Journal of Experimental Psychology:
Human Perception and Performance

© 2024 American Psychological Association
ISSN: 0096-1523

2024, Vol. 50, No. 8, 785–807
https://doi.org/10.1037/xhp0001210

"Leap Before You Look": Conditions That Suppress Explicit, Knowledge-Based Learning During Visuomotor Adaptation

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When learning a novel visuomotor mapping (e.g., mirror writing), accuracy can improve quickly through explicit, knowledge-based learning (e.g., aim left to go right), but after practice, implicit or procedural learning takes over, producing fast, natural movements. This procedural learning occurs automatically, whereas it has recently been found that knowledge-based learning can be suppressed by the gradual introduction of the novel mapping when participants must make fast movements and visuomotor perturbations are small (e.g., 30° rotations). We explored the range of task instructions, perturbation parameters, and feedback that preclude or encourage this suppression. Using a reaching task with a rotation between screen position and movement direction, we found that knowledge-based learning could be suppressed even for an extreme 90° rotation, but only if it was introduced gradually and only under instructions to move quickly. If the rotation was introduced abruptly or if instructions emphasized accuracy over speed, knowledge-based learning occurred. A second experiment indicated that knowledge-based learning always occurred in the absence of continuous motion feedback, evidenced by the time course of learning, the aftereffects of learning when the rotation was abruptly removed, and the outcome of formal model comparison between a dual-state (procedural and knowledge-based) versus a single-state (procedural only) learning model of the data. A third experiment replicated the findings and verified that the knowledge-based component of the dual-state model corresponded to explicit aiming, whereas the procedural component was slow to unlearn.

Public Significance Statement

Some situations require adaptation to a novel mapping between visual directions and motor directions, such as when attempting to cut one's own hair in the mirror. Prior results established that slowly learned procedural adaptation to a novel visuomotor mapping is automatic and always occurs. More recent results established that explicit, knowledge-based learning (e.g., a learned strategy to move left for a rightward target or to move south for a target located due east) can be suppressed by introducing the novel mapping gradually. The current study replicates this finding and demonstrates that this suppression can occur even for visuomotor remappings of large magnitude (a rotation of 90°). Importantly, it also establishes that this suppression does not occur when task instructions emphasize accuracy nor in the absence of continuous online visual feedback during motor actions.

Keywords: visuomotor adaptation, state space models, implicit and explicit learning, procedural learning

Supplemental materials: https://doi.org/10.1037/xhp0001210.supp

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The spatial mapping between visual signals and motor actions is arbitrary and must be learned. For example, the retinal image is upside down and mirror-reversed, and yet for a baby learning to interact with the world, this is no more or less intuitive than if the inversion and reflection were not present—retinal positions are arbitrary from the perspective of the brain, and through extensive experience we simply

This article was published Online First May 16, 2024.
Ines Jentzsch served as action editor.
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This work was supported by an National Institutes of Health Grant (RF1MH114277) awarded to the principal investigators Rosemary A. Cowell and David E. Huber. We would like to thank all the undergraduate research assistants of the Cognitive Experiments Models and Neuroscience Lab and Computational Memory and Perception Lab for their help in data collection.

Tejas Savalia served as lead for conceptualization, data curation, formal analysis, investigation, methodology, project administration, software, visualization, and writing–original draft and served in a supporting role for writing–review and editing. Rosemary A. Cowell contributed equally to resources and supervision and served in a supporting role for investigation, methodology, validation, writing–original draft, and writing–review and editing. David E. Huber served as lead for supervision and writing–review and editing, contributed equally to investigation, methodology, and validation, and served in a supporting role for conceptualization. Rosemary A. Cowell and David E. Huber contributed equally to funding acquisition.

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learn that to grasp an object appearing at the top right of the retinal image, we should move our hand downward and to the left. In some situations, the learned spatial mapping between vision and action is abruptly altered, requiring explicit or knowledge-based correction. For instance, during the early months of the COVID-19 pandemic, when hair salons were widely shuttered, some readers may have attempted to cut their own hair in the mirror for the first time. Moving the scissors from in front of the forehead toward the head requires a motion that pulls toward oneself, and yet the image in the mirror displays this as a motion pushing away from oneself. Thus, using the visual feedback from the mirror requires a person to purposely do the opposite of their natural impulse, because the visual information specifies motion away and yet the hand must pull toward. With practice, such novel mappings are procedurally learned, and action becomes automatic.

In laboratory studies, sensorimotor learning has been studied using paradigms that distort visual or motor feedback while participants perform reaching tasks, such as with kinematic distortion via force field manipulations (Criscimagna-Hemminger et al., 2010; Klassen et al., 2005; Schween et al., 2020; Smith et al., 2006), locomotor manipulations (Sawers et al., 2013), visual distortions with prism glasses (Redding & Wallace, 2006), or visuomotor adaptation tasks that involve center-out reaching under a rotated mouse-to-cursor mapping (Bond & Taylor, 2015; Day et al., 2016; Galea et al., 2010; Haith et al., 2015; Izawa & Shadmehr, 2011; Kagerer et al., 1997; McDougle & Taylor, 2019; Modchalingam et al., 2019; Morehead et al., 2011, 2017; Taylor & Ivry, 2011; Taylor et al., 2011, 2014). Results from these studies suggest there are two qualitatively different kinds of sensorimotor learning—one explicit or knowledge-based and one implicit or procedural—that operate simultaneously, competing against each other to learn a new sensorimotor mapping over repeated trials. The fast-to-learn, knowledge-based system (i.e., a system that quickly adapts to the new sensorimotor mapping) produces slow but accurate responses early in learning. The slow-to-learn, procedural system guides fast, automatic actions, but only after considerable practice. Studies supporting this distinction have, for instance, compared conditions that give aiming instructions about the sensorimotor perturbation (Mazzoni & Krakauer, 2006; Taylor & Ivry, 2011), compared conditions with versus without online visual feedback (Hinder et al., 2008), or compared gradual versus abrupt introduction of a sensorimotor perturbation (Albert et al., 2022; Kagerer et al., 1997; Yin & Wei, 2020). Aftereffects of a sensorimotor perturbation are often examined by abruptly returning the sensorimotor mapping to the standard situation in a "washout" phase (Kagerer et al., 1997), by examining whether sensorimotor learning transfers to other actions (Werner et al., 2019) or by examining "savings" when the novel mapping is reintroduced (Yin & Wei, 2020).

A particularly clear demonstration of the knowledge-based/procedural learning distinction is found in the study of Mazzoni and Krakauer (2006), in which participants were explicitly told to aim 45° counterclockwise to compensate for a 45° clockwise visuomotor rotation in the mapping between visually displayed targets and reaching direction in a pointing task. This instruction allowed almost perfect performance soon after rotation, but paradoxically, movements slowly drifted in the direction of "overcorrection" (e.g., even further counterclockwise than was needed to counteract the rotation). That is, the procedural, implicit system continued to slowly adjust to the rotation even though the knowledge-based strategy was sufficient for good performance. Thus, even when knowledge-based learning is maximized through an explicit aiming strategy, procedural learning still occurs even if it results in worse performance. In other words, procedural motor adaptation is automatic.

As applied to learning a novel visuomotor rotation, "dual-state" models of motor learning assume that actions on each trial reflect the summation of the rotation estimates provided by two different learning systems (aka, two "states" that estimate the required rotation; McDougle et al., 2015; Smith et al., 2006; Taylor & Ivry, 2011). When referring to the dual-state model we adopt the terminology of the "fast-learning system" for explicit or knowledge-based learning and the "slow-learning system" for implicit or procedural learning (McDougle et al., 2015). A point of potential confusion, which we clarify here, is that the fast-learning system is thought to produce slower movements. These slower movements may take the form of a longer time period spent planning/aiming before initiation of the movement (Langsdorf et al., 2021). In contrast, the slow-learning system is thought to produce faster movements (e.g., participants initiate their movements quickly because they do not take the time to explicitly aim). Besides slower/faster movement initiation times, there may also be differences in motion times when continuous feedback is provided, reflecting mid-course corrections that might or might not involve additional attempts to explicitly correct for the rotation. However, rather than directly addressing movement times, the dual-state model is typically applied to explain motion accuracy. This provides a descriptive account of what happens when a fast-learning and slow-learning system compete to produce motion errors.

The conclusion that the explicit and implicit motor learning systems exist in parallel and compete with each other has recently been supported in a comprehensive investigation that compared explicit aiming to actual motion error in a variety of situations (Albert et al., 2022). Because the rotation estimates from each system are summed, accurate motion could reflect a perfect estimate of the rotation in the fast system combined with no rotation in the slow system, or vice versa, or a situation in which each system provides a partial estimate of rotation, with these adding up to the correct total. Thus, manipulations that suppress one system or the other will affect the magnitude of learning for the other system. More specifically, if the explicit knowledge-based learning system can be "turned off," there should be greater implicit procedural learning. In the current study, we investigate the conditions that suppress knowledge-based learning.

One consequence of parallel learning systems that compete with each other is that learning curves should exhibit a quick reduction in error as the fast system rapidly develops a relatively accurate estimate of rotation, followed by a longer tail as the estimate of rotation gradually shifts from the fast to the slow system, which further fine-tunes the rotation estimate (Taylor et al., 2014). Because the slow system not only learns slowly but also forgets slowly, the dual-state model successfully explains aftereffects upon abrupt removal of the rotation, as well as the spontaneous recovery during readaptation with the reintroduction of the rotation (Ethier et al., 2008; Morehead et al., 2015; Smith et al., 2006). Supporting the assumption that the fast system reflects explicit, knowledge-based learning (aka, aiming strategies), the fast system has been found to reflect the explicit aim reported by participants (Taylor et al., 2014) and to capture conditions where participants are given a strategy to counter the perturbation (Taylor & Ivry, 2011).

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Most studies supporting the dual-state model instruct participants to be both fast and accurate. Because there is always some emphasis on accuracy, this may lead participants to use some form of knowledge-based aiming strategy. Thus, these instructions may be critical for ensuring that the explicit, knowledge-based system plays some role in adapting to a novel sensorimotor perturbation. In other words, the success of the dual-state model in explaining initial learning, unlearning, and relearning may reflect the combination of obligatory procedural learning (Mazzoni & Krakauer, 2006; Taylor & Ivry, 2011), which is captured by the slow-learning state (McDougle et al., 2015), and an explicit aiming strategy induced by instructions that emphasize accuracy, which is captured by the fast-learning state. Providing support for this claim, forcing participants to wait before moving has been found to increase accuracy through explicit aiming strategies (Langsdorf et al., 2021). Conversely, because the fast- and slow-learning systems interact to produce a combined error signal in the dual-state model (Albert et al., 2020), pressure to respond quickly should lead to an increased contribution of the slow-to-learn (but fast-to-deploy) procedural system (Haith et al., 2015).

Another important factor for the knowledge-based system may be whether errors are sufficiently large to be noticeable. For instance, if a large rotation is abruptly introduced, participants will become explicitly aware of the rotation, and this awareness may underlie learning in the knowledge-based system even in the absence of pressure to be accurate. One way to address this possibility is by introducing the rotation gradually in increments such that participants are never explicitly aware of any large discrepancies between their movements and the desired outcome (e.g., the gradual introduction of a 90° or 60° counterclockwise rotation in steps of 10°, with time to procedurally adapt to each additional change of 10°). Prior work with a gradual introduction of rotation found that it results in a larger washout aftereffect (Kagerer et al., 1997; Saijo & Gomi, 2010). That is, when participants adapt to a 90° visuomotor rotation that is introduced all at once (sudden perturbation), participants tend to make fewer errors when the rotation is subsequently removed as compared to when the 90° rotation is introduced in small increments (gradual perturbation). These results are consistent with the claim that a gradual introduction of rotation more effectively promotes procedural learning, which is then more slowly forgotten, producing greater errors upon removal of the rotation. This claim finds additional support in the finding that Parkinson's patients can successfully adapt to a gradual perturbation but not a sudden perturbation (Venkatakrishnan et al., 2011). In other words, lacking effective knowledge-based movement control, Parkinson's patients struggle to adapt to the sudden introduction of a large rotation, but their intact procedural motor control system can nonetheless adapt gradually if environmental conditions permit.

Beyond an emphasis on speed and the introduction of the perturbation gradually, another factor that may enhance procedural adaptation is continuous on-screen cursor feedback during motions as compared to feedback that shows only the final result of the motion (Morehead et al., 2011; Taylor et al., 2014). In other words, allowing participants to see only the end result, but not the motion path, encourages the use of explicit aiming strategies. To maximize the contribution of the procedural learning system, our first and third studies always presented continuous cursor feedback during each motion (see the Method section).

Recent work has found evidence that explicit knowledge-based learning is suppressed for a 30° or 60° visuomotor rotation, as measured by explicit aim reports, if the rotation is introduced gradually (Albert et al., 2022; Yin & Wei, 2020). It appears that gradual introduction of the rotation is necessary for the suppression of explicit knowledge, but it may not be sufficient. For example, participants in these studies were instructed to make "rapid center out shooting movements" or make "a brisk movement" in less than 325 ms, which may maximize the role of implicit procedural learning; thus, it is not known whether rapid movement is also a necessary condition for suppression. Furthermore, these studies presented on-screen continuous motion feedback, which is also likely to maximize procedural learning, and therefore may be another necessary condition for the suppression of explicit knowledge. The current study investigated whether the gradual introduction of rotation is sufficient to suppress knowledge-based learning even when other factors (e.g., instructions that emphasize accuracy over speed and/or removal of continuous motion feedback) that might short-circuit the suppression by encouraging explicit learning are present. Furthermore, although earlier work with the gradual introduction of rotation used extreme 90° rotations (Kagerer et al., 1997), this work could not examine whether suppression of explicit knowledge occurred because it did not employ a technique that can ascertain the relative contributions of the two learning systems (e.g., application of dual-state model or collection of explicit aiming directions). The two studies that did demonstrate such suppression used smaller rotations (30° and 60° and thus the possibility of suppressing explicit knowledge with a more extreme rotation of 90° has not been examined.

