# Influence of Task Complexity on Visuomotor Adaptation

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**Abstract**

Recent work has shown that visuomotor adaptation is supported by both implicit recalibration, which appears to be highly constrained, and explicit strategies which seem more flexible and capable of delivering rapid performance gains. However, explicit strategies appear to have strict capacity constraints, bearing remarkable similarity to the limits observed with spatial working memory, which could limit their usefulness in more complex learning problems. Here, we sought to determine the ability of both explicit strategies and implicit recalibration to overcome a complex set of visuomotor perturbations. We find that implicit recalibration is unable to track multiple perturbations, in line with prior findings. In contrast, explicit strategies are effective when task complexity is within the capacity of working memory. These findings highlight the constraints that working memory imposes on visuomotor adaptation and suggest that motor skill learning may be limited by the demands placed on working memory.

**Keywords:** motor adaptation; task complexity; explicit strategies; implicit recalibration

## Introduction

Motor control is essential to daily life. Humans are capable of not only learning sophisticated motor skills but also rapidly adapting to external perturbations (Krakauer et al., 2019; Shadmehr et al., 2010; Wolpert & Ghahramani, 2000). While this process of sensorimotor adaptation has traditionally been attributed to a unitary implicit process (Jordan & Rumelhart, 1992; Mazzoni & Krakauer, 2006; Squire, 2004), recent work has revealed that explicit, cognitive strategies play a larger role than previously thought (see McDougle et al., 2016). An increasing number of studies leveraging a classic visuomotor rotation task, which induces an angular mismatch between hand movements and visual feedback, have found that the implicit process is highly inflexible: it is insensitive to perturbation magnitude, often saturates below full adaptation, is context independent, and is incapable of consolidating multiple perturbations (Bond & Taylor, 2015; Morehead et al., 2017; Schween et al., 2019; Taylor et al., 2014; Wilterson & Taylor, 2021). Conversely, explicit strategies have been shown to be remarkably flexible to task demands, are seemingly essential for rapidly improving performance, and may even account for the lion's share of adaptation (Bond & Taylor, 2015, 2017; Fernandez-Ruiz et al., 2011; Haith et al., 2015; Taylor & Ivry, 2011; Wilterson & Taylor, 2021). Given that both processes play important – and distinct – roles in visuomotor adaptation, there has been considerable interest in further characterizing their capacities and constraints.

Prior research has highlighted two classes of explicit strategies that can be deployed in visuomotor rotation tasks: algorithmic and retrieval strategies (Georgopoulos et al., 1989; Georgopoulos & Massey, 1987; Georgopoulos & Pellizzer, 1995; Pellizzer & Georgopoulos, 1993). Algorithmic strategies (e.g., visuomotor mental rotation), which involve mentally simulating aiming solutions to counteract the rotation, seem to be highly flexible (McDougle & Taylor, 2019; Stransky et al., 2010) but come with a cost: preparation time linearly increases with rotation magnitude (Bhat & Sanes, 1998; McDougle & Taylor, 2019; Shepard & Metzler, 1971), indicative of higher computational demands. Alternatively, participants could avoid this computational cost by retrieving a previously successful solution from working memory (Anguera et al., 2010; Fresco et al., 2023; Haith & Krakauer, 2018; Velazquez-Vargas & Taylor, 2024b). However, retrieval strategies have been shown to be subject to working memory capacity constraints: participants may be able to cache strategies when task complexity is low, but this may break down as complexity increases (Velazquez-Vargas & Taylor, 2024b).

