19.49 ± 1.90° (mean ± SEM); the last 5 blocks of practice Day 9 under Mapping B, 17.32 ± 1.36°; paired *t* test, $t_{(6)} = 1.38$; $p = 0.217$] and reaction time (Mapping A, 295.40 ± 18.43 ms; Mapping B, 325.43 ± 22.93 ms; paired *t* test, $t_{(6)} = -2.18$; $p = 0.072$). Thus, people were able to learn a second De Novo mapping, and there did not appear to be any interference, positive or negative, from prior learning of Mapping A on subsequent learning of Mapping B.

On Day 11, we checked whether participants still retained the ability to perform under Mapping A after having learned Mapping B. Participants performed three blocks of the center-out task under Mapping A, followed by three blocks under Mapping B (Fig. 5, Day 11, NB—this analysis included five participants since two participants did not complete a switching assessment on Day 11). The reaction time and initial direction

←

in Figure 2. ***C***, ***E***, Each column shows behavior in different trials relative to a switch from the Baseline to the De Novo mapping. Each row shows a different hand (LH, left hand; RH, right hand). ***D***, ***F***, The inferred probability of each mapping (or neither mapping) as a function of trials postswitch. For Participant 1 (***C***, ***D***), their behavior after the switch was reasonably well aligned with the De Novo policy in most trials. However, in a subset of trials immediately following a switch, their hand movements were more consistent with the Baseline policy. Participant 2 (***E***, ***F***), in contrast, successfully applied the appropriate policy with high probability, even from the first trial. ***G***, ***H***, Average probability of applying each policy across participants when switching from the Baseline to the De Novo mapping (***G***) and from the De Novo to the Baseline mapping (***H***; magenta, De Novo policy; blue, Baseline policy; green, neither policy). Dashed horizontal lines indicate policy probabilities from an analogous analysis applied to blocks with no switching. Shaded regions indicate ± SEM. ***I***, Comparison of the magnitude of directional errors observed in the first trial following a switch of mappings with the predicted magnitude of directional errors in the same trial attributable to persistence of the preswitch policy.