We used a 2 × 2 between-subjects design (speed/accuracy emphasis crossed with sudden/gradual introduction of a visuomotor rotation) in a center-out reaching task to determine how speed/accuracy emphasis interacts with the finding that gradual introduction of a rotation can suppress explicit knowledge-based aiming strategies. The combination of speed emphasis and gradual introduction of the rotation may be unique in suppressing knowledge-based learning. This combination may encourage participants to begin moving (i.e., "leap") without knowledge-based correction for the motion direction. That is, rather than "look before you leap," this may produce "leap before you look."

Prior work with the dual-state model assumed that both learning systems play an active role in explaining behavior across initial learning of a rotation and the unlearning or relearning of the rotation (Smith et al., 2006). However, the dual-state model has never been applied to the time course of learning for a gradually introduced rotation. If the knowledge-based system is suppressed by gradual rotation learning with instructions to move quickly, then only one learning system should be needed to explain the time course of learning. Thus, rather than applying just the dual-state model, we also applied a single-state model so that we could ascertain, via model comparison, whether the second state is necessary (Donchin et al., 2003; Smith et al., 2006).

In Experiments 1 and 2, after initial learning of the rotation, the rotation was suddenly removed in a "washout" phase to examine whether there was more of a rotation aftereffect in some conditions than others. More specifically, if the knowledge-based system is suppressed with the gradual introduction of the rotation, then there should be a larger aftereffect (i.e., errors in the opposite direction) owing to a greater contribution from the slow-to-adapt procedural system. However, because the sudden removal of the rotation is likely to engage the knowledge-based learning system, the single-state model would likely fail to capture both initial learning as

well as washout (e.g., a single learning system may be sufficient for initial learning of the gradually introduced rotation, but with the sudden removal of the rotation, both systems will play a role). Thus, the sudden removal of the rotation would bias the comparison between the dual-state and single-state models in favor of the dual-state model; therefore, we applied the models only to the initial learning of the rotation. The main use of the washout phase was an empirical assessment of the predicted rotation aftereffect (e.g., there should be a larger aftereffect in the washout phase for conditions where initial learning was better fit by the single-state model than the dual-state model).

Following Experiments 1 and 2, we partially replicated Experiment 1 in a third experiment while also examining how the results relate to explicit aiming strategies, verifying that the fast state corresponds to explicit knowledge-based learning. This study also examined the relearning of the rotation, to additionally test predictions from the slow state. To preview our results, we found that the fast-to-learn, knowledge-based system is suppressed only with the specific combination of a gradually introduced rotation under instructions to move quickly and with the presence of on-screen continuous motion feedback. Our conclusion that the knowledge-based system can be suppressed under certain conditions complements prior investigations of the procedural, implicit system, which concluded that the procedural system is obligatory (Mazzoni & Krakauer, 2006; Taylor & Ivry, 2011).

Experiment 1

Method

Participants

The sample size was determined using a power analysis in relation to our main statistical test of interest, which was an assessment of the proportion of participants in each condition that required both learning systems, rather than just procedural learning. Whether both systems were required was determined separately for each participant using formal model comparison, and then the proportions of such participants in each condition were compared using a chi-square test. To compute power, we made the a priori assumption that only 25% of the population in the gradual speed condition would require both learning systems whereas 75% of the population in the other three conditions would require both learning systems. Using our own code written in Matlab, we simulated 1,000 hypothetical experiments with 15 participants per condition, determining the frequency of participants in each condition that required both learning systems using random samples from a binomial distribution. With this simulation, we found 87% power to detect differences between the conditions (i.e., 87% of the simulated experiments produced significant results based on a chi-square test with a significance criterion of .05) under the effect size stated above.

Sixty undergraduate students from the University of Massachusetts Amherst participated in the study in 2019. The study was approved by the Institutional Review Board at the University of Massachusetts Amherst. Participants received course extra credit as compensation for time spent in the study. There were 15 participants in each of the four between-subjects conditions. This sample size was sufficient for comparing proportions across the four conditions, according to the power analysis, under the assumption that the participants in each condition were drawn from the same population. However, this sample size is insufficient to further break down the data by demographic groups, and demographic data for the particular sample were not collected. Participants were randomly assigned to the four conditions, and the demographics of the University of Massachusetts undergraduate population are 54% assigned female at birth, 17% from underrepresented groups (Black, Latinx, and Indigenous American), and 7% international. Because this was a study of visuomotor learning, all participants had normal or corrected-to-normal vision and the ability to hold and manipulate a stylus with their dominant hand. However, because the experiment was inadequate for breaking the data down for different demographic groups, it is unknown whether our conclusions are generalizable beyond the population of undergraduate students or generalizable across all demographic groups within this population.

Paradigm

Each participant was seated in front of an Asus LCD screen with a resolution of 1,920 × 1,080 pixels that displayed experimental stimuli. A trackpad with an active area of 10 × 6.25 in. was placed in front of the monitor, and motor responses were made with the preferred hand using a stylus on the trackpad. Movements were recorded using Psychtoolbox routines within MATLAB 2018, run on a Windows 7 PC.

The experiment design is illustrated in Figure 1. On each trial, participants used the stylus on the trackpad to move the on-screen cursor from its center starting position to the displayed target. Each trial started with the presentation of a small circle ("cursor") at the center of the screen. Next, a target circle appeared 0.75–1.25 s later (stimulus onset asynchrony drawn from a uniform distribution). The target appeared at one of the four possible locations, which were the four diagonal directions relative to the central cursor (upper-left, upper-right, lower-left, and lower-right), centered at 60% of the distance to the corner of the screen. Participants moved the cursor to the target in order to complete a trial. They were provided with continuous feedback on cursor movements, which allowed them to correct their motion until they hit the target.

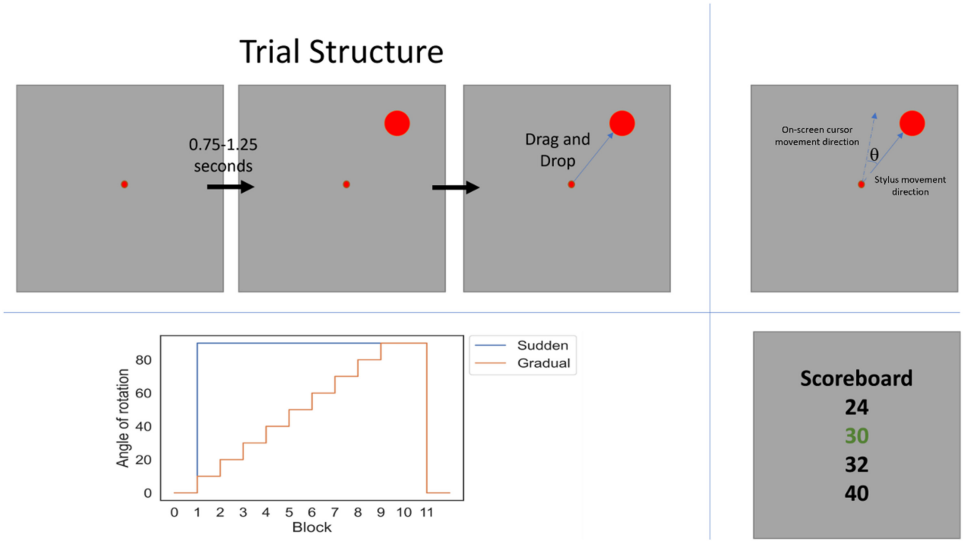
In some trials, participants lifted their pen before reaching the target. This tended to occur if they ran out of space on the trackpad as might be the case if they made large errors in their motion or if they failed to initiate the trial at the center of the trackpad. When this occurred, the particular trial was reset (i.e., the trial was repeated until the target was hit without lifting the pen). Once the target was reached, the cursor reset to the center of the screen, indicating the start of the next trial. To initiate each trial, the first point of contact of the stylus to the trackpad was mapped to the cursor position at the center of the screen. All subsequent on-screen cursor positions for the trial were displayed relative to this first point of contact at the start of the trial. Thus, by placing the pen somewhere on the trackpad, participants simultaneously started the trial and defined the center starting position, from which they made "center-out" movements toward the target. In this manner, participants did not have to return to the exact center of the trackpad to initiate each trial.

Trial resets were fairly common, and for some conditions, more than 10% of trials needed to be repeated one or more times before the participant was able to reach the target without lifting the pen. This rate of repeated trials was the direct consequence of movement error. Specifically, if participants moved in the wrong direction, it was more likely that they would run out of room on the trackpad,

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Figure 1

Trial Sequence, Gradual/Sudden Introduction of Rotation, and Speed/Accuracy Emphasis Manipulation Used for All Experiments



Note. Top left: Trial sequence for an example trial with an upper-right target: Each trial began with a small red (dark gray) circle in the center of the screen, which was the starting point for movements. After a variable delay of 1 s on average, a target circle appeared at one of four predefined locations on the screen (in one of four diagonal positions relative to the central dot: upper-right, upper-left, lower-left, or lower-right). Using a stylus, participants dragged the cursor from the center of the screen to the large target circle in a drag-and-drop motion. Top right: Visuomotor perturbation. The stylus-cursor mapping was perturbed such that the on-screen cursor direction was rotated in the counterclockwise direction by angle (θ) from the direction of stylus movement (the ideal movement direction for an error-free movement was thus rotated clockwise). Bottom left: Sudden/gradual manipulation: The sudden perturbation schedule presented 10 blocks of 90° rotation, whereas the gradual perturbation schedule gradually achieved a 90° rotation by implementing 10° increments across nine blocks with the final two blocks inducing 90° rotations. Each block included 64 trials. Bottom right: Speed/accuracy manipulation: The participant's score, shown in green, was calculated based on either speed or accuracy for all trials within a block. This feedback appeared on a scoreboard shown at the end of each block. The other scores in the scoreboard were fictitious and were randomly drawn from a normal distribution centered around the participant's score. See the online article for the color version of this figure.

in which case the trial would reset for another attempt. Figures 14 and 15 in the online supplemental materials report graphs for how often trial repeats occurred for each of the conditions during each block of rotation learning (these are reported for Experiments 1 and 3 but not Experiment 2 because Experiment 2 involved swiping movements for which there was no such thing as a failed trial). As seen in the graphs, the situations that produced the highest movement errors (e.g., the first block of trials with the sudden introduction of the rotation) were also the situations that produced the highest number of repeated trials. It is important to note that repeated attempts at the same trial entailed more opportunities to learn. Therefore, rather than remove the failed attempts from the analyses, the motion error measure for a particular trial included these failed attempts to hit the target. In other words, the motion error for each trial was averaged across all attempts to complete the trial (i.e., any initial failed attempt(s) at the trial, which likely involved a high degree of motion error, as well as the final successful attempt).

The experimental paradigm consisted of 12 blocks of 64 trials each, divided into three unequally sized phases (one block, 10 blocks, one block). Each block of 64 trials consisted of 16 reaching movements to each of the four targets. Trials in a block were pseudorandomly ordered with four sub-sequences of 16 trials, which each contained a random order of four reach movements to each of the four targets. After a short set of familiarization trials for which the experimenter was present to ensure successful understanding of the task, the first phase, "baseline," lasted for one block of 64 trials. During the baseline phase, the mapping between trackpad and on-screen directions was standard (unrotated). The second phase, "rotation," lasted for 10 blocks of 64 trials. The mapping was distorted by rotating the on-screen cursor by a maximum of 90° counterclockwise relative to the position of the stylus on the trackpad (see Figure 1 bottom left for details of perturbation schedule). The final phase, "washout," lasted for one block of 64 trials without rotation (identical to the baseline phase). The start of each block was self-paced—the participant indicated by a stylus click when they were ready to start a new block. Many prior studies have used ballistic shooting motions. However, such motions may tend to emphasize explicit aiming, and so we did not use them.

Participants were randomly divided into four groups of 15. Two of the groups were asked to make their movements as quickly as possible, while the other two were asked to make their movements as accurately as possible. To reinforce the speed/accuracy instruction, at the end of each block, participants were shown a scoreboard indicating their performance in that block relative to four other scores of

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hypothetical competitors. Block scores were calculated by adding up a participant's performance across all 64 trials within a block. For speed-emphasis participants, the score for each trial was calculated as the inverse of the time between the target's appearance and the time at which the target was reached. For accuracy emphasis participants, the score for each trial was the inverse of Euclidean distance in pixels between each sample of the participant's trajectory and the closest point on a straight line from the center to the target. In the scoreboard shown at the end of the block, the participant's total score (indicated by green text) was always shown at Positions 2–4. The other three scores were created by taking random draws from a normal distribution centered on the participant's score. If a participant's score happened to be the highest in the random draw of four scores, scores were resampled until there was at least one random score better than the participant's, thus giving the participant some incentive for continued improvement. Participants were not provided any information about where the additional scores on the scoreboard came from. The purpose of the scoreboard was to motivate participants to adhere to the speed/accuracy instructions.

All 60 participants adapted to a 90° counterclockwise rotation. In the rotation phase, one of the speed groups of participants and one of the accuracy groups of participants were assigned to receive a "sudden" rotation. These groups experienced the 90° rotation for all 10 blocks of the rotation phase. The other two groups were assigned to receive a "gradual" rotation by gradually building up to the 90° rotation in nine increments of 10° across nine blocks, with the tenth block holding steady at 90°.