Such constraints call into question the true usefulness of strategies for visuomotor adaptation beyond relatively simple learning situations – e.g., successful adaptation has only been observed in studies demanding one or a few strategies (McDougle & Taylor, 2019; Velazquez-Vargas & Taylor, 2024b). Furthermore, implicit recalibration processes have been shown to not be amenable to more complex situations, especially when the consolidation of multiple visuomotor mappings is needed (e.g., dual adaptation), except in tightly controlled situations (Avraham et al., 2022; Wang et al., 2024). Naturalistic environments, on the other hand, often require learning complex and context-dependent visuomotor mappings. For instance, in order to effectively play a video game, players must learn and adaptively utilize a number of unique sensorimotor transformations. Little prior research has examined how visuomotor adaptation might unfold, especially with respect to explicit and implicit processes, in such situations, or indeed more generally explored how variables such as task complexity influence such learning. This is a critical gap in the literature – while it is likely that even in complex settings, implicit recalibration may interact with explicit strategies, prior studies have not examined this in situations involving multiple sets of perturbations. Furthermore, as described above, prior research has shown that explicit retrieval strategies are critically constrained by task complexity, due to their dependence on working memory



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capacity. However, no prior study has parametrically examined the manner in which these constraints play out in visuomotor tasks as a function of complexity.

Here, we examine the ability of explicit strategies, and implicit recalibration, to handle a complex learning task; one that goes beyond previous studies and would be a step closer to the challenges inherent in naturalistic environments. Specifically, participants were tasked with simultaneously adapting to either four or eight visuomotor rotations, each linked to a specific target. Crucially, the contribution of explicit strategies was dissociated from implicit recalibration by asking participants to report their intended aim before reaching. Thus, by comparing learning in situations in which the number of solutions was within or beyond working memory capacity, we sought to highlight how working memory capacity might constrain participants' ability to effectively adapt to complex perturbations.

## Experiment 1

Participants performed a center-out visuomotor rotation task, attempting to bring a visually displayed cursor to a virtual target by making planar shooting movements with their right hand (Bond & Taylor, 2017; Krakauer et al., 2000; Wilterson & Taylor, 2021). Prior to reaching on each trial, participants used their left hand to tap the surface of a horizontally mounted touch-sensitive monitor to indicate their intended reach location (i.e., explicit aim report). We ran two conditions: participants in the 4x4 condition trained to bring the cursor to four target locations, each of which was randomly associated with a different rotation magnitude; participants in the 8x8 condition were presented with eight unique target-rotation pairings. This design allowed us to examine participants' ability to simultaneously adapt to multiple perturbations, and dissociate explicit and implicit contributions to adaptation.

### Method

**Participants** 34 undergraduates [10 men, 24 women; mean age 19.4 years (SD 1.20)] completed this experiment. Three participants were excluded for failure to follow task instructions. The final sample included 15 participants in the 4x4 condition and 16 participants in the 8x8 condition. Participants received course credit or $10/hr of participation. All participants had normal or corrected-to-normal vision and were right-handed. The protocol was approved by IRBs at Hamilton College and Princeton University, and all participants provided written informed consent.

**Experimental Apparatus** Visual stimuli were displayed on a horizontally mounted 21.5-in. touch-sensitive monitor (60 Hz refresh rate), which also recorded participants' explicit aim reports (Fig. 1A). Participants' reaches were sampled at 60 Hz by a digitizing pen as they slid their hand across the surface of a tablet mounted 25 cm below the monitor. The game was controlled by a Dell desktop PC running custom MATLAB and Psychtoolbox software (Brainard, 1997).

**Procedure** Participants began each trial with their right hand at the center of the visual workspace (Fig. 1B). To aid them in finding the center, a white circle expanded or contracted with the radial distance of their hand position from the center of the tablet. Once their hand was 10mm from the center of the start area (0.3cm radius), a white circular cursor (0.15cm radius) appeared. After holding this position for 300ms, a circular orange target (0.25cm radius) appeared 7cm from the start position, along with a blue "aiming" ring (7cm radius) centered on the start location. Participants were instructed to report their intended aim location by tapping the aiming ring with their left hand. Once a touch was recorded, the target turned from orange to green, the aiming ring disappeared, and participants could reach with their right hand. If they attempted to reach before reporting aim location, "Remember to report aim" was displayed and the trial was restarted.