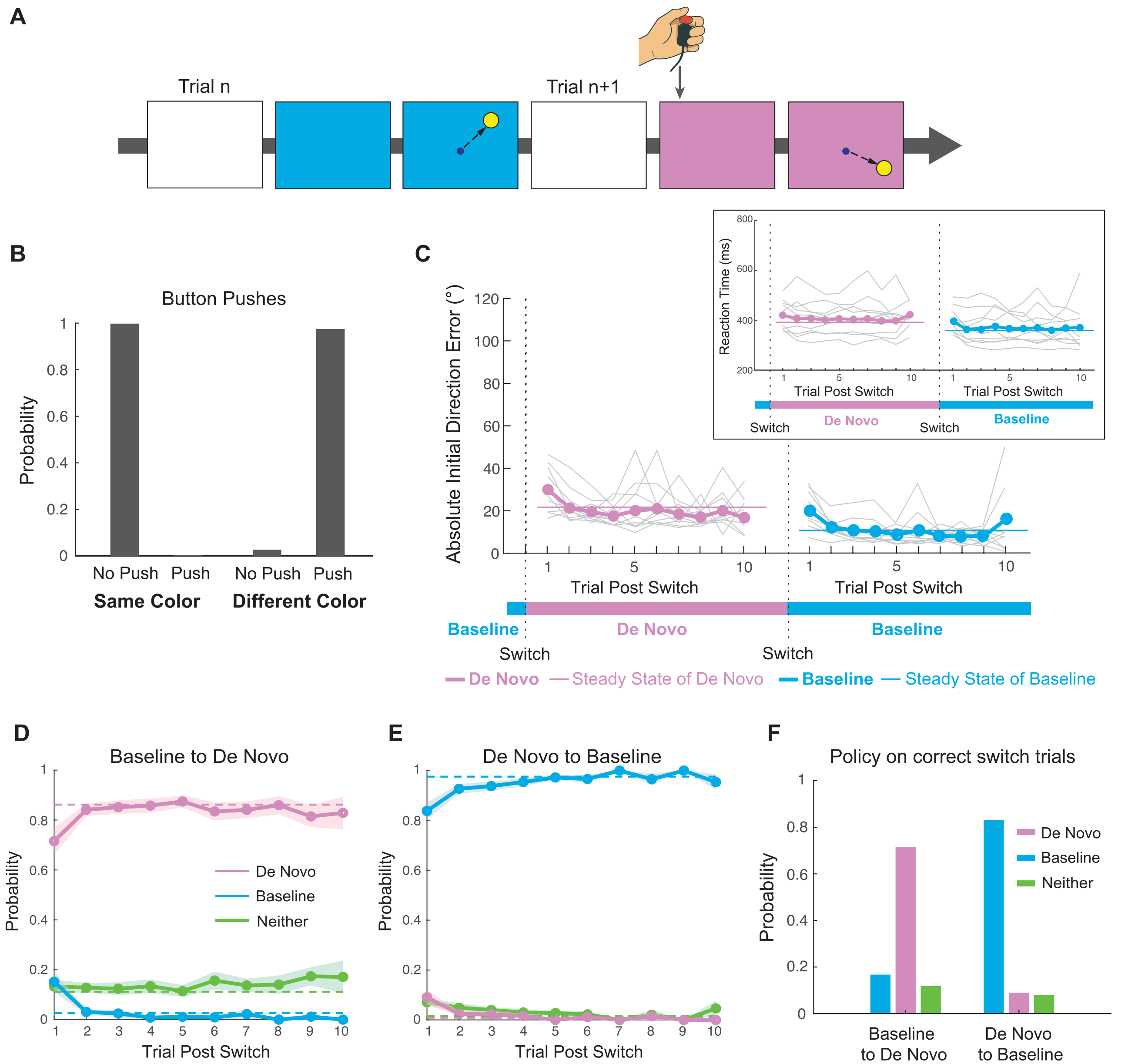

Figure 4. Switch costs were not due to perceptual lapses. ***A***, In Experiment 2, participants held a push-button switch in their left hand and were instructed to press the button whenever they noticed that the background color was different from the previous trial. ***B***, Average proportion of trials in which participants pushed the button at the start of trials in which either the background color was the same or different from the previous trial. Participants almost always pushed the button only at the appropriate time. ***C***, Performance across all participants (as in Fig. 2C). ***D***, ***E***, Probability of different policies used by participants in the first trials following a switch (as in Fig. 3G,H). Participants still occasionally persisted with the preswitch policy despite correctly reporting the change of the background color. Dashed horizontal lines indicate policy probabilities from an analogous analysis applied to blocks with no switching. Shaded regions indicate ± SEM. ***F***, Selected policy on trials immediately following a change of screen color that participants successfully reported by pushing the button ("Different Color" and "Push" in **B**, right).

errors (Fig. 6C) were similar for both mappings [reaction time, Mapping A, 481.57 ± 54.68 ms (mean ± SEM); Mapping B, 455.28 ± 51.10 ms; paired *t* test, $t_{(4)} = 1.71$; $p = 0.163$; initial direction error, Mapping A, 35.80 ± 6.63°; Mapping B, 26.98 ± 2.49°, $t_{(4)} = 1.72$; $p = 0.160$], and participants maintained distinct hand movements for each mapping. The initial performance for Mapping A did appear to be slightly worse at the start of Day 11 than at the start of Day 6, suggesting possible retrograde interference; this decrement in performance was short-lived, however, and participants rapidly improved their reaction time and direction error to levels comparable to their earlier performance ("savings"). Therefore, participants' memory for controlling the cursor under Mapping A was not erased by the intervening learning of Mapping B, indicating no retrograde interference. Upon close scrutiny, we did, however, observe some slight changes in participants' policies for Mapping A before versus after learning Mapping B, which was apparent when we applied our policy-inference analysis to trials long after a switch (>6 trials post-switch) and found a relatively low probability of using the policy for Mapping A [$p = 0.70 \pm 0.23$ (mean ± SD) in 6–15 trials post-switch on Day 16], despite apparently good performance in terms of directional error.