Measurement of Motion Accuracy

Most studies in the visuomotor adaptation literature use initial angular error as the measure of motion accuracy. Panel A of Figure 2 shows a hypothetical movement trial to demonstrate how initial angular error is measured by finding the angle between the starting point and the target versus the starting point and the first point at which the movement crosses an invisible circle with a radius equal to 10% of the Euclidean distance to the target. Results using initial angular error are reported in the online supplemental materials for comparison to the literature and for comparison to the results reported below using an alternative measure of angular error. This alternative measure was developed because, compared to initial angular error, the alternative measure more accurately captured the true state of learning and proved to be more statistically reliable, particularly for the speed/accuracy emphasis manipulation.

Panel B of Figure 2 shows the movement made by a participant under accuracy emphasis. This participant began the motion by moving very slowly (the sampled data points are very close together), and it was likely that this participant was making many small adjustments to the movement direction. As a result, at the point when they reached 10% of the distance, their initial angular error was low, giving the false impression that they had learned the rotation. However, as they sped up during the later stages of their movement, it became clear that they had not yet learned the rotation. This behavior stands in stark contrast to the movement shown in Panel C of Figure 2. This participant was under speed emphasis. Owing to the rotation, they initially headed in the wrong direction but then corrected themself.

The crux of the problem with initial angular error is deciding the point in the movement trajectory at which to calculate the angle. For the movements shown in Panel B of Figure 2 (accuracy emphasis) versus Panel C of Figure 2 (speed emphasis), if the initial angle were based on 10% of the distance, this would indicate that the accuracy emphasis participant was perfectly accurate whereas the speed emphasis participant was wildly inaccurate. But if a different cutoff were used (e.g., 30% of the distance), this would suggest that both participants were equally inaccurate. Given that participants can speed up and slow down and make midcourse corrections based on visual feedback, and considering that the speed/accuracy emphasis manipulation would likely alter these behaviors, it was unclear how to define initial angular error in a manner that would consistently and faithfully capture motion error across conditions.

Rather than using initial angular error, a trial-averaged measure of motion error was used. Consider, for instance, the two angles shown in Panel A of Figure 2. Both show the difference between the direction to the target versus the direction to the next sampled position. To characterize motion error across the entire movement (as well as prior failed attempts at the trial), all such angles were averaged. Critically, this average was across absolute angles (e.g., if the average was across signed angles, the average angle in Panel B of Figure 2 would be zero considering the participant first veered in one direction and then overcorrected, veering in the opposition direction).

When comparing the results of this trial-averaged absolute angular error to initial angular error (see the online supplemental materials), the trial-averaged measure proved to be more reliable. In terms of statistical conclusions, the results from Experiment 1 were the same for both the trial-averaged measure and the traditional measure of initial angular error. For Experiment 2, neither measure produced reliable differences between the conditions for the washout period and the pattern of results during the learning period were similar. For Experiment 3, the trial-averaged measure replicated the results of Experiment 1, whereas initial angular error was too noisy to reach any conclusions. Most importantly, a comparison of the trial-by-trial plots reveals that the signal-to-noise ratio was considerably higher for the trial-averaged measure as compared to initial angular error. This greater reliability at the level of trials was important for the application of the state models, which were fit to the trial-by-trial data of each participant. To further reduce noise in the trial data, all analyses were performed on an across-trial smoothed version of this within-trial average angular error. Smoothing was calculated using a weighted average across trials within a block, with weights determined by a Gaussian kernel with an *SD* of two trials.

Model Fitting

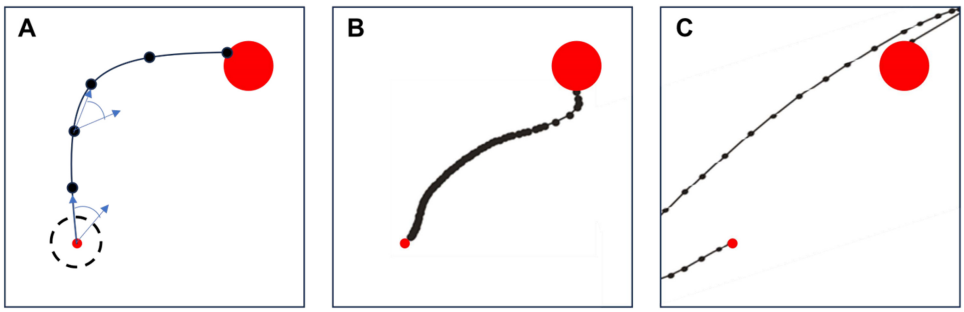
Both the single-state and dual-state models were fit to the data from the rotation phase, separately for each participant, to determine which participants required both learning systems for an adequate description of their learning. The baseline block was not included in model fitting because performance was highly accurate in this block and there was nothing to be learned (the actual rotation was zero, and the model estimate of rotation was initialized to be zero). The washout block was not included because it would bias model comparison in favor of the dual-state model considering that all participants were likely to become explicitly aware of the sudden removal of rotation.

To fit data, the model took on parameter values that were constant across the entire trial sequence of rotation learning; constant learning/retention rate parameters produce a learning curve of gradually

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Figure 2

Calculation of Angular Error for Different Kinds of Motion Trajectories When Under Accuracy Versus Speed Emphasis Instructions



Note. Panel A: A hypothetical motion trajectory with five sampled data points between the initial position (small red [dark gray] circle) and the first point of contact with the large red (dark gray) target circle. Angular error is the angle between a straight line to the target and the actual motion path (two such angles are shown). Prior studies reported initial angular error using an invisible threshold circle at 10% of the distance to the target based on the first sampled point that crosses the threshold, and results with this measure are reported in the online supplemental materials. Panel B: An actual trajectory on a particular trial for a participant under accuracy emphasis instructions. Initial angular error at 10% distance would incorrectly suggest that they had learned the rotation. Panel C: A trajectory for a participant under speed emphasis. Depending on the choice of distance for measuring initial angular error, comparison between Panel B and Panel C could either indicate a large difference in accuracy between these two trials (e.g., using a 10% threshold) or a small difference in accuracy (at 30% of the distance to the target, both trajectories would show a similar initial angular error). Instead of initial angular error, the results were analyzed in terms of angular error across the entire motion trajectory by taking the trial-averaged absolute angular error. See the online article for the color version of this figure.

decreasing angular error across trials. Thus, the model produced a sequence of predicted angular errors, simulating the performance of a hypothetical participant, where that hypothetical participant is exposed to a particular sequence of rotations determined by the specific condition of the experimental design (e.g., a fixed 90° rotation in the sudden condition, or rotations of increasing magnitude in the gradual condition). In theory, the model predictions are signed angular error (e.g., in theory, estimated rotation could be clockwise or counterclockwise from the actual rotation). Thus, in relating the model to the observed unsigned angular error data, the model predictions were converted to unsigned rotational error. However, in practice, this did not require any adjustment because the model was fit only to the rotation learning phase of the experiment and the predicted angular error was always positive during this phase. When the rotation is suddenly removed (Experiments 1 and 2) or reversed (Experiment 3), the model predicts negative signed angular error (an aftereffect), but the model was not fit to the aftereffects because doing so would bias model comparison in favor of the dual-state model. Nevertheless, the model parameters that best fit the rotation learning curves can be used to predict the magnitude of the aftereffect.

We first explain the single-state model because the dual-state model is an extension of the single-state model. For the single-state model, the error that dictates learning in the model is the difference between the rotation estimate based on the experience in the previous trial and the actual rotation of the current trial, as dictated by the experimental design sequence (Equation 1). Note that the observed data do not play a role; the observed data only matter in terms of optimizing the parameter values, which are fixed for the entire trial sequence. The first trial starts with an estimate of no rotation. The estimate of rotation, r_{est}, at the end of the current trial, t, is a weighted average (parameters A and B determining the weights) between the previous estimate of the rotation and the currently experienced error (Equation 2; Donchin et al., 2003; Smith et al., 2006).

$$\text{Error}\ (t) = R - r_{\text{est}}\ (t-1). \tag{1}$$

$$r_{\text{est}}\ (t) = A \times r_{\text{est}}(t-1) + B \times \text{error}\ (t). \tag{2}$$

Here, R is the rotation for the current trial as dictated by the experimental design, $r_{est}(t)$ is the estimate of rotation on trial t, the parameter A represents a "retention" factor, and the parameter B represents a learning rate.

We also fit the dual-state model to error data (Smith et al., 2006). The dual-state model postulates that there are two competing systems involved in successful adaptation to a rotated stylus-cursor mapping (McDougle & Taylor, 2019; McDougle et al., 2015; Smith et al., 2006; Taylor & Ivry, 2011) as described in the following equations.

$$\text{Error}\ (t) = R - r_{\text{est}}(t-1). \tag{3}$$

$$f_{\text{est}}\ (t) = A_{\text{f}} \times f_{\text{est}}\ (t-1) + B_{\text{f}} \times \text{error}\ (t). \tag{4}$$

$$s_{\text{est}}\ (t) = A_{\text{s}} \times s_{\text{est}}\ (t-1) + B_{\text{s}} \times \text{error}\ (t). \tag{5}$$

$$r_{\text{est}}\ (t) = f_{\text{est}}\ (t) + s_{\text{est}}\ (t). \tag{6}$$

$$0 < A_{\text{f}} < A_{\text{s}} < 1, 0 < B_{\text{s}} < B_{\text{f}} < 1. \tag{7}$$

The total estimate of rotation is modeled as the sum of two independent systems: A "fast" system (f) that learns quickly and forgets quickly and a "slow" system (s) that learns slowly but retains the learned mapping better than the fast system.

Data fitting was done in two stages: First, all 640 trials from the rotation phase were fit with three separate model comparison measures (chi-square, Akaike information criterion [AIC], and Bayesian

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information criterion [BIC]); Second, the data were fit using cross-validation that randomly divided the data into training and test sets. AIC and BIC can either be determined from least-squares error under an assumption that the residual error is normally distributed or they can be determined more directly when using a model that specifies the likelihood of the observed data. However, chi-square error requires a model that specifies the likelihood of the observed data. Thus, we built the assumption of normally distributed error into the single and dual-state models by assuming that the model equations specify the predicted average angular error, with normally distributed variation about the predicted average as dictated by a standard deviation parameter. This standard deviation parameter is mathematically equivalent to the typical application of least-squares/general linear modeling under the normal assumption, but, rather than dropping a degree of freedom for residual error, the noise/deviation parameter is explicitly included in the model. In this manner, the model not only fits the mean of the data but also fits trial-by-trial variability that is unrelated to the learning curve. Thus, to the extent that the model is able to capture the observed data, the standard deviation will be set to smaller values to increase the likelihood of the observed data. In theory, the normality assumption might be violated because unsigned error is bounded at zero (i.e., the observed data can never be negative, and yet the normal distribution is unbounded). However, the best-fitting standard deviation parameters were typically at least half the size of the predicted mean rotational error. In other words, the predicted mean error was usually more than 2 *SD*s above the lower bound of zero. Thus, the normality assumption was adequate in this case.

In the first stage, which fits all trials from rotation learning, a global best fit for each participant was found by running multiple instances of simplex minimization, with each instance using a different set of starting parameters determined by a small grid of parameter values. This was done separately for each model, and the best-fitting parameter values were used to generate three different model comparison measures (chi-square, AIC, and BIC). In the second stage, which used cross-validation, the trials for each participant were divided into a training set of 90% (576) trials picked at random with the remaining 10% (64) trials serving as the test set. One hundred different train-test sets were created for each participant and fit separately using the simplex minimization routine. For each cross-validation fit of the training data, the parameter values from the first stage were used as the starting point, thus ensuring that the parameter values were "in the ballpark" for each sample of training data. Model performance for the second stage was assessed by examining how well each model predicted, a priori, the 100 different held-out samples of test data for each participant, using the best-fit parameters from the corresponding training samples. These predictions for the held-out data were not assessed using point estimates of the angular errors but rather the likelihood of the observed held-out data according to the model with parameters that had been fit to the training data. In this way, the models were also assessed in terms of their ability to capture the reliability of the predictions (e.g., whether the error variance parameter was well matched to variability in the predicted data).

Transparency and Openness

The power analysis described above determined the sample size in the first experiment, and we note that this power to detect differences across conditions was slightly increased in the second experiment, which recruited 16 rather than 15 participants for each of the four conditions. The first experiment was administered using MATLAB Psychtoolbox (Brainard & Vision, 1997), whereas the second experiment was administered using PsychoPy (Peirce, 2007). All analyses were achieved using Python with the help of packages: statsmodels (Seabold & Perktold, 2010) for statistical analyses, scikit-learn (Pedregosa et al., 2011) for model fitting, and seaborn (Waskom, 2021) for plotting. The study design and analyses were not preregistered. All data and code for analyses are available publicly on GitHub (https://github.com/tejas-savalia/vma_behavioral).

Results

The online supplemental materials report full trial sequence graphs for initial motion direction signed angular error (e.g., clockwise vs. counterclockwise). As described in the Method section, initial angular error is particularly variable for these drag-and-drop motions. The main result from initiation/movement times is a manipulation check for the speed/accuracy emphasis manipulation, as demonstrated with the inferential statistics, reported below.