Participants were instructed to make a reaching movement by "shooting" their right hand through the target. If the reach duration exceeded 600ms, participants received a "too slow" auditory warning. Only end-point feedback, presented for 500ms as a cursor position on the virtual ring (7 cm), was provided for each reach (except for Baseline-Online, which provided continuous online feedback). For all other trials, the white cursor was removed when the participant's hand exceeded a radial distance of 0.4 cm from the start position and reappeared when their hand passed the virtual ring. If the final cursor position overlapped the target, participants heard a pleasant "ding" sound; otherwise, they heard an unpleasant "buzz." After feedback, the display was cleared, and participants were guided back to the start position.

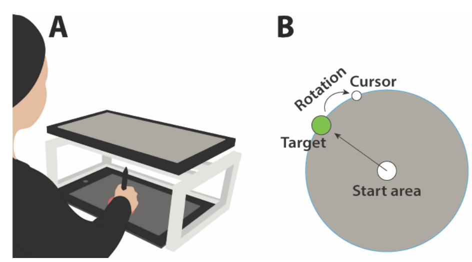


Fig 1. Visuomotor rotation task. (A) Experimental apparatus. (B) Schematic showing a typical trial.

**Conditions** All conditions followed the same six-block structure. In the first block, participants were provided with veridical, continuous online feedback for 16 trials (Baseline-Online block) to familiarize them with the task. In the second block, online feedback was replaced by endpoint feedback for 32 trials (Baseline-Endpoint block). In the third block, participants were provided with aim reporting instructions as outlined above and continued to receive endpoint feedback for 8 trials (Baseline-Report block). A clockwise/counter clockwise rotation (counterbalanced across participants) was introduced in the fourth block of 320 trials (Rotation block). In the fifth block of 40 trials, visual feedback of the cursor was removed (No-Feedback block), and participants were provided with specific aiming instructions: "Please aim directly to the green target. You no longer need to report where you are aiming on each trial, and you also won't see any cursor feedback for a while. Instead of hearing a "ding"