Participants were unable to switch between two De Novo mappings shortly after initial learning but could switch after more extensive practice

After they had successfully learned both Mapping A and Mapping B, we examined participants' ability to switch between

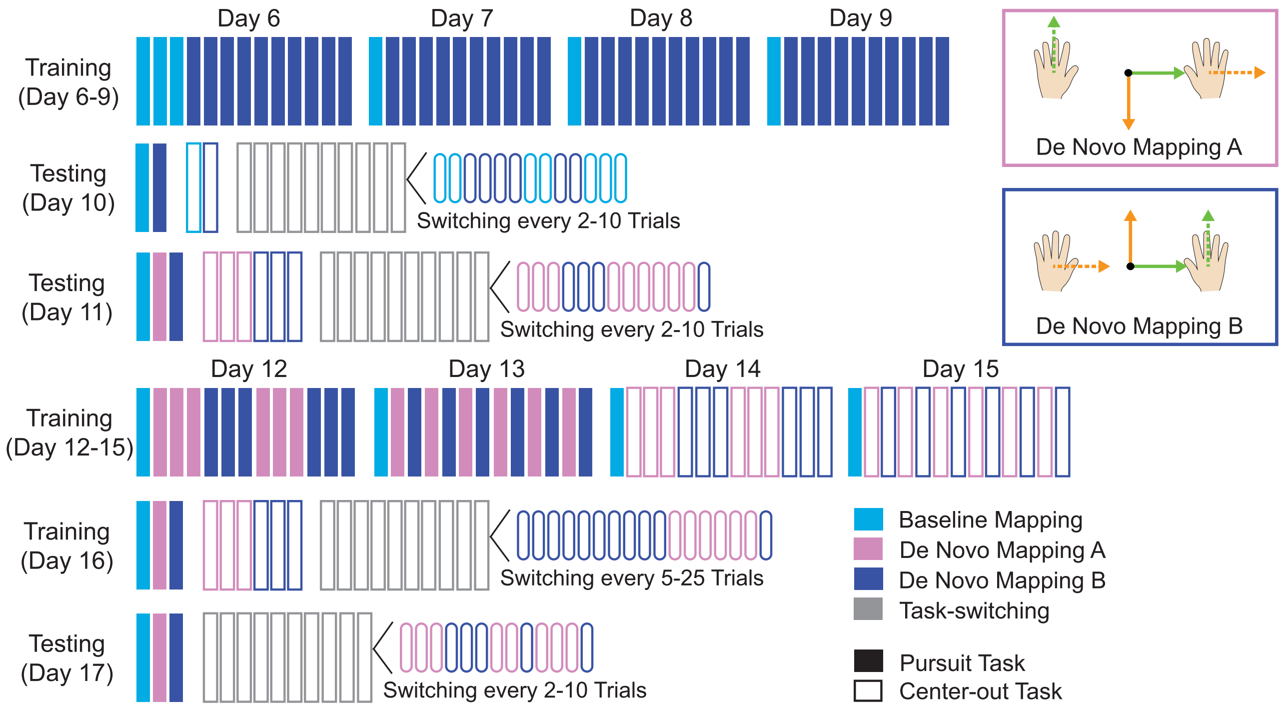

Figure 5. Experiment 3—switching between two De Novo mappings. After the end of Experiment 1 (Days 1–5), a subset of participants learned a new De Novo mapping (Mapping B; 600 trials per day, Days 6–9). On Day 10, we tested participants' ability to switch between the Baseline mapping and De Novo mapping B on a trial-by-trial basis based on a color cue. On Day 11, we assessed participants' ability to switch between the two De Novo mappings. From Day 12 to Day 16, participants practiced switching between mappings. On Day 12, the mapping switched every three blocks with participants performing the pursuit task (Fig. 1*B*). On Day 13, the mapping switched every block. On Days 14–15, we repeated this process with the center-out task rather than the pursuit task (Fig. 1*B*). On Day 16, the mapping switched every 5–25 trials with the center-out task. Finally, on Day 17, we repeated the assessment with the mapping switching every 2–10 trials. Participants performed 6 blocks of 60 trials for each mapping in total on Days 12–15. Two of the seven participants did not complete the initial switching assessment on Day 11 and instead directly started switching training (Days 12–16).