Performance After Learning

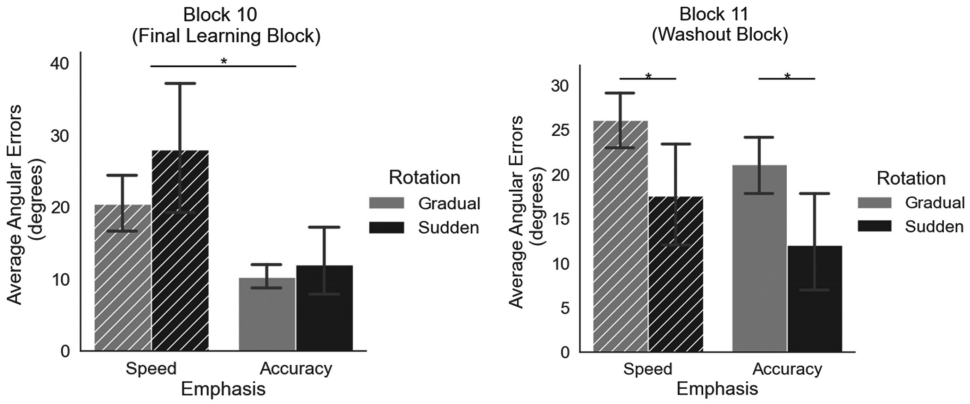
The first nine blocks of rotation learning were nonequivalent between the sudden and gradual groups because each of the nine blocks introduced an additional rotation change for the gradual condition but not the sudden condition. This nonequivalence made it difficult to compare the conditions during the first nine blocks of rotation learning, although, as reported below, the time course of learning can be compared by applying learning models to the data. To compare conditions after learning, we analyzed the 10th block (final block of rotation) and 11th block ("washout"), which were identical across conditions. The 10th block was a continuation of the 90° rotation for all groups, and the washout block was the sudden removal of the rotation for all groups. These analyses used a between-subjects 2×2 analysis of variance with the factors of type of rotation learning (sudden/gradual) and performance emphasis (speed/accuracy), with either average absolute angular error or median latency as the dependent measure.

As shown in the left panel of Figure 3, for the angular error during the final block of rotation learning, there was a main effect of performance emphasis, $F(1, 56) = 18.07$, $p < .001$, with lower error for the accuracy emphasis groups, demonstrating that accuracy emphasis instructions produced more accurate movements. There was no evidence for a main effect of the type of learning, that is, sudden versus gradual, $F(1, 56) = 1.54$, $p = .22$, or for an interaction between the two factors of performance emphasis and learning type, $F(1, 56) = 0.92$, $p = .32$. As shown in the right panel of Figure 3, the subsequent washout block produced very different results, with no support for an effect of performance emphasis, $F(1, 56) = 2.75$, $p = .102$, and yet there was a main effect for type of rotation, $F(1, 56) = 13.39$, $p < .001$, with greater error for the gradual rotation groups. This effect of gradual versus sudden rotation learning during the washout block replicates prior work (Kagerer et al., 1997). There was no reliable evidence that these two factors interacted during the washout block, $F(1, 56) = 0.017$, $p = .89$. Demonstrating that the elimination of the performance emphasis effect and the emergence of the type of rotation effect between Blocks 10 and 11 were both reliable, a three-way analysis of variance that also included block

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Figure 3

Accuracy After Learning in Experiment 1



Note. Left panel: During the final block of rotation learning, participants in the speed conditions made larger errors than participants in the accuracy conditions for both the gradual and sudden introduction of rotation, demonstrating that the speed/accuracy instructions affected behavior as expected. Right panel: During the washout block in which the rotation was removed, participants who had learned the rotation gradually produced larger errors than those who had learned the rotation suddenly. Error bars are 95% CIs. CIs = confidence intervals.
* $p < .05$.

(final rotation, 10, vs. washout, 11) revealed a significant interaction between block and performance emphasis, $F(1, 56) = 4.8$, $p = .03$, and a significant interaction between block and type of rotation, $F(1, 56) = 10.89$, $p = .001$.

To examine whether participants adhered to the speed versus accuracy instructions, median latency was examined separately for the time to initiate movement and movement time. When including all phases of the experiment, there was no reliable difference in median movement initiation time between the speed and accuracy groups, $t(58) = -0.85$, $p = .39$, whereas median movement times were affected by emphasis, with faster movements for the speed emphasis groups of participants, $t(58) = -2.22$, $p = .03$, confirming the expected effect of emphasis. Thus, in conjunction with the accuracy results reported above, there was a speed-accuracy tradeoff when comparing the speed emphasis groups to the accuracy emphasis groups.

Although movement times confirmed the effect of speed/accuracy emphasis, it might seem surprising that there was no effect for movement initiation times. However, this likely reflected an analysis that collapsed over all phases of the experiment. Supporting this claim, a more focused analysis of movement initiation times for the baseline and first rotation blocks revealed a main effect of speed/accuracy emphasis, $F(1, 112) = 5.37$, $p = .02$, with speed emphasis participants initiating movement more quickly. In addition, movement initiation times slowed down with the first rotation block, $F(1, 112) = 13.79$, $p < .001$, and this slow-down interacted with the type of rotation, $F(1, 112) = 7.27$, $p = .008$: Participants who experienced a sudden 90° rotation took longer to initiate movement than those in the gradual conditions. As seen in the online supplemental materials, the participants in the gradual conditions did not appear to slow down at all with the onset of rotation, as might be expected if they were not aware of the rotation.

In summary, accuracy versus speed emphasis affected speed and accuracy as expected during rotation learning, and yet, in the washout block, the main finding was lower accuracy following the gradual introduction of the rotation, regardless of speed/accuracy emphasis. This pattern implies that a longer lasting form of learning took place during the nine blocks of rotation learning for the gradual introduction of the rotation. Next, we turn to analyses of the time course of learning, using the single- and dual-state learning models to interpret the results.

Learning Curves: Are Two Learning Systems Needed?

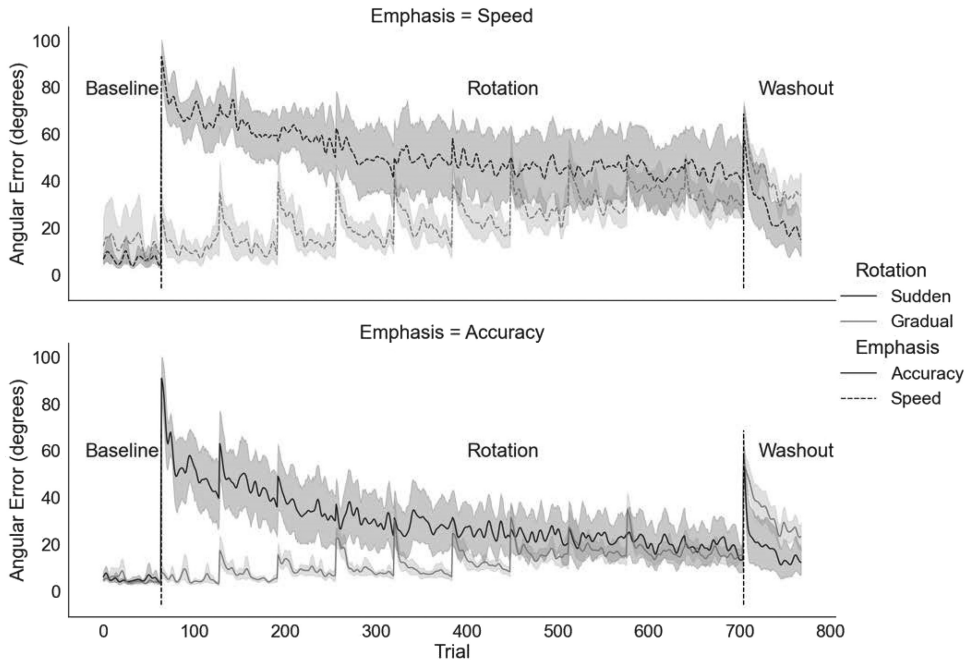
Our central question was whether both the knowledge-based, fast-to-learn system and the procedural, slow-to-learn system are necessary or whether in some cases behavior is better explained using only the slow-to-learn procedural system. The latter scenario would suggest that some conditions suppressed knowledge-based learning of the rotation. To address this question, we used formal model comparison, comparing the dual-state model to the single-state model as applied to the trial-by-trial data from the 10 blocks of rotation learning, as seen in Figure 4. Although the slow-to-learn, procedural system may be an obligatory component of motor learning, as indicated by prior studies (Morehead et al., 2011; Taylor et al., 2014), the fast-to-learn, knowledge-based system might be suppressed in some cases (i.e., conditions that favor the single-state model).

The main difference between the models is that the dual-state model can capture a learning curve that shows both very rapid improvements over just a few trials as well as much slower improvements over the course of hundreds of trials. Such patterns are readily apparent in the average results shown in Figure 4, for the sudden rotation conditions (black lines). In these conditions, after the 90° rotation is suddenly introduced at the 65th trial, the average angular error is approximately 90°, but then this error is rapidly reduced to approximately 50° (accuracy emphasis) or 70° (speed emphasis) over the first 10–20 trials of rotation learning. After this initial rapid error reduction, a very slow time course of additional error reduction ensues. Something similar is seen in the gradual accuracy condition (solid gray line, lower plot), in the first 10–20 trials of every new block (every set of 64 trials) of rotation learning,

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Figure 4

Average Angular Error for Each of the Four Groups of Participants as a Function of Trial in Experiment 1



Note. Darker lines indicate the groups that experienced a sudden introduction of the 90° rotation, whereas lighter lines indicate the groups that were introduced to the rotation gradually. Top panel: Results for speed emphasis groups (dotted lines). Bottom panel: Results for accuracy emphasis groups (solid lines). Shaded regions indicate the 95% CI. CI = confidence interval.

whenever a 10° rotational increment is introduced. It can perhaps be observed that, in the gradual speed condition (dotted gray line, upper plot), the period of error reduction in each block is more drawn out (i.e., the error reduction happens less sharply) than in the gradual accuracy condition (solid gray line, lower plot); this may provide an important clue to the involvement of the two systems in the different conditions. However, these descriptions are speculative and are based on average results, which can be misleading if there are different learning patterns for different participants (e.g., perhaps some participants learn quickly and others learn slowly, in which case the average pattern would show an initial rapid decrease followed by a long tail of additional learning as an artifact of averaging).

To test the nature of the learning curves, both models (dual state and single state) were fit separately to the learning curves of each participant to determine, for each participant, whether learning entailed both fast and slow learning (i.e., the dual-state model), or whether learning entailed only slow learning (i.e., the single-state model). The dual-state model has more free parameters that can be fine-tuned to fit data, allowing it to capture a wider range of behaviors. Thus, a head-to-head comparison between these two learning models requires some sort of penalization for the extra flexibility of the dual-state model (Pitt & Myung, 2002). Table 1 shows the results using four different penalization techniques. The values in Table 1 are the number (and proportion) of participants in each group whose behavior was better explained by the dual-state model; the remainder were better fit by the single-state model. For instance, where the table shows 0, this means that none of the participants in the corresponding group produced learning curves that were better explained by the dual-state model. The final column shows the observed p values from chi-square tests comparing the frequencies of observed dual-state selections. A $p < .05$ indicates that the number of participants for whom the dual-state model is required significantly differs across conditions. Providing a more qualitative sense of how well the models fit, the best fits to each participant were treated in the same manner as the real data to produce model average learning curves for each model in each condition as reported in Figures 16–21 and Tables 1 and 2 in the online supplemental materials, including report of R^2 metrics and summed AIC/BIC differences between the models. Cutting straight to the main result, all four methods of model comparison indicated that the dual-state model was not needed for the specific combination of

Table 1

Model Comparison Results for Experiment 1 Showing How Often the Dual-State Model Was Preferred

Comparison metric	Sudden speed	Sudden accuracy	Gradual speed	Gradual accuracy	p
χ^2	6 (40%)	12 (80%)	0 (0%)	9 (60%)	<.001
AIC	7 (46%)	13 (87%)	0 (0%)	9 (60%)	<.001
BIC	5 (33%)	11 (73%)	0 (0%)	6 (40%)	<.001
CrossVal	9 (60%)	13 (87%)	3 (20%)	10 (67%)	.0015

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion; CrossVal = cross-validation.

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speed emphasis instructions and a gradual introduction of the rotation. That is, for the "gradual speed" condition, the single-state model provided a sufficient explanation of behavior without requiring a second state.

Different Methods of Model Comparison

First, we compared the two models using chi-square tests. Because the single-state model is nested under the dual-state model, one can ask whether the single-state model provides a significantly worse fit considering that it is a special case of the dual-state model that removes two of the parameters. More precisely, there are two circumstances in which the dual-state model is the same as the single-state model: (a) if the slow-learning state learning parameter (B_s) is fixed at 0 (no learning) and hence the fast-learning state remains; or (b) if the fast- and slow-learning states of the dual model have the same rates of retention as the single-state model ($A_f = A_s = A$), and the learning rates of the slow- and fast-learning states add up to the learning rate of the single-state model ($B_f + B_s = B$). In the first case, the contribution of the slow-learning state is turned off (i.e., it always predicts a zero rotation), and the fast-learning state is the only state that learns the rotation. However, we emphasize that in this first case, the constraint that $0 < A_f < A_s < 1$, and $0 < B_s < B_f < 1$ (Equation 7) mandates that any learning loads onto the fast-learning state parameters, A_f and B_f. Therefore, such a result emerging in the dual-state model could, in fact, reflect that only the slow-learning state is in operation, with its parameters labeled as "fast-learning state" owing to model constraints. In the second case, the two states learn (and forget) at the same speed as the single-state model, and their individual estimates of rotation add up to be the same value as that of the single-state model.