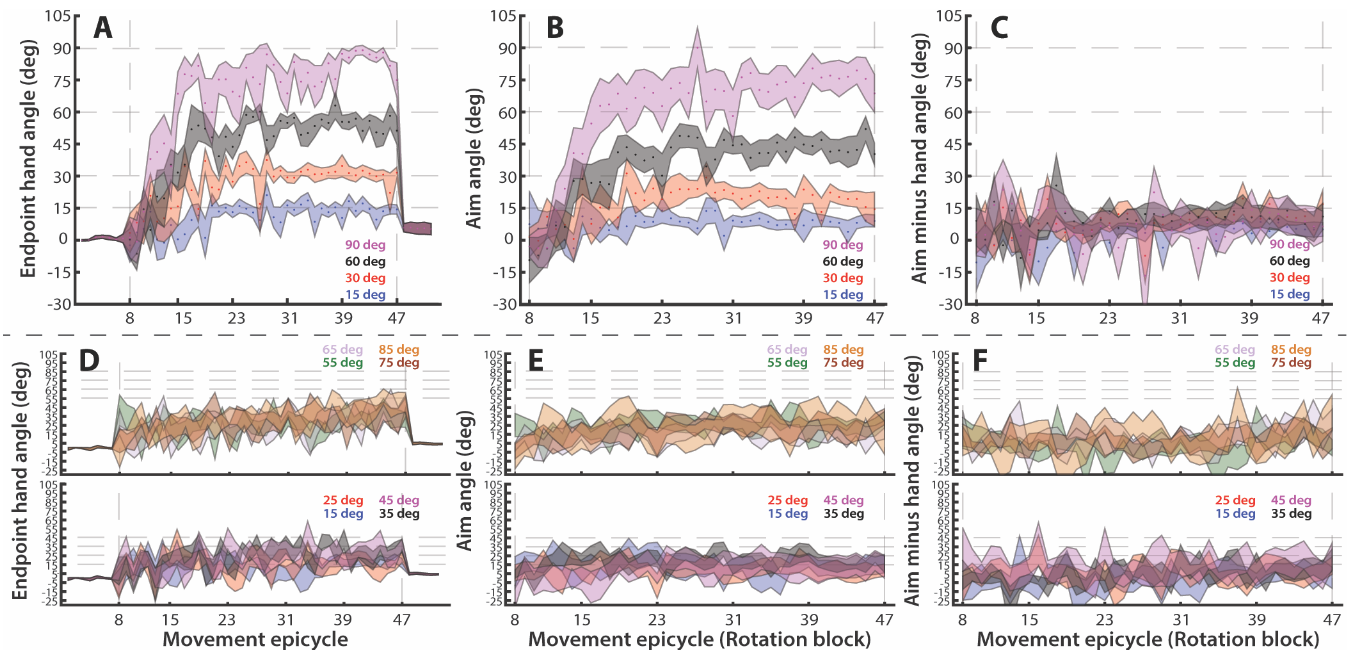


Fig 2. Learning in *Experiment 1* for each rotation in the 4x4 (A-C) and 8x8 condition (D-F). (A,D) End-point hand angles during Baseline, Rotation and No-Feedback blocks. (B,E) Explicit learning during Rotation block. (C,F) Implicit learning during Rotation block. Time courses in (D-F) separated into small/large rotations for ease of display. Vertical dashed lines denote start and end of Rotation block. Shading represents SEM across participants.

or a "buzz", you'll hear a "thunk" sound that lets you know that you have reached far enough." In the final 40 trials (Washout block), veridical cursor feedback was restored.

Participants in the 4x4 condition reached towards one of four targets (located at 0°, 90°, 180° or 270°), each of which was associated with one of four magnitudes of visuomotor rotation (±15°, ±30°, ±60° or ±90°). Participants in the 8x8 condition reached towards one of eight targets (located at 0°, 45°, 90°, 135°, 180°, 225°, 270° or 315°), each of which was associated with one of eight magnitudes of visuomotor rotation (±15°, ±25°, ±35°, ±45°, ±55°, ±65°, ±75°, or ±85°). The association between targets and rotation magnitudes in both conditions was randomized across participants.

**Data Analysis** Kinematic and statistical analyses were performed with MATLAB (MathWorks, Natick, MA). To assess performance, we examined the endpoint hand angle measured when movements passed a radial distance of 7 cm. Each movement trajectory was transformed from Cartesian to polar coordinates and rotated to a common reference axis with the target location set at 0°. Trials were separated by rotation magnitude during the rotation block, into either four bins (the 4x4 condition) or eight bins (the 8x8 condition). The endpoint hand angles for each rotation were then averaged in eight-trial bins (epicycles) for further analyses. Note that for the 4x4 condition, each epicycle consisted of an average across two trials, while in the 8x8 condition each epicycle consisted of a single trial. We opted to consider epicycles spanning eight trials because our task included up to eight target locations, which were pseudo-randomized. Moreover, since the sequence of target locations was randomized across participants, this procedure removes biases associated with specific target locations.

We examined participants' reach locations in the first and last epicycles in the rotation block for each rotation. We submitted the endpoint hand angles in the first epicycle, for each rotation, to a one-sample *t*-test to evaluate the speed of learning. We submitted the difference between the endpoint hand angles in the last epicycle and the magnitude of the rotation, to evaluate the extent of learning. Finally, to quantify any aftereffect, we submitted the first epicycle of the No-Feedback block to a one-sample *t*-test. Note, to remove potential biases in reaching, we subtracted the endpoint hand angles from the Baseline-Report block, from all subsequent phases, as is custom in visuomotor rotation studies.

To quantify the contributions of explicit and implicit learning, we first transformed the tapped aim location from Cartesian to polar coordinates and rotated to a common reference axis with the target location set at 0°. Implicit learning was computed by subtracting the aiming angles from the endpoint hand angle on each trial. Trials were again separated by rotation magnitude during the Rotation block, and both explicit and implicit learning measures were considered in eight-trial epicycles. Our analyses once again focused only on the first and last epicycles of the Rotation block. Furthermore, to evaluate whether the magnitude of explicit and implicit learning differed as a function of rotation magnitude, we ran a one-way repeated measures ANOVA on the explicit and implicit measures observed in the final epicycle of the Rotation block.