these two mappings (Fig. 5, Day 11). As in Experiment 1, we assessed this in a center-out version of the task, with the background screen color indicating the mapping to be used in the upcoming trial. This switched every 2–10 trials. Participants now exhibited substantially increased directional errors in the trials following a switch from Mapping B to Mapping A (Fig. 6*D*). Using the same approach as for Experiment 1, we used a maximum likelihood approach based on participants' individual hand movement directions to estimate, on a trial-by-trial basis, the probability that participants used different policies postswitch and determined the cause of errors: either persisting with the wrong policy or failing to correctly execute either policy. When switching from Mapping B to Mapping A, participants had a relatively low probability of using their policy for Mapping A (∼0.5), with substantial and sustained persistence of using the preswitch policy (Fig. 6*G*). Participants were more successful when switching from Mapping A to Mapping B but still exhibited persistence with the preswitch policy that lasted for several trials (Fig. 6*G*). The asymmetry between mappings likely reflected a bias toward the most recently learned mapping.

Although participants struggled to switch between mappings shortly after they had learned both mappings, we wondered whether participants might be able to switch more readily if we allowed them some practice at switching between mappings. Over 5 d (Fig. 5, Days 12–16), participants practiced switching between Mapping A and Mapping B. This practice began with the mapping switching every three blocks (60 trials per block), while participants performed the pursuit task on Day 12 and then every block on Day 13. We then changed to a center-out task and switched the mapping every three blocks on Day 14 and every block on Day 15. On Day 16, participants practiced switching between mappings every 5–25 trials. Finally, on Day 17, we repeated the same task-switching assessment as on Day 11, switching every 2–10 trials (Fig. 5, Day 17).

Participants showed smaller directional errors following a switch in the second task-switching assessment on Days 16 and 17 in comparison with the switching assessment that was performed immediately after learning Mapping B on Day 11 (Fig. 6*E*,*F*). At a group level, on Day 17, when switching from Mapping A to Mapping B or from Mapping B to Mapping A, participants showed transiently increased initial direction errors in trials immediately following a switch [Mapping A to Mapping B, 6th–10th trials, 20.44 ± 2.92° (mean ± SEM); 1st trial, 27.80 ± 2.96°; paired t test, $t_{(6)} = 3.66$; $p = 0.011$; Mapping B to Mapping A, 6th–10th trials, 18.72 ± 2.55°; 1st trial, 26.68 ± 3.71°; paired t test, $t_{(6)} = 4.47$; $p = 0.004$; 2nd trial, 24.06 ± 3.38°; paired t test, $t_{(6)} = 3.51$; $p = 0.013$; all comparisons are uncorrected].

As before, we examined participants' hand movements to infer the cause of any increased errors following a switch. We found that participants became much more successful at rapidly adopting the correct policy following a switch of mapping the more they practiced switching (Fig. 6*H*,*I*). By Day 17, participants exhibited minimal costs when switching between mappings [Mapping A to Mapping B, 6th–10th trials postswitch from 0.81 ± 0.07 (mean ± SEM); 1st trial, 0.72 ± 0.06; paired t test, $t_{(6)} = -4.00$; $p = 0.007$; 2nd trial, 0.72 ± 0.07; $t_{(6)} = -4.74$; $p = 0.003$; 3rd trial, 0.73 ± 0.08; $t_{(6)} = -3.10$; $p = 0.021$; Mapping B to Mapping A, 6th–10th trials, 0.83 ± 0.06; 1st trial, 0.79 ± 0.04; $t_{(6)} = -1.26$; $p = 0.254$; all comparisons are uncorrected].

In summary, participants initially struggled to switch between two different, newly learned mappings, and inappropriate persistence