For nested models, one test of whether the extra parameters of the more complicated model provide some benefit is based on the likelihood ratio test and the corresponding G^2 goodness-of-fit metric (Batchelder & Riefer, 1999); accordingly, we used a chi-square test with 2 *df* to assess whether the single-state model provided a significantly worse fit, separately for each participant. The top row of Table 1 shows the results of this nested model comparison, revealing that the extra free parameters of the dual-state model were not warranted for any participant in the gradual speed group. In contrast, nearly all of the participants (80%) in the sudden accuracy group produced learning curves that were better explained by the dual-state model. The sudden speed and gradual accuracy groups were more mixed, with a more moderate proportion of participants that were better explained by the dual-state model than the single-state model.

The chi-square test for nested models assumes that the parameters can take on any value, and yet this is not strictly true with the dual-state model because it imposes rank order constraints between the two states. For instance, it is not allowed to have one state with slower forgetting (A) but faster learning (B) as compared to the other state (the slow-learning state is constrained to always have both slower forgetting and slower learning, Equation 7). Thus, nested model comparison somewhat unfairly handicaps the dual-state model, which is not truly free to set its parameters to any value. There are a wide variety of techniques that can be applied to nonnested models, and Table 1 also reports model comparison using the AIC (Sakamoto et al., 1986) and the BIC (Vrieze, 2012). It is commonly understood that AIC, which is based on predicting data, tends to favor more flexible models, whereas BIC, which is based on identifying the more likely model, tends to favor less flexible models. Correspondingly, as seen in Table 1, the dual-state model did somewhat better on average when using AIC and somewhat worse on average when using BIC, as compared to the chi-square results. However, for both AIC and BIC, it was still the case that no participant in the gradual speed condition produced behavior that was better explained by the dual-state model.

AIC and BIC are parameter-counting measures and assume that each additional free parameter entails the same degree of extra flexibility. However, some parameters are likely to be more important than others (e.g., the inclusion of a second state might affect the goodness of fit only for trials occurring early in learning, whereas the error variance parameter affects all trials). Furthermore, as mentioned above, the dual-state model may be overly penalized on the basis of a simple parameter count because the rank order constraints between the two states (Equation 7) reduce the extra flexibility provided by the second state. To seek a fairer model comparison metric, we examined available techniques for nonnested models that avoid parameter-counting (for a review, see Pitt & Myung, 2002, and from among these, we opted to use cross-validation; Myung et al., 2005), which is relatively assumption free and easy to implement through a nonparametric sampling of the data. When using cross-validation, an overly flexible model will fit noise in the training data and produce a worse prediction for held-out data. As with the chi-square test, we asked whether the extra flexibility of the dual state was warranted. This framing of the question implies a default selection of the simpler model in the case of nondiagnostic data (Jang et al., 2011). Thus, the dual-state model was selected to be the winner for a particular participant if it performed better than the single-state model significantly more often, which corresponded to 59 of the 100 cross-validation predictions (Binomial test cutoff for $p = .05$, $n = 100$) when comparing the likelihood of the held-out test data based on parameters fit to the training data. As seen in the bottom row of Table 1, the dual-state model did somewhat better on average for cross-validation, as compared to the other methods of model comparison. However, only 20% of the participants in the gradual speed group were better fit by the dual-state model. Thus, even when using a technique that accurately addresses the flexibility of the models, the addition of the fast-to-learn, knowledge-based system was not often needed in the gradual speed condition.

Does the Single State Correspond to Procedural Learning?

In reaching conclusions from the model comparison results, we assumed that when a second learning state was not needed (i.e., when the dual-state model failed to fit better than the single-state model), the single state reflected the slow-to-learn, procedural learning system. This interpretation was based on prior evidence that the procedural system is an obligatory component of learning (Izawa & Shadmehr, 2011; Mazzoni & Krakauer, 2006). Nevertheless, this assumption can be checked directly by examining the best-fitting learning and retention rate parameter values. If only one learning state was needed, did this single state correspond to a relatively slow time course of improvement? The time course of improvement for a state reflects both the learning parameter and the retention parameter. For instance, a high learning parameter would cause learning on every trial, but if the retention parameter were low, then the learning from the previous trial would be immediately forgotten, and there would be little improvement. The rate of accuracy

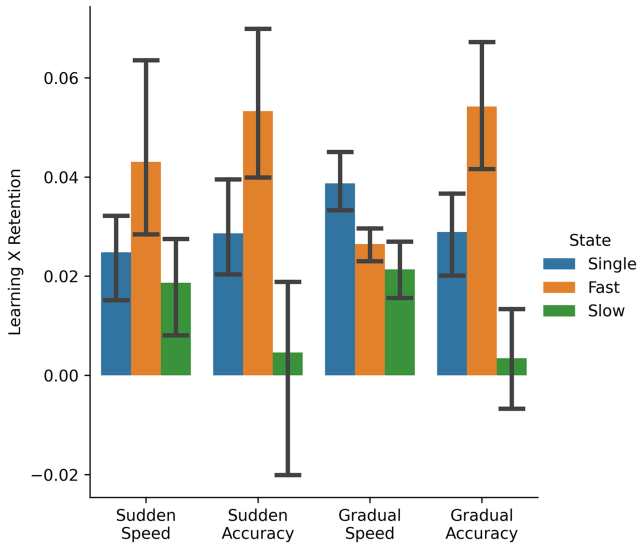
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improvement is related to the multiplication of the learning and retention parameters (e.g., it can be algebraically proven that this relationship is directly proportional to the change from the second to the third step of learning), and so we used this multiplication term in our analysis, as a proxy for the rate of improvement. The results are shown in Figure 5, which plots side by side the rate of improvement for the single-state model, the fast-learning state, and the slow-learning state separately for each of the four conditions.

As Figure 5 shows, the rate of improvement for the three states takes on a qualitatively different pattern (i.e., the relative heights of the three colored bars) for the gradual speed condition. For the other three conditions, the fast-learning state has a higher rate of improvement than that of the single-state model, $t(14) = 4.27$, $p < .001$. In contrast, for the gradual speed condition, the rate of improvement for the fast-learning state is significantly lower than that of the single state, $t(44) = 3.37$, $p = .002$. Furthermore, in the gradual speed condition, the rate of improvement for the fast- and slow-learning states are approximately equal and approximately half the value of the rate of improvement for the single-state model. This is expected in a situation, described earlier, where the dual-state model mimics the single-state model (e.g., when $B_f + B_s = B$ and $A_f = A_s = A$). This corroborates the model comparison results that favor the single state in this condition. In addition, the rate of improvement for the fast-learning state in the gradual speed condition was much slower than the fast-learning state in the other three conditions, as would be the case if the learning curve in the gradual speed condition required only a single state with a slow rate of learning.

Figure 5

The Multiplication of the Best-Fitting Learning Rate (B) and Retention Rate (A) Parameter Values, as a Proxy for the Rate of Accuracy Improvement, for Each of the Three States (the Single State, the Fast-Learning State, and the Slow-Learning State) as Applied to the Rotation Learning Phase of Experiment 1



Note. As seen in the figure, only for the gradual speed condition does the fast-learning state have a lower rate of improvement than the single state. In this case, the fast- and slow-learning states add up to approximately the same rate of improvement as the single state, as expected in a situation that does not require two states. Furthermore, the rate of improvement for the fast-learning state in the gradual speed condition is similar to that of the slow-learning state for the other conditions, as expected if the gradual speed condition involves only slow, procedural learning. Error bars are 95% CIs after applying the correction suggested by Cousineau (2005). CIs = confidence intervals. See the online article for the color version of this figure.

Experiment 2: Removal of Online Visual Feedback During Motion

Experiment 1 identified circumstances that produced procedural learning without knowledge-based learning (the gradual speed condition). This conclusion builds on prior studies demonstrating that the gradual introduction of a rotation can suppress explicit learning, as measured with aiming judgments after learning (Albert et al., 2022; Yin & Wei, 2020). More specifically, Experiment 1 demonstrates that the gradual introduction of the rotation does not always suppress knowledge-based learning; this suppression did not occur in the gradual-accuracy condition (prior studies used a speed emphasis). Next, we ask if there are other circumstances for which the gradual introduction of the rotation fails to suppress knowledge-based learning. Continuous visual feedback was provided during motion based on prior work finding that this leads to a larger contribution of procedural learning (Heuer & Hegele, 2008; Izawa & Shadmehr, 2011; Taylor & Ivry, 2011). In the case of the gradual introduction of rotation, this continuous visual feedback may be crucial for blocking awareness of each additional 10° rotation. In Experiment 1, participants could see when their motion first deviated from the desired direction, and they may have automatically adjusted their motion, thus failing to realize that the mapping between the trackpad and on-screen direction was modified. However, if there is no online visual feedback during motion, participants will not adjust midstream and will simply miss the target by a full 10°. Because these 10° errors will occur in a systematic direction, the rotation may become noticeable even with speed emphasis, allowing the knowledge-based system to contribute to learning. To test this hypothesis, Experiment 2 was identical to Experiment 1 except that visual feedback was removed during motion except at the end point. Instead, participants were given only final outcome feedback after their motion was completed. If the removal of online feedback elicits knowledge-based learning, the gradual speed condition should become similar to the other conditions. All experimental methods were the same as Experiment 1, except for the removal of online visual feedback, and other minor differences as noted. All modeling procedures were the same as for Experiment 1.

Method

Participants

Sixty-four individuals participated, with 16 randomly assigned to each of the four conditions. This study was conducted in 2021.

Paradigm

The experimental task was built using the PsychoPy platform (Peirce, 2007). In each trial, participants were shown a circular band formed by two concentric white circles centered on the center of the screen. A trial started with the appearance of a red circular cursor at the center of the screen along with a red circular target within

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the white-edged band. Participants were asked to make ballistic "shooting" movements to hit the target using the stylus. Once the movement was initiated, the dot at the center of the screen disappeared. Next, once the heretofore invisible movement crossed the inner boundary of the circular band, the dot reappeared at the corresponding location between the inner and outer circular bands, providing visual end-point feedback the target remained on the screen for the entire duration of the trial.

Results

Because these were shooting movements rather than drag-and-drop movements, the magnitude of movement error was computed as the angle formed by the lines joining the start point and the target and the line joining the start point and the actual endpoint.

The online supplemental materials report full trial sequence graphs for signed angular error (e.g., clockwise vs. counterclockwise), movement initiation time analyses, model average learning curves, and additional model fit metrics.

Performance After Learning

As seen in Figure 6, there was a main effect of the speed/accuracy emphasis manipulation after the nine blocks of rotation learning, with smaller angular errors for the accuracy groups, $F(1, 60) = 8.6$, $p = .004$. However, in the subsequent washout block in which the rotation was removed, there were no apparent differences between the conditions. Unlike prior results (Kagerer et al., 1997), and unlike Experiment 1, there was no reliable evidence that participants who received a gradual introduction to the rotation made larger errors than those who learned the rotation suddenly, $F(1, 60) = 0.07$, $p = .78$. This failure to find a larger washout effect for the gradual conditions is expected if the elimination of visual feedback during motion resulted in knowledge-based learning for all conditions.

To examine whether participants adhered to the speed versus accuracy instructions, median movement latency was examined. When including all phases of the experiment, there was a main effect of emphasis, with faster movements for the speed emphasis groups of participants in the final learning block, $F(1, 60) = 32.99$, $p < .001$, confirming the expected effect of emphasis. Thus, in conjunction with the accuracy results reported above, there was a speed-accuracy tradeoff when comparing the speed emphasis groups to the accuracy emphasis groups.

Model Comparison of Learning Curves

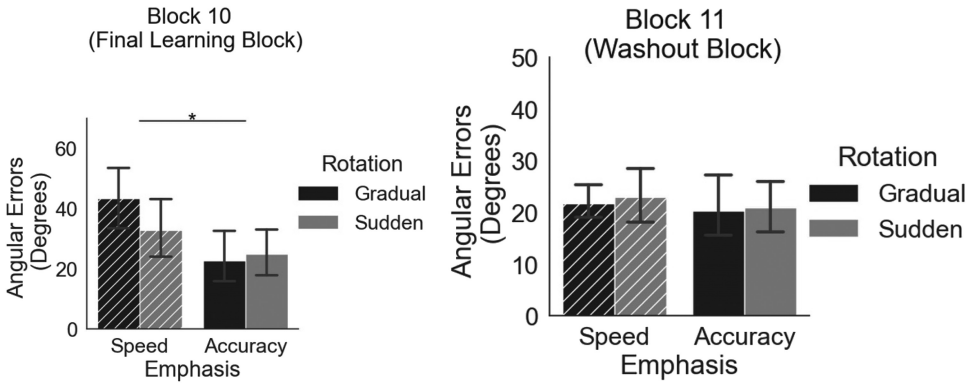
Each model was applied to the trial-by-trial rotation learning data shown in Figure 7, using the same fitting routines and model comparison metrics as Experiment 1.

As seen in the last column of Table 2 (chi-square test of frequencies across conditions), there were no reliable differences between the different conditions in terms of how often each model was preferred when the models were compared with BIC or with cross-validation, bearing in mind that cross-validation is likely the most accurate method for comparing the models. When using chi-square, AIC, or BIC to compare the models, the single-state model was almost always preferred, regardless of condition, but with modest differences across conditions for chi-square and AIC. In contrast, when using cross-validation, more than half of the participants in each condition were better explained by the dual-state model. As outlined above, the parameter-counting metrics (AIC, BIC, and chi-square) may unfairly penalize the dual-state model, whereas the cross-validation metric is likely to appropriately take account of true model flexibility. The cross-validation results might therefore be considered more reliable in this case of conflicting outcomes, suggesting that two states are operating in many participants. Most importantly, however, it is no longer the case that the gradual speed condition is reliably different from the other conditions, in terms of model comparison.