Finally, for each participant and target-rotation pair, we computed the average reaction time (RT) across the entire

Rotation block. RT was measured as the time elapsed from target appearance to the hand leaving the start area. We submitted these measures to a one-way repeated measures ANOVA to evaluate the extent to which participants' RTs varied as a function of the rotation.

## Results

**Performance:** By the end of the Baseline block, participants' end-point hand angles did not differ from the target locations in both the 4x4 ($t_{14}$ = 0.25, $p$ = 0.81; Fig. 2A) and 8x8 conditions ($t_{15}$ = -1.31, $p$ = 0.21; Fig. 2D). At the outset of the Rotation block, participants in both conditions were slow to adjust their reaches to offset the rotations, as would be expected given the complexity of the task; participants' end-point hand angles did not differ from the true target locations within the first epicycle for the 4x4 condition (all *p*s > 0.7; Fig. 2A) or in the 8x8 condition (6 out of 8 *p*s > 0.43), except for reaches to 55° ($t_{15}$ = 2.55, $p$ = 0.028) and marginally so for 65° ( $t_{15}$ = 1.98, $p$ = 0.066; Fig. 2D). However, by the final epicycle of the Rotation block, participants in the 4x4 group successfully adapted to all four rotation magnitudes – we found no difference between endpoint hand angles and the rotation magnitudes (15°: $t_{14}$ = -0.39, $p$ = 0.7; 30°: $t_{14}$ = 0.56, $p$ = 0.58; 60°: $t_{14}$ = -1.32, $p$ = 0.21; 90°: $t_{14}$ = -1.82, $p$ = 0.09). In contrast, participants failed to adapt to all the target-rotation pairs in the 8x8 condition. Crucially, this failure was not uniform; participants only failed to adapt to large rotations. By the end of the Rotation block, we found no difference between endpoint hand angles and the rotation for the 15°, 25°, 35° and 45° targets (all *p*s > 0.19); but found reliable or marginal differences for the 55° ($t_{15}$ = -2.91, $p$ = 0.011), 65° ($t_{15}$ = -1.89, $p$ = 0.079), 75° ($t_{15}$ = -2.77, $p$ = 0.014) and 85° ($t_{15}$ = -3.15, $p$ = 0.007) targets.

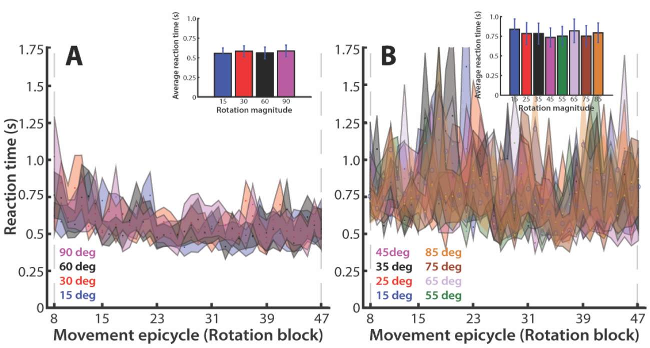


Fig 3. *Experiment 1* RTs for each rotation in the 4x4 (A) and 8x8 condition (B). Insets: average RTs across the Rotation block. Shading represents SEM across participants.