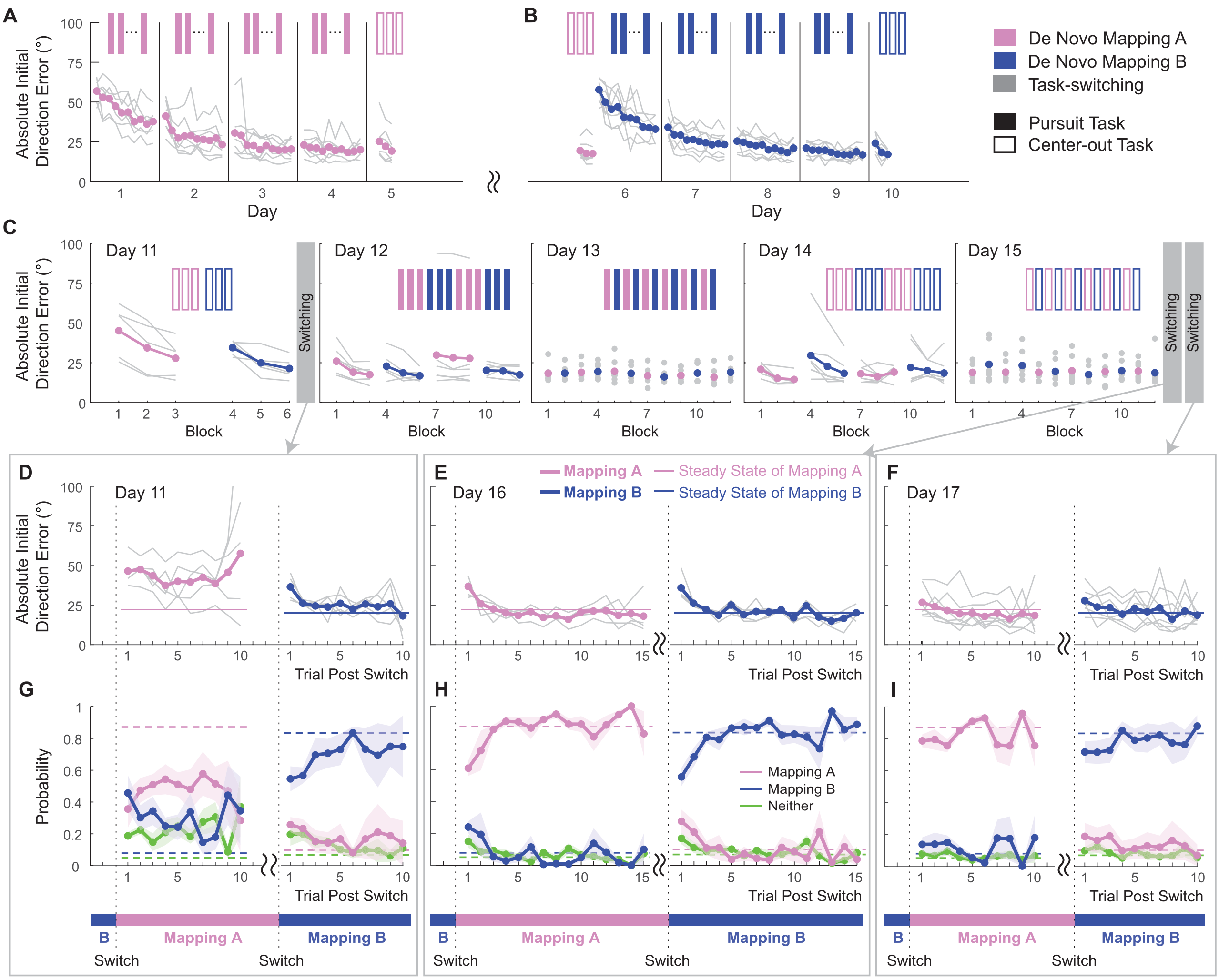

Figure 6. Learning and switching between two De Novo mappings. ***A***, ***B***, Performance improvement during initial training for each mapping (Days 1–10). ***C***, Performance in subsequent training blocks that had a fixed mapping throughout, but with the mapping varying from block to block (Days 11–15). ***D–F***, Performance (absolute initial directional error) in blocks in which the mapping switched within block (Days 11, 16, 17), plotted as a function of trial number relative to a switch. ***G–I***, Probability of using each policy (established based on performance on Day 16, at least 6 trials after a switch, for both Mapping A and Mapping B) as a function of trial number relative to a switch. ***D***, ***G***, Day 11 assessed switching performance immediately after learning both mappings, with the mapping switching every 2–10 trials. ***E***, ***H***, Day 16 assessed switching performance after further training, with the mapping switching every 5–25 trials. ***F***, ***I***, Day 17 repeated the same switch assessment as on Day 11, with the mapping switching every 2–10 trials. Thick magenta lines indicate average across participants for Mapping A; thick dark blue lines indicate those of the Mapping B. Gray dots/lines indicate data for individual participants. Thin magenta and dark blue lines indicate steady-state performance of under Mapping A on Day 5 and Mapping B on Day 10. In the probability of choice, green thick lines indicate the probability neither Mapping A nor Mapping B were used. Dashed horizontal lines indicate policy probabilities from an analogous analysis applied to trials in which behaviors were stable (>6 trials after a switch on Day 16). Shaded regions indicate ± SEM.