As seen in Figure 8, the rate of improvement measure (given by the learning parameter multiplied by the retention parameter) shows a very similar pattern across all conditions, especially regarding the

Figure 6

Accuracy After Learning in Experiment 2

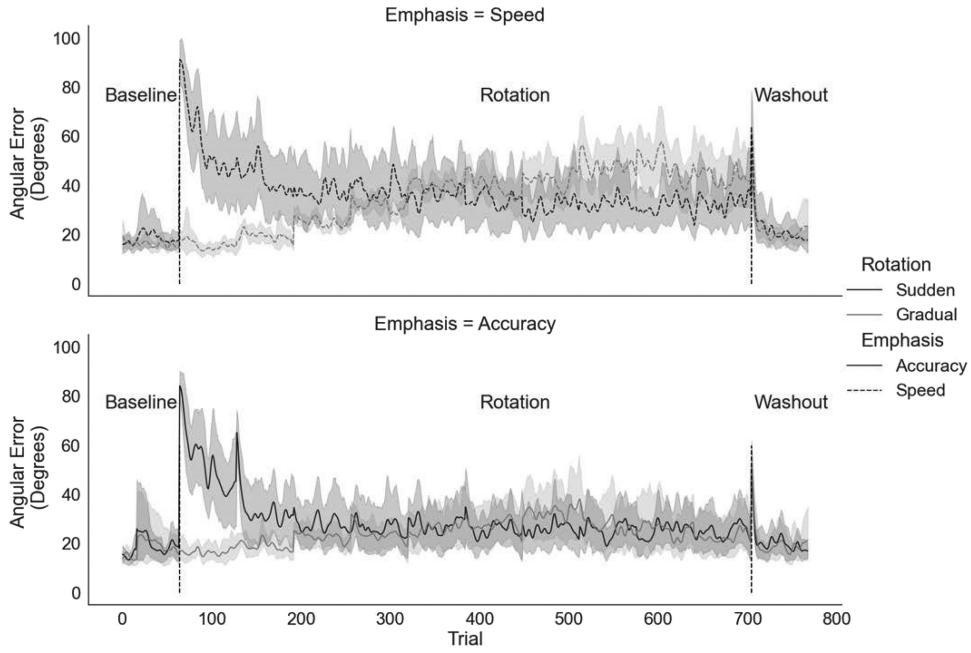


Note. Left panel: During the final block of rotation, participants in the speed conditions made larger errors than participants in the accuracy conditions for both the gradual and sudden introduction of rotation, demonstrating that the speed/accuracy instructions affected behavior as expected. Right panel: Unlike in Experiment 1, there were no apparent differences between conditions during the washout block. Error bars are 95% CIs. CIs = confidence intervals.
* $p < .05$.

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Figure 7

Average Absolute Angular Motion Direction Error for Each of the Four Groups of Participants as a Function of Trial for Experiment 2



Note. Darker lines indicate the groups that experienced a sudden introduction of the 90° rotation, whereas lighter lines indicate the groups that were introduced to the rotation gradually. Top panel: Results for speed emphasis groups (dotted lines). Bottom panel: Results for accuracy emphasis groups (solid lines). Shaded regions indicate the 95% CI. CI = confidence interval.

comparison of the single-state and fast-learning state parameters. That is, in all conditions, there is no apparent difference between the rate of improvement for the single-state model and the fast-learning state of the dual-state model. Moreover, the rate of improvement for the slow-learning state is generally close to zero, whereas the fast-learning state's rate of improvement mimics that of the single-state model. As discussed above, one way in which the dual-state model can mimic the single-state model is when the slow-learning state is completely switched off, such as by setting either learning to zero or retention to zero. However, the (cross-validation) model comparison results indicate that two states are needed in a substantial number of participants. Thus, the best explanation for these results seems to be that both states are needed and that learning in this paradigm is primarily accomplished by the fast, explicit, knowledge-based state but with a small amount of slower, implicit, procedural learning in some or all participants. This dominance of the fast-learning state likely explains the equivalence of the rate of improvement for the single-state model and the fast-learning state of the dual-state model (see Figure 8).

Finally, we note that the rate of improvement metric in Experiment 2 shows substantially lower values overall than in Experiment 1. This is not surprising considering that in the absence of continuous feedback, Experiment 2 is much more of a guessing game for participants as they determine which direction to move to hit the target (errors were generally much higher and more variable). Without visual feedback on the position of the cursor during the hand movement, the opportunity for learning of either kind is much reduced. In Experiment 1, there was not only feedback regarding initial movement directions but there was ample opportunity to learn from mid-course corrections made during the extended time period of the drag-and-drop motion.

Table 2

Model Comparison Results for Experiment 2 Showing How Often the Dual-State Model Was Preferred

Comparison metric	Sudden speed	Sudden accuracy	Gradual speed	Gradual accuracy	*p*
χ^2	3 (19%)	2 (13%)	0 (0%)	0 (0%)	.05
AIC	4 (25%)	3 (19%)	0 (0%)	0 (0%)	.01
BIC	2 (13%)	2 (13%)	0 (0%)	0 (0%)	.12
CrossVal	10 (63%)	11 (69%)	9 (56%)	11 (69%)	.84

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion; CrossVal = cross-validation.

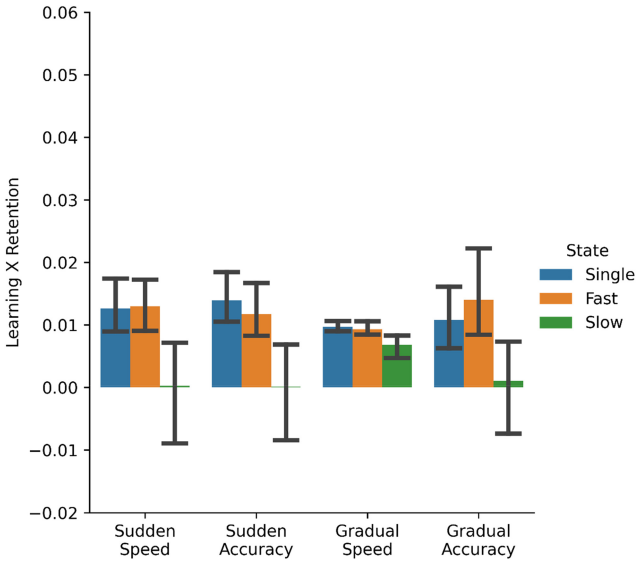
Experiment 2 Discussion

This follow-up study investigated the impact of removing continuous feedback on the previously reported suppression of knowledge-based learning under a gradual introduction of rotation. Unlike all previous studies comparing the sudden/gradual conditions, there were no apparent differences in the rotation aftereffect during the washout phase of the experiment. In addition, there was no difference in how often the dual-state model was selected between the experimental conditions. Collectively, these results suggest that knowledge-based learning played a role in all conditions, regardless

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Figure 8

The Multiplication of the Best-Fitting Learning Rate and Retention Rate Parameter Values Shows the Rate of Accuracy Improvement for Each of the Three States (the Single State, the Fast State, and the Slow State) in Experiment 2



Note. All conditions show similar patterns where the rate of improvement for the single-state model is very similar to the fast state of the dual-state model. The slow state contributes minimally to the overall improvement, and learning is mostly through the fast state when continuous feedback is not provided. Error bars are 95% CIs after applying the correction suggested by Cousineau (2005). CIs = confidence intervals. See the online article for the color version of this figure.

of whether the rotation was introduced gradually/suddenly and regardless of speed/accuracy emphasis.

Why did removal of continuous feedback lead to knowledge-based learning despite the gradual introduction of rotation? It might be that the lack of continuous feedback weakened implicit procedural learning. In the absence of strong procedural learning, explicit knowledge-based learning could play an important role even with a small increment in rotation (Albert et al., 2022). In Experiment 1, the procedural system could learn from the small 10° change in rotation owing to mid-course corrections. However, because participants made these small mid-course corrections, they easily hit the target and may have failed to realize that a small rotation occurred. But in the absence of this continuous feedback, performance is worse (compare the left panels of Figures 3 and 6), and even a small rotation may be revealed to participants by their systematic missing of the target. Thus, because the only feedback was the endpoint, which consistently revealed to participants when they missed the target in the same systematic way, the gradual introduction of rotation failed to suppress knowledge-based learning regardless of speed/accuracy emphasis.

Experiment 3: Assessing Relearning and Directly Measuring Explicit Aiming

Experiments 1 and 2 build on prior studies reporting the suppression of knowledge-based learning with the gradual introduction of rotation (Albert et al., 2022; Yin & Wei, 2020). Specifically, Experiment 1 demonstrated that this suppression of knowledge-based learning was smaller, or absent, under accuracy emphasis, and Experiment 2 demonstrated that this suppression of knowledge-based learning does not occur in the absence of continuous motion feedback. However, there are some important differences between Experiments 1 and 2 on the one hand and prior studies investigating suppression of knowledge-based learning during gradual introduction of a rotation on the other. Experiments 1 and 2 used an extreme 90° rotation, whereas prior work used a more modest 30° or 60° rotation. In addition, Experiments 1 and 2 examined washout effects, whereas prior studies examined relearning with the reintroduction of the rotation. Finally, and perhaps most importantly, the prior studies assessed knowledge-based learning with an explicit aiming measure whereas Experiments 1 and 2 used formal model comparison applied to learning curves. Model comparison indicated that the fast-learning system was not needed to explain the learning curve for the gradual introduction of rotation under speed emphasis. But does the fast-learning system correspond to explicit aiming? Experiment 3 directly tests this question.

Experiment 3 replicated the interaction between speed/accuracy emphasis and sudden/gradual introduction of rotation in a drag-and-drop continuous feedback task with three key changes relative to Experiment 1: (a) The maximum rotation was 60° rather than 90° (with increments of 10° in the gradual conditions, rotation learning entailed seven blocks, with the final two learning blocks at 60°); (b) After rotation learning, participants were asked to explicitly report their aiming directions on a circular wheel, similar to Taylor et al. (2014); and (c). Following these explicit aiming judgments, participants unlearned the rotation by experiencing one block with a 60° rotation in the opposite direction. Finally, participants were given two blocks of relearning of the original 60° rotation.

If the suppression of the fast-learning system in Experiment 1 reflects suppression of explicit aiming, we predict that participants in the gradual speed condition should be less aware of their movement direction as measured by explicit aiming and that they should have the greatest retention of the original rotation when relearning that rotation, reflecting the slow and incomplete unlearning of the original rotation during the single opposite-rotation block of trials. Explicit awareness of motion direction was assessed by asking participants to (a) explicitly report the aiming direction (i.e., a clock hand number) they had been using when under rotation and (b) make a swipe movement without visual feedback immediately after providing the explicit aim report. In theory, the swipe movements should match the explicit aim report (their instructions were to swipe at the clock hand number they had just entered). However, if the rotation was learned implicitly, they might unknowingly swipe in a different direction than the explicit aiming direction that was reported just a second ago (e.g., because the learned rotation was counterclockwise, they might unknowingly swipe with a clockwise offset during their attempt to hit the just-reported clock hand number). In contrast, if the rotation was learned explicitly, such that there is no carryover of the previously learned rotation, their swipe movements should accurately match their explicit aim reports.

Method

Participants

Sixty-two individuals participated, with 16 participants each assigned to the sudden-speed and gradual-accuracy conditions

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whereas 15 were randomly assigned to sudden-accuracy and gradual-speed conditions. This study was conducted in Spring 2023. Forty-two participants were between 18 and 20 years old, 14 were between 21 and 25, one was between 26 and 30, and five chose not to provide age information. Forty-five of the participants identified as female, 14 identified as male, one identified as nonbinary, and one declined to answer.

Paradigm

The experimental task was built using the PsychoPy platform (Peirce, 2007). The experimental procedures were the same as Experiment 1 except as noted. There were five phases of the experiment across 12 blocks, with a total of 720 movement trials. After the baseline phase, the rotation learning phase contained seven blocks rather than 11 blocks, as needed for the gradual learning of the 60° counterclockwise rotation in increments of 10°, with the last two blocks at full rotation (participants in the sudden conditions experienced the full rotation for all seven blocks).

In the "aiming" phase, which followed the seven blocks of rotation learning, participants were asked to report their aiming direction to hit the target in light of the rotation they had just learned (see Figure 9). For each of the 16 aiming trials, a target appeared in one of the same four locations seen during the rotation phase, and participants first reported their aiming direction by typing in a number from a circular wheel around the target and then immediately swiped in the direction of their aim without any feedback (neither continuous motion feedback nor endpoint feedback). Once participants covered 50% of the total distance required to hit the target, they were informed that their swipe was registered and the next aiming trial started.

Following the aiming phase, participants returned to the task of performing drag-and-drop center-out reaching movements in two further phases. In the first of these phases, the "unlearning" phase, participants performed these movements for one block (64 trials) while under a clockwise 60° rotation (i.e., the opposite rotation). Finally, in the second of these phases, the "relearning" phase, to test the prediction that the implicit system should be slow to unlearn, and thus promote greater retention of the rotation, participants returned to reaching movements under the original 60° counterclockwise rotation for two blocks (64 trials per block).