**Explicit and Implicit Learning:** We leveraged two different procedures to elucidate the influence of explicit and implicit processes: via the aim report procedure, and via aftereffects. During the first epicycle of the Rotation block, aim angles and inferred implicit learning (via subtraction of aim angle from endpoint hand angle) did not reliably differ from target location for any rotation magnitude in the 4x4 condition (explicit and implicit, all *p*s > 0.4; Fig. 2B,C), and for most rotation magnitudes in the 8x8 condition (explicit 7 out of 8 *p*s > 0.12 except for reaches to 55° [$t_{15}$ = 1.9, $p$ = 0.077] and implicit 7 out of 8 *p*s > 0.12 except for reaches to 65° [$t_{15}$ = 2.04, $p$ = 0.059]; Fig. 2E,F). However, by the end of the Rotation block participants' aim angles scaled with rotation magnitude for the 4x4 condition ($F_{3,42}$ = 26.21, $p$ < 0.0001). In the 8x8 condition, while aim angles were in the correct direction to counteract the rotations, they did not appropriately scale with rotation magnitude ($F_{7,105}$ = 0.81, $p$ = 0.58). We found no reliable difference in implicit recalibration as a function of rotation magnitude for both conditions (4x4 condition: $F_{3,42}$ = 1.09, $p$ = 0.36; 8x8 condition: $F_{7,105}$ = 1.2, $p$ = 0.31). Taken together, this pattern suggests that participants' reach locations were driven primarily by explicit aiming strategies. This pattern is unlikely to be explained by participants not having sufficient exposure for implicit recalibration to develop – several prior studies have demonstrated that implicit recalibration saturates in a similar time frame (Bond & Taylor, 2015; Morehead et al., 2017; Wang & Taylor, 2021; Wilterson & Taylor, 2021).

Following the Rotation block, cursor feedback was removed and participants were instructed to aim directly at the target (No-Feedback block). This procedure is designed to measure aftereffects, considered to be a hallmark of implicit recalibration. Participants in the 4x4 condition displayed a marginal aftereffect ($t_{14}$ = 1.89, $p$ = 0.08; Fig. 2A), while participants in the 8x8 condition showed a significant aftereffect ($t_{15}$ = 3.43, $p$ = 0.004; Fig. 2D), in the first epicycle of the No-Feedback block. Notably, the size of the aftereffect was quite small in both conditions (4x4: 5.1 ± 10.4°; 8x8: 4.5 ± 5.3°) further supporting the notion that behavior in the Rotation block was almost entirely driven by explicit strategies.

**Preparation time:** Finally, we examined participants' reaction time – i.e., time elapsed from target appearance to the hand leaving the start area. When participants utilize an explicit algorithmic strategy (e.g., mental rotation), RTs scale with rotation magnitude (McDougle & Taylor, 2019). In contrast, when participants leverage a retrieval strategy, RTs do not scale with rotation, but rather scale with the number of strategies held in memory (set size effect; McDougle & Taylor, 2019; Velazquez-Vargas & Taylor, 2024; Pellizer & Georgopoulous 1993). Across the Rotation block, we found the longest RTs early in the block, and a monotonic decrease in RTs as a function of exposure (Fig. 3). Notably, we found no differences in RTs as a function of rotation magnitude in either the 4x4 ($F_{3,42}$ = 0.38, $p$ = 0.77; Fig. 3A) or 8x8 condition ($F_{7,105}$ = 0.85, $p$ = 0.55; Fig. 3B). This pattern is consistent with an explicit memory retrieval strategy where participants cached the solutions for the target-rotation pairs, and on each trial retrieved the appropriate strategy for the presented target. However, note that because of the aim report procedure, this RT data should be viewed with caution – preparation could have extended from target appearance, through aim report, and into the reaching movement.

## Experiment 2

In experiment 1, we found that human observers can flexibly, and on a trial-by-trial basis, adapt to multiple sets of visuomotor perturbations. In particular, our findings from the 4x4 condition show that observers can simultaneously adapt to four different rotations and that they do so in a manner consistent with an explicit memory retrieval strategy. However, participants' ability to flexibly utilize memory retrieval to deal with task complexity is limited. When tasked with adapting to eight visuomotor rotations, they are unable to adapt successfully to all the rotations. Crucially, this failure was not uniform – participants successfully adapted to the smaller rotations, but failed to adapt to the larger rotations.