with the preswitch policy was the major contributor to their difficulty. With practice, however, participants eventually became able to successfully rapidly switch between the two mappings.

Discussion

Here, we tested whether participants could rapidly and repeatedly switch between a preexisting baseline controller and a controller learned through *de novo* learning, when prompted by a color cue. We found that, in both switch directions (De Novo to Baseline and Baseline to De Novo), participants generally did not have much difficulty in switching their behavior according to these two mappings. Most participants did, however, exhibit some increased errors in the first 1–2 trials following a switch. By closely analyzing participants' movements of both their hands, we determined that these errors were attributable to inappropriate persistence with the policy used before the switch of mapping rather than imperfect execution of the policy associated with the new mapping.

We subsequently asked whether participants could learn multiple skills associated with different mappings and switch between them. We found that participants were able to learn two De Novo mappings with minimal interference but initially struggled to switch between these two mappings. However, after further training that included frequent switching between mappings, they became able to switch more easily. Similar to the first experiment, we found that the errors participants exhibited after a switch were mostly attributable to inappropriately persisting with the policy associated with the preswitch mapping rather than failing to correctly implement the appropriate policy for the postswitch mapping.

Task switching has been extensively studied in cognitive tasks (Jersild, 1927; Allport et al., 1994; Rogers and Monsell, 1995; Kiesel et al., 2010). These studies have primarily focused on transient increases in reaction time. However, this approach yields limited insight into the underlying reason for these switch costs since it is unclear why additional reaction time might be needed.

In our experiments, we applied time pressure to participants through the threat of the target disappearing, with the goal of eliminating any transient increases in reaction time and instead revealing potential errors in action selection (Hardwick et al., 2019). This approach was largely successful; participants did not transiently increase their reaction time following a switch of the mapping and instead exhibited increased task errors.

The continuous nature of the actions in our task provided much richer information about the nature of participants' errors compared with button-pressing tasks and allowed us to infer that errors were primarily due to inappropriate persistence with the wrong mapping. In a second experiment, we ruled out that this persistence was due to participants failing to notice that the background color had changed. These findings are therefore consistent with the idea that task switching in general is attributable to difficulty in overcoming the previously active task policy rather than a difficulty in retrieving the one required after the task changes—often referred to as "task set inertia" (Allport et al., 1994; Wylie and Allport, 2000). Indeed, persistence of the components of the preswitch task set has been observed in cognitive tasks. In an fMRI experiment, reaction time costs of switching to one task were predicted by activation of the region that had been activated during another task, although different regions were activated during each task (Wylie et al., 2006; Yeung et al., 2006), suggesting that "task set inertia" can at least partially explain switch costs. Our behavioral findings parallel these neuroimaging findings.

One caveat to our results is that most participants' reaction times were overall elevated during the switching blocks compared with blocks without any switching. These increased reaction times did not, however, seem to reflect participants taking additional time in order to overcome the persistence of the preswitch mapping. While one might expect that participants with longer reaction times would have been more successful in switching their behavior, we in fact found the opposite pattern: participants who had a greater increase in reaction time also tended to perform worse in trials immediately following a switch. These effects might therefore have reflected differences in overall task engagement across individuals.

Our third experiment examined whether or not people could learn and switch between two different de novo skills. Participants found this very challenging at first but became able to switch proficiently after some practice. The improving ability to switch between policies for different mappings might have been due to either participants getting more practice at switching between them. However, it could also have been due to participants undergoing a shift from a deliberate to an automatic performance mode, as is widely thought to occur with prolonged practice (Shiffrin and Dumais, 1981; Haith and Krakauer, 2018; Du et al., 2022). We were not able to dissociate between these explanations for participants improving switch ability based on our current data.