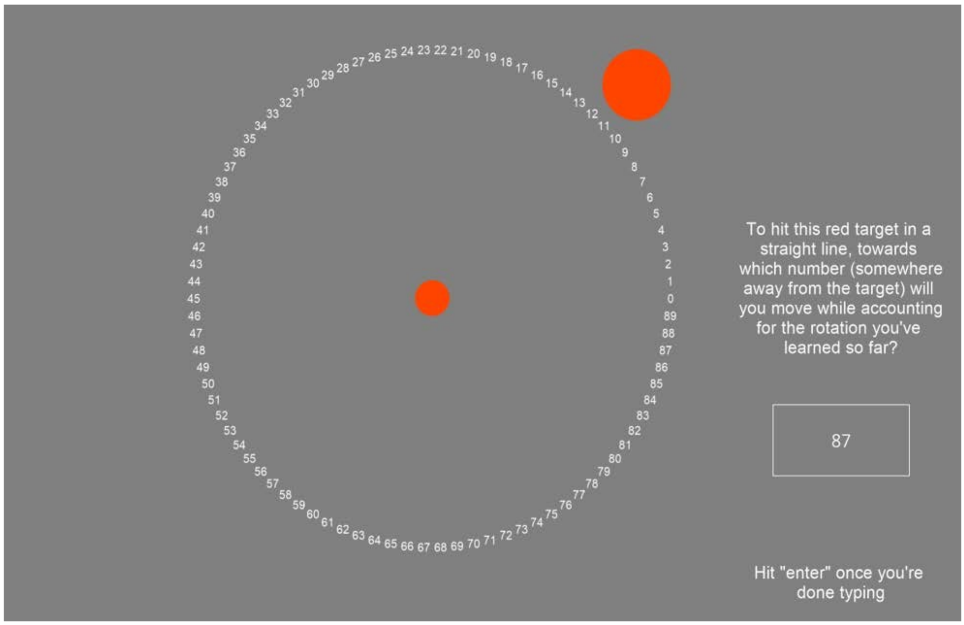
Results

As with Experiment 1, the online supplemental materials report additional analyses of signed initial angular error, average signed error, movement initiation times, total movement times, model average learning curves, and additional model fit metrics.

Performance After Learning

As seen in the left panel of Figure 10, there was a main effect of the speed/accuracy emphasis manipulation after the seven blocks of rotation learning, with smaller errors for the accuracy groups, $F(1, 58) = 9.84$, $p = .002$. Additionally, there was a main effect of rotation type, with participants in the sudden condition making more accurate motions than participants in the gradual condition, $F(1, 58) = 7.01$, $p = .01$. To assess retention of the rotation after a

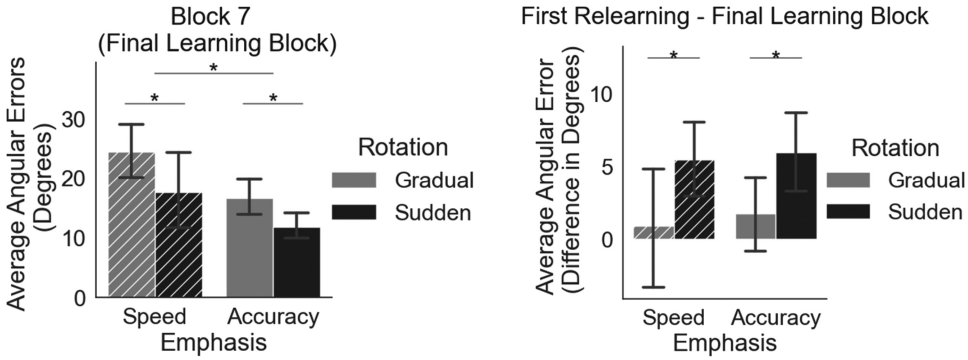
Figure 9
Example Aiming Phase Trial in Experiment 3



Note. Participants were first asked to report the direction they think they should move in order to hit the target. After recording their aim report, participants were asked to perform a swiping motion in the direction they just reported. No feedback was provided during this swiping motion. See the online article for the color version of this figure.

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Figure 10
Accuracy After Learning in Experiment 3



Note. Left panel: During the final block of rotation, participants in the speed conditions made larger errors than participants in the accuracy conditions for both the gradual and sudden introduction of rotation, demonstrating that the speed/accuracy instructions affected behavior as expected. Right panel: Participants in the gradual conditions performed as well during relearning of the rotation (i.e., good retention; aka, minimal unlearning) as they did at the end of initial rotation learning, whereas participants in the sudden conditions did significantly worse, suggesting they had partially forgotten the rotation. Error bars are 95% CIs. CIs = confidence intervals.
* $p < .05$.

single block of counterrotation learning, errors in the first block of the final relearning phase were compared to the final block of the initial learning phase. In line with the larger washout effects for the gradual conditions of Experiment 1, participants who learned the rotation gradually appeared to retain information about the original rotation for a longer period of time: Their relearning accuracy was nearly the same as at the end of initial learning (i.e., they did not forget the rotation), whereas participants in the sudden groups did significantly worse with relearning, $F(1, 58) = 7.45$, $p = .008$. Also, similar to the washout results from Experiment 1, relearning did not appear to show a reliable difference between the speed and accuracy emphasis groups, $F(1, 58) = 0.18$, $p = .66$.

To examine whether participants adhered to the speed versus accuracy instructions, median latency was examined separately for the time to initiate movement and movement time. When including all phases of the experiment, there was a significant difference in median movement initiation time between the speed and accuracy groups, $F(1, 58) = 20.32$, $p < .001$, with speed participants initiating movements faster than accuracy participants. There no main effect of rotation type, with participants in sudden groups slower to initiate their movements than participants in the gradual groups, $F(1, 58) = 0.75$, $p = .38$. There was also a speed/accuracy emphasis effect in terms of median movement times, $F(1, 58) = 10.03$, $p = .002$, in the expected direction. Thus, in conjunction with the accuracy results reported above, there was a speed-accuracy tradeoff when comparing the speed emphasis groups to the accuracy emphasis groups.

Participants in the gradual conditions appeared to better retain rotation information than participants in the sudden conditions, as expected if learning in the gradual conditions was more procedural. In other words, forgetting of the procedural information during the single block of counterrotation learning was not complete, resulting in smaller differences between relearning and the final block of initial rotation learning. However, there was no difference between speed versus accuracy emphasis in terms of this relearning measure.

We assessed knowledge-based and procedural learning with model comparison of learning curves (see below), similar to Experiments 1 and 2. In addition, the question of whether knowledge-based learning is explicit and procedural learning is implicit is addressed by comparing participants' explicit report of aiming directions to the swipe motions that were made after each explicit aim report. These swipe motions were supposed to be in the direction of the explicitly reported clock hand number. However, if learning is implicit, participants might unknowingly swipe in a different direction than the explicitly reported clock hand number.

As reported in Figure 10 in the online supplemental materials, there were no differences between the conditions in terms of the explicit aiming clock hand numbers. More to the point, these aiming reports were not reliably different than zero in terms of the difference between the reported explicit aiming direction and the direction of the on-screen target. On average, participants tended to report the clock hand number that was directly in line with the on-screen target. However, close examination of the individual differences suggests confusion regarding the explicit aiming task, with some participants reporting aiming directions that were clockwise, as was appropriate to counteract the previously learned counterclockwise rotation, and other participants reporting aiming directions that were counterclockwise, as if they took the instructions to mean that they should indicate the nature of the rotation, rather than the manner in which they sought to counteract the rotation. In light of this confusion, these explicit aiming numbers were not particularly useful on their own. Nevertheless, these explicit aiming judgments were informative in comparison to the swipe motions made immediately after typing each aiming direction.

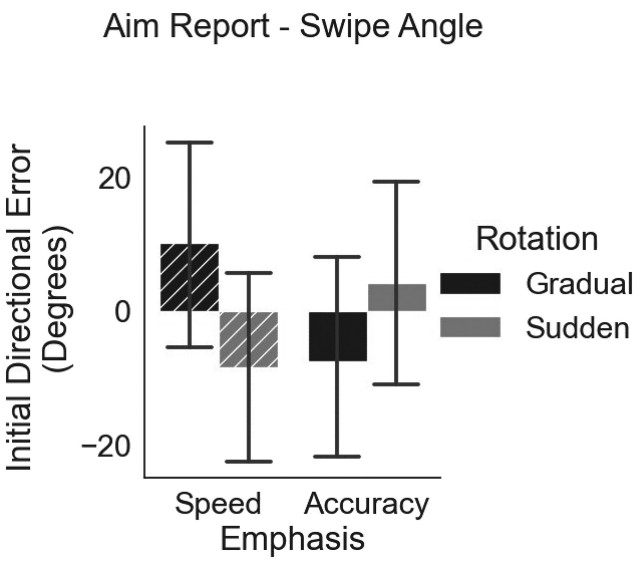
If the rotation was implicitly learned, participants might have retained some of that learning and might unknowingly swipe in an offset direction during their attempt to indicate the just-reported clock hand number. We therefore examined the direction and magnitude of the swipe error relative to the explicit clock hand report. Because the swipes were made without visual feedback, the signed

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angle of the initial swipe direction was used for this analysis (i.e., the direction of motion as indicated by crossing the 10% threshold). As seen in Figure 11, for this comparison between explicitly reported aiming direction versus nonfeedback swipe motion direction, there was no significant main effect of speed/accuracy instructions, $F(1, 58) = 0.01$, $p = .90$, or type of rotation, $F(1, 58) = 0.24$, $p = .62$. However, there was a significant interaction between these two factors, $F(1, 58) = 4.52$, $p = .03$, although the swipe errors were not reliably different from zero for any of the conditions. As seen in the figure, the effect of the gradual/sudden manipulation was more pronounced under speed emphasis and was, if anything, slightly reversed under accuracy emphasis. Thus, participants who had initially learned the rotation gradually under speed emphasis swiped somewhat more clockwise than their just-reported aiming direction, as compared to the participants in the other conditions. In their attempt to swipe at the just-reported clock hand number, participants in this condition unknowingly swiped somewhat clockwise, as if their motor system expected the ongoing existence of a counterclockwise rotation. The direction of this interaction is in agreement with the modeling of the learning curves (Experiments 1 and 3), the washout results (Experiment 1), and relearning results (Experiment 3). Because this finding reflected a difference from explicit aiming direction (i.e., participants' explicit aiming was not affected in the same way by the initial learning phase), this provides support for the conclusion that explicit knowledge-based learning was suppressed for the gradual introduction of the rotation, but only under speed emphasis instructions.

Figure 11

Aim Report Relative to Swiping Motion Direction for Experiment 3



Note. Participants made swipe motions that were supposed to be toward the just-entered explicit aiming clock hand numbers (see Figure 9), although if the rotation had been learned implicitly, they might unknowingly swipe in a slightly different direction in their attempt to indicate the reported clock hand number. Values above zero indicate that the swipe direction was clockwise relative to the explicitly reported aiming direction, as would be the case if the swipe motions were unknowingly made to counteract the previously learned counterclockwise rotation. Any effects of swiping in the wrong direction were subtle and none of these average values were significantly different from zero. However, there was a significant interaction between the sudden/gradual manipulation and the speed/accuracy manipulation ($p = .03$). All error bars are 95% CIs. CIs = confidence intervals.

Model Comparison of Learning Curves

Similar to the first two experiments, both models were applied to the rotation phase of the smoothed trial-by-trial average angular error data, as shown in Figure 12. The other phases were omitted because they would bias the results in favor of the dual-state model.

As seen in the last column of Table 3 (chi-square test of frequencies across conditions), all model comparison metrics indicate a significant difference between the number of participants' data best explained by the dual-state model. Specifically, the dual-state model offers the least advantage in explaining the data from participants in the gradual speed condition.

As seen in Figure 13, the pattern across conditions for the best-fitting parameter values was largely similar to Experiment 1, except that the gradual-accuracy condition was somewhat more similar to the gradual-speed condition. The best-fitting parameters for the sudden group indicated a faster rate of improvement (i.e., the multiplication of the learning and retention parameters) for the fast state of the dual-state model as compared to the single state, $t(29) = 5.83$, $p < .001$, whereas there were no reliable differences between these states for the gradual groups, $t(29) = -0.9$, $p = .36$. Unlike Experiment 1, there was no reliable difference between the rate of improvement for the fast state of the gradual-speed condition versus the gradual-accuracy condition, $t(29) = -0.9$, $p = .36$. This is perhaps not surprising considering that the magnitude of rotation was smaller in Experiment 3 as compared to Experiment 1 and perhaps the participants in the gradual-accuracy condition were less aware of the rotation, meaning that their behavior became more similar to that of the participants in the gradual-speed condition.

Experiment 3 Discussion

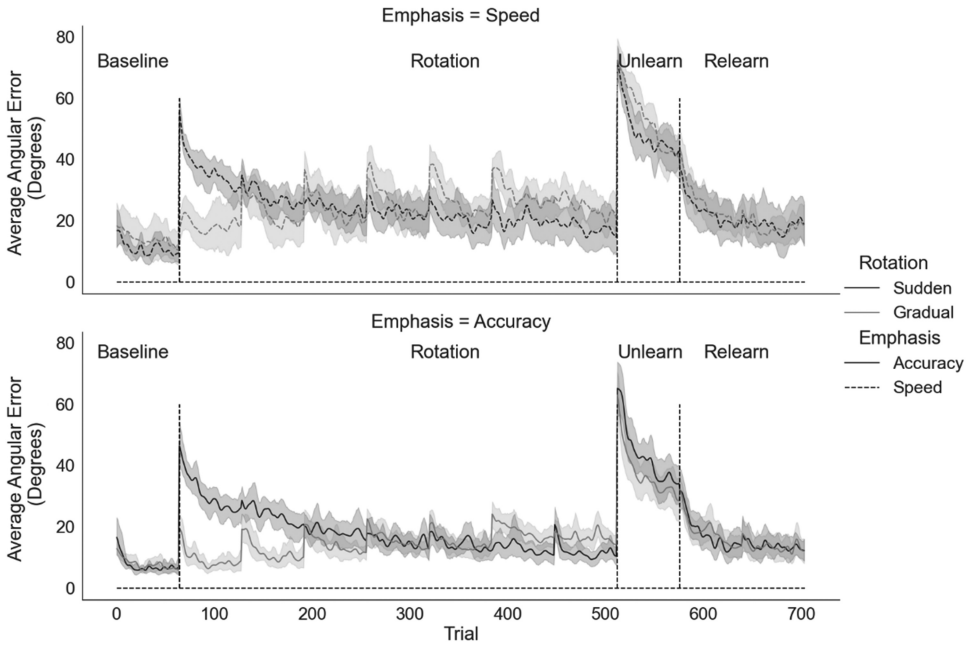
Experiment 3 replicated the main results of Experiment 1 in terms of model comparison, as applied to the rotation learning phase of the experiment. As with Experiment 1, model comparison indicated that a single, slow-to-learn state was sufficient to capture the learning curve in the case of a gradually introduced rotation when under instructions that emphasized speed over accuracy. In addition, Experiment 3 confirmed the longer lasting effects of the gradually learned rotation, as measured by relearning of the rotation after unlearning the rotation through a block of trials with the opposite rotation—because unlearning block was brief, the slow-to-learn procedural system was also slow to forget, resulting in easier subsequent relearning.