In experiment 2, we sought to further probe the visuomotor adaptation we observed in experiment 1. In particular, we found that participants' behavior was primarily driven by explicit strategy use. This finding builds upon several recent studies which have shown that explicit learning may be the dominant driver of visuomotor adaptation (Bond & Taylor, 2015; Morehead et al., 2015; Schween et al., 2019; Schween et al., 2018; Wilterson & Taylor, 2021). In experiment 2, we replicated the visuomotor adaptation task we used in experiment 1, but with a primary focus on highlighting the use of explicit strategies. Specifically, in order to limit implicit recalibration and better isolate explicit learning, feedback was delayed on every trial (Brudner et al., 2016; Kitazawa et al., 1995; Schween & Hegele, 2017). Participants were also not required to explicitly report their aim angle – their endpoint hand angle directly represented their explicit aim angle. Furthermore, by eliminating aim reports, and directly measuring participants' explicit learning, we expect to get a better estimate of participants' preparation time when overcoming a complex set of visuomotor perturbations.

### Method

**Participants** 40 undergraduates [19 men, 21 women; mean age 19.9 years (SD 1.24)] participated in this experiment, equally split between a 4x4 and 8x8 condition. Participants received course credit or $12/hr for participation. All participants had normal or corrected-to-normal vision and were right-handed. The protocol was approved by the IRB, and all participants provided written informed consent.

**Procedure, Experimental Apparatus, and Analysis** The task procedure, experimental apparatus, and analyses were nearly identical to that used in experiment 1 except for the following changes: 1) Endpoint cursor feedback was delayed by 1 second to limit implicit recalibration; 2) Participants were not required to report their aim location before reaching on each trial; 3) The number of trials was extended from 320 to 400 to provide more exposure to the task; 4) The washout block was removed from the end of the experiment to provide more time for training in the Rotation block; 5) target locations were adjusted such that they did not align with cardinal directions. In the 4x4 condition, targets appeared at 15°, 105°, 195° or 285°, each randomly associated with a different visuomotor rotation magnitude (±30°, ±50°, ±70° or ±90°). In the 8x8 condition, targets appeared at 15°, 60°, 105°, 150°, 195°, 240°, 285° or 330°, each randomly associated with a different visuomotor rotation magnitude (±20°, ±30°, ±40°, ±50°, ±60°, ±70°, ±80°, or ±90°).

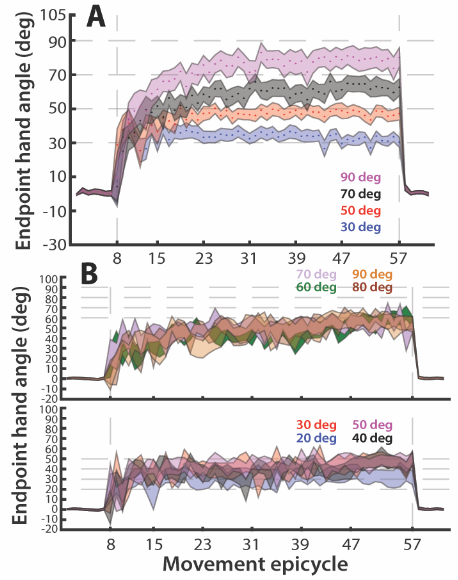


Fig 4. End-point hand angles during Baseline, Rotation and No-Feedback blocks in *Experiment 2* for each rotation in the 4x4 (A) and 8x8 (B) condition. Time courses in (B) separated into small/large rotations for ease of display. Vertical dashed lines denote start and end of Rotation block. Shading represents SEM across participants.