The ease with which participants could switch between the De Novo mapping and the Baseline mapping stands in stark contrast to findings from adaptation, where it does not seem possible to revert to baseline control based on an explicit cue (Osu et al., 2004; Addou et al., 2011; Forano et al., 2021). This inability to switch appears to be an inherent property of the implicit recalibration mechanisms involved in adaptation (Huberdeau et al., 2015; McDougle et al., 2016; Morehead et al., 2017; Krakauer et al., 2019). When countering very large perturbations, such as visuomotor rotations exceeding 90°, people do appear to be able to rapidly switch between two learned perturbations (Cunningham and Welch, 1994). In this instance, however, compensation is likely achieved through a simple re-aiming heuristic (Morehead et al., 2015; Wilterson and Taylor, 2021). Therefore, although people can, in some cases, switch readily between opposing perturbations, they likely do so by switching reaiming strategies rather than by switching to an entirely new controller. *De novo* learning tasks, in contrast, do not appear to depend on reaiming strategies for learning (Yang et al., 2021, 2022), and therefore our experiments genuinely reflect switching between controllers rather than switching between simplistic re-aiming strategies.

Although not the primary focus of our study, our results demonstrate for the first time (to our knowledge) that participants can learn two distinct De Novo mappings with little interference—either retrograde (i.e., learning of Mapping B potentially disrupting the memory for Mapping A) or anterograde (i.e., prior learning of Mapping A making it easier or harder to subsequently learn Mapping B). The exact way participants behaved under Mapping A did appear to change slightly after having learned Mapping B. However, there was no catastrophic loss of ability to perform the skill. Interference between motor memories has long been studied in the context of adaptation, with the goal of better understanding how multiple motor memories interact with one another (Brashers-Krug et al., 1996; Shadmehr and Brashers-Krug, 1997; Bock et al., 2001; Goedert and Willingham, 2002; Caithness et al., 2004; Krakauer et al., 2005; Krakauer and Shadmehr, 2006). Motor memories for adaptation are extremely weak, however. Adapted states are short-lived (Kitago et al., 2013), and so studies of long-term motor memory using adaptation paradigms have typically had to focus on the fact that adaptation would be slightly faster the second time the same perturbation was experienced. We suggest that *de novo* learning paradigms provide a more ecologically meaningful approach to studying interference between motor memories.

Our findings have important implications for the neural basis of motor control and motor learning. Current theories propose that movements are generated through the dynamics of neural activity in the primary and premotor cortex generating signals that drive EMG activity (Churchland et al., 2012; Michaels et al., 2016; Gallego et al., 2017). The fact that people can rapidly alter their movement policy suggests that these dynamics can be easily reconfigured. It has been proposed that such switching could be mediated by thalamic neurons whose activity can reconfigure cortical dynamics, allowing rapid switching between motor behaviors (Logiaco et al., 2021). The fact that we found that such switching is not possible between two newly learned skills, at least at first, suggests that it may only be possible to reconfigure motor cortical dynamics for relatively well-learned skills.

An alternative solution to switching the dynamics of the motor cortex may be to construct a controller that can be suitable for both tasks. Although the ultimate motor commands issued for each skill are very different, it may be possible for high-dimensional neural activity associated with each skill to occupy distinct neural subspaces and thus avoid interference with one another (Losey et al., 2024). Even at the level of arm kinematics, we observed some evidence, during early attempts at switching between mappings, that participants would adopt movement strategies that led to reasonable performance under either mapping. Even though the movements themselves were refined, it is possible that a similar process occurred at the level of neural activity. Lastly, rather than altering neural dynamics or representations within a single brain region, it may be that rapid switching is enabled by deferring control to entirely different regions or subpopulations or neurons. Understanding the neural basis of flexible motor behavior and how it changes with practice is an important goal for future work examining the neural basis of motor skill.

Data Availability

All data and the code for reproducing the results are available at the corresponding author's personal GitHub page: https://github.com/kahorikita/TaskSwitching

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