At first blush, these results appear inconsistent with prior work demonstrating greater savings for explicit learning system as compared to the implicit system (Avraham et al., 2021; Morehead et al., 2015). However, this highlights the distinction between "savings" versus "retention." In a savings paradigm, the initially learned information is completely unlearned after an extensive washout period, followed by assessment of relearning (i.e., savings is faster relearning of fully unlearned information). In contrast, the current experiment used a single block of counterrotation learning that was too brief to support complete unlearning of the original rotation within the slow-to-learn and slow-to-unlearn implicit system. Thus, the reported relearning experiment assessed retention (i.e., information that was

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Figure 12

Average Angular Error for Each of the Four Groups of Participants as a Function of Trial for Experiment 3



Note. Darker lines indicate the groups that experienced a sudden introduction of the 60° rotation, whereas lighter lines indicate the groups that were introduced to the rotation gradually. Top panel: Results for speed groups (dashed lines). Bottom panel: Results for accuracy emphasis groups. Shaded regions indicate the 95% CI. CI = confidence interval.

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not completely unlearned) rather than savings. This lingering retention of the original rotation within the implicit system might explain other reports that the implicit system can support relearning (Coltman et al., 2019; Yin & Wei, 2020).

Experiment 3 also provides evidence that participants were less aware of the manner in which they had adapted to the rotation in the conditions that promoted slow learning; this supports the conclusion that the slow-learning system is more implicit. The evidence is as follows. Because participants were apparently confused as to whether the explicit aiming judgments were supposed to indicate the direction of their correction versus the direction of the rotation, the explicit aiming judgments were not informative in their own right. However, immediately after giving each explicit aiming judgment, participants made a swiping motion at the explicit aiming clock hand number they had just entered. There was a significant interaction between sudden/gradual and speed/accuracy manipulations for these swipe directions as compared to the just-entered clock hand numbers. Furthermore, the interaction was in the same direction as the modeling results and washout/relearning results from Experiments 1 and 3, indicating that the conditions for which there was less fast learning were also the conditions for which participants unknowingly swiped as if to counteract the no-longer-present rotation. In brief, they were not aware that they were swiping in the wrong direction. In combination with the modeling results, this result indicates that participants in the gradual speed condition were less aware of the manner in which they had learned the rotation, suggesting that explicit aiming was suppressed for this condition. The finding that the gradual introduction of rotation can suppress explicit strategic aiming replicates prior work (Albert et al., 2022; Yin & Wei, 2020), but, in addition, Experiment 3 demonstrates that this primarily occurs with speed emphasis rather than accuracy emphasis.

Table 3

Model Comparison Results for Experiment 3 Showing How Often the Dual-State Model Was Preferred

Comparison metric	Sudden speed	Sudden accuracy	Gradual speed	Gradual accuracy	*p*
χ^2	16 (100%)	15 (100%)	1 (7%)	6 (40%)	<.001
AIC	16 (100%)	15 (100%)	1 (7%)	6 (40%)	<.001
BIC	16 (100%)	15 (100%)	0 (0%)	2 (13%)	<.001
CrossVal	15 (94%)	15 (100%)	3 (20%)	8 (53%)	<.001

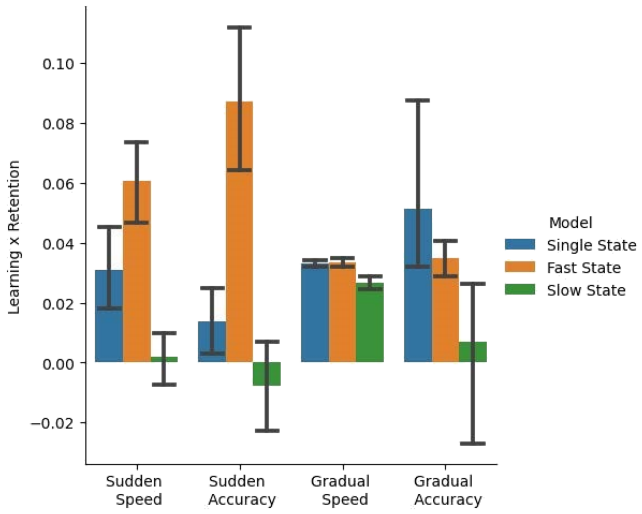
Note. AIC = Akaike information criterion; BIC = Bayesian information criterion; CrossVal = cross-validation.

General Discussion

Prior studies found that visuomotor adaptation occurs automatically to a change (e.g., a rotation) in the mapping between the required motor direction and the on-screen motion of visual targets in a reaching task (Izawa & Shadmehr, 2011; Kagerer et al., 1997; McDougle & Taylor, 2019; McDougle et al., 2015). Such implicit, procedural learning appears to be obligatory (Heuer & Hegele, 2008; Heuer et al., 2011) and slowly learned (McDougle et al., 2015; Smith et al., 2006), resulting in slow extinction of the

Figure 13

The Multiplication of the Best-Fitting Learning Rate (B) and Retention Rate (A) Parameter Values, as a Proxy for the Rate of Accuracy Improvement, for Each of the Three States (the Single State, the Fast-Learning State, and the Slow-Learning State) as Applied to the Rotation Learning Phase of Experiment 3



Note. The general pattern is similar to that of Experiment 1, except that both of the gradual conditions show some evidence that the fast-learning system was suppressed (for both of these conditions, the rate of improvement when fitting the single-state model was comparable to the rate of improvement for the fast-learning system when fitting the dual-state model). Error bars are 95% CIs after applying the correction suggested by Cousineau (2005). CIs = confidence intervals. See the online article for the color version of this figure.

newly learned visuomotor mapping when it is subsequently removed. In contrast, explicit, knowledge-based learning can produce accurate motions after just a few trials and can be quickly modified when the rotation is eliminated (McDougle et al., 2015; Smith et al., 2006). Thus, theories that include both slow learning and fast learning on every trial provide a good explanation of visuomotor adaptation behavior (Smith et al., 2006; Taylor & Ivry, 2011).

Despite the success of dual-state models and theories that include both learning systems, recent results indicate that explicit, knowledge-based learning (e.g., strategic aiming) can be suppressed when the rotation is gradually introduced (Albert et al., 2022; Yin & Wei, 2020), although the extent of this suppression was not quantified, and the conditions required for suppression were not fully explored. The current study used model comparison to ask whether this suppression was absolute, in which case only the implicit procedural system would be engaged. The current study also places important caveats on prior results, providing a more complete account of the conditions that can suppress explicit knowledge-based learning. Experiments 1 and 3 indicate that this suppression occurs to a lesser extent when instructions emphasize accuracy rather than speed. Experiment 2 found that this suppression requires on-screen continuous movement feedback. In the absence of continuous feedback, all conditions appeared to reflect knowledge-based learning. Collectively, these results indicate that knowledge-based learning can be fully suppressed (i.e., behavior is best explained by implicit procedural adaptation without any contribution from explicit knowledge-based learning) when the visuomotor perturbation is small (gradually introduced), in situations where there is immediate visual feedback for the motion trajectory, and where the emphasis is to move quickly. Thus, when participants were encouraged to "leap before you look," learning appeared to reflect only the slow, procedural learning system.

Our use of visual feedback in combination with accuracy emphasis instructions is relatively unique in the visuomotor adaptation literature. This combination resulted in slow, careful movements in which participants made online course corrections (e.g., see Figure 2B). Such situations likely occur in real life (e.g., slow and error-prone progress when cutting one's own hair in the mirror for the first time), and our results suggest that this situation selectively enhances explicit knowledge-based learning even if the visual perturbation is minor. However, under speed emphasis with the same minor change of the visuomotor mapping (e.g., a video game with a joystick controller held at a slight angle), explicit knowledge-based learning is suppressed.

Because our experiments involved both slow, careful movements and fast, inaccurate movements in different conditions, rather than using initial angular direction error as others have done, we adopted an error measure that averaged across the entire motion trajectory (see also Kagerer et al., 1997; Stillman et al., 2018) to consistently assess motion accuracy despite different motion strategies. The more traditional measure of initial angular direction error produced similar qualitative results to this trajectory-averaged measure (see the online supplemental materials), but initial angular direction proved to be less reliable (lower signal-to-noise ratio), particularly at the level of the individual trial data, which is the level at which the learning curve models were applied.

Our conclusions regarding the extent of suppression of knowledge-based learning in different conditions were primarily based on fitting both single and dual-state models to the initial learning curves, asking whether learning was better described by a single learning process or whether there was both rapid initial learning as well as a slower tail of learning. However, this approach could be questioned considering that the dual-state model was developed for its ability to capture unlearning and relearning rather than just initial learning (Smith et al., 2006). We did not include unlearning/relearning in the model fits because doing so would bias the results in favor of the dual-state model (these subsequent phases involve the sudden removal or sudden reintroduction of rotation, which would release knowledge-based learning from suppression). Nevertheless, examination of the unlearning/relearning phases of the experiment provides converging support for the modeling results. Model comparison indicated that a single, slow-learning system was sufficient to describe rotation learning behavior in the gradual-speed conditions of Experiments 1 and 3. Correspondingly, this condition also exhibited a greater aftereffect during the unlearning washout phase (Experiment 1) and greater retention of the rotation during relearning (Experiment 3), as would be expected if initial learning was primarily based on the slow-to-learn yet slow-to-forget implicit, procedural learning system.

Fast versus slow learning does not necessarily imply explicit versus implicit learning (Ruttle et al., 2021). To address this

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concern, Experiment 3 tested for the presence of explicit learning by collecting explicit aiming judgments in terms of clock hand numbers as well as swiping motions made at the just-given clock hand numbers. Supporting the claim that the slow-learning system is more implicit, the swiping motions systematically differed from the explicit aiming judgments in a manner that was similar to the modeling results and washout/relearning results: The conditions that tipped things toward greater single-system slow learning were also the conditions that produced more erroneous swiping motions as if to adjust for the previously learned rotation (even though there was no rotation at this point in the experiment and the instructions were to swipe at the just-reported clock hand number). This is not to say that participants were unaware that there was a rotation in the initial learning phase. During rotation learning, they could clearly see which direction their hands were moving to hit the target. Instead, this indicates that when the rotation was learned gradually with visual feedback, under instructions to move quickly, participants were less aware of the manner in which their motor system had adapted to this novel visuomotor mapping.

Model-Based and Model-Free Learning

Implicit, procedural, slow learning versus explicit, knowledge-based, fast learning in visuomotor adaptation is closely related to different kinds of computational reinforcement learning models termed "model-free" versus "model-based," respectively (Daw et al., 2005; Savalia et al., 2016). Put simply, model-free is trial-and-error learning-by-doing, whereas model-based involves mental simulation of possible outcomes before choosing between action alternatives. As might be expected, model-free learning is very slow and inflexible whereas model-based learning more quickly adapts to changes in the environment. Furthermore, because model-based learning requires some form of mental simulation to calculate the subsequent outcomes that may arise from different actions (e.g., different movement directions), it follows that an emphasis on speedy action rather than accuracy may promote greater use of model-free learning. Our results mesh with this literature, suggesting that a model-free system that slowly learns inflexible representations can dominate the learning of a gradual motor adaptation under conditions of speed emphasis.

Analogous to the dual-state model, it has recently been proposed that model-free and model-based learning can operate in a coordinated fashion, perhaps with model-based learning serving as the offline teacher of the model-free system (Gershman et al., 2014; Kool et al., 2016). When applying the dual-state model to learning curves that appear to require both states, the fast-learning state rapidly learns the rotation, explaining the initial rapid reduction in error. But after many learning trials, the slow-learning state eventually learns the rotation and is able produce fast, accurate movements without any help from the fast-learning state. Once this happens, the fast-learning state loses its knowledge of the rotation because there is no longer enough movement error to maintain its estimate of rotation considering that the fast state is also fast to forget the rotation. Thus, there is a transition of information regarding the rotation from the fast- to the slow-learning state. This transition of information is similar to the proposal that the model-based system can serve as the teacher of the model-free system. Our results indicate that the fast-learning, knowledge-based system is not always needed to explain behavior. By analogy, this suggests that some learning situations (e.g., a need for fast decisions during gradual change of the environment) may short-circuit explicit, model-based learning. However, even when model-based learning is unavailable, the model-free system continues to learn through direct experience.

Conclusions

In this article, we explored the role of procedural versus knowledge-based, explicit learning in adaptation to novel motor mappings. While standard models of motor learning suggest that humans need both procedural and knowledge-based components to successfully adapt to new motor mappings, we show that when the new motor mappings are introduced gradually, under time pressure, and with online feedback, participants may be able to adapt without using knowledge-based learning.

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Received November 22, 2022
Revision received March 7, 2024
Accepted March 14, 2024 ■

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