### Results

**Performance:** By the end of the Baseline block, participants were accurate in reaching toward the targets in both the 4x4 ($t_{19}$ = 0.14, $p$ = 0.89; Fig. 4A) and 8x8 conditions ($t_{19}$ = 0.55, $p$ = 0.59; Fig. 4B). At the outset of the Rotation block, participants in both conditions were slow to adjust their reaches to offset the rotations, as in experiment 1; participants' end-point hand angles did not differ from the true target locations within the first epicycle for the 4x4 condition (3 out of 4 $p$s > 0.49; Fig. 4A), except for reaches to 50° ($t_{19}$ = 3.06, $p$ = 0.006), nor in the 8x8 condition (6 out of 8 $p$s > 0.12), except for reaches to 50° ($t_{19}$ = 2.47, $p$ = 0.023) and marginally so to 70° ($t_{19}$ = 2.08, $p$ = 0.051; Fig. 4B). However, by the final epicycle of the Rotation block, participants in the 4x4 group successfully adapted to all rotation magnitudes (30°: $t_{19}$ = 0.11, $p$ = 0.91; 50°: $t_{19}$ = -0.76, $p$ = 0.46; 70°: $t_{19}$ = -1.48, $p$ = 0.16; 90°: $t_{19}$ = -1.73, $p$ = 0.10). In contrast, as in experiment 1, participants failed to adapt to all the target-rotation pairs in the 8x8 condition. Crucially, this failure was once again not uniform. We found no difference between endpoint hand angles and the rotation for only the 20°, 50° and 60° targets (all $p$s > 0.11); but found reliable or marginal differences for the 30° ($t_{19}$ = 3.03, $p$ = 0.007), 40° ($t_{19}$ = 1.8, $p$ = 0.087), 70° ($t_{19}$ = -3.25, $p$ = 0.004), 80° ($t_{19}$ = -3.91, $p$ < 0.001) and 90° ($t_{19}$ = -4.83, $p$ < 0.001) targets. This pattern is qualitatively different from that observed in the 8x8 condition in experiment 1, where participants only failed to adapt to large rotations.

Next, we examined participants' aftereffects. After the Rotation block, the rotation and cursor feedback were removed, and participants were instructed to aim directly toward the target (No-Feedback block). As in experiment 1, participants in the 4x4 condition displayed only a marginal aftereffect ($t_{19} = 2.06$, $p = 0.053$; Fig. 4A), while participants in the 8x8 condition did not show a reliable aftereffect ($t_{19} = 1.25$, $p = 0.23$; Fig. 4B). The size of the aftereffect was again small in both conditions (4x4: 3.7 ± 8.1°; 8x8: 1.4 ± 5°) which confirms that learning was the result of explicit strategies.

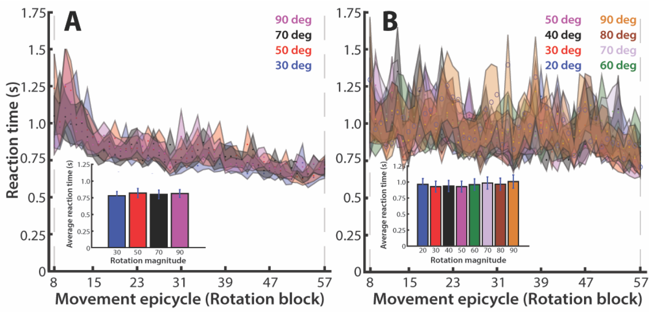


Fig 5. *Experiment 2* RTs for each rotation in the 4x4 (A) and 8x8 condition (B). Insets: average RTs across the Rotation block. Shading represents SEM across participants.

**Preparation time:** Finally, we analyzed RTs, now defined as time elapsed from target appearance to the hand leaving the start area without an intervening report of aim location. Across the Rotation block, we found the longest RTs early in the block, and a monotonic decrease in RTs as a function of exposure (Fig. 5). Notably, we found no differences in RTs as a function of rotation magnitude in either the 4x4 ($F_{3,57} = 0.69$, $p = 0.56$; Fig. 5A) or 8x8 ($F_{7,153} = 1.15$, $p = 0.34$; Fig. 5B) conditions. This pattern is once again consistent with an explicit memory retrieval strategy.

## Discussion

We sought to explore how task complexity affects visuomotor adaptation. Previous work has found that explicit strategies are highly flexible, unlike implicit recalibration (Bond & Taylor, 2015; Wilterson & Taylor, 2021), but are subject to substantial capacity limits, calling into question the efficacy of such strategies in complex situations (Velazquez-Vargas & Taylor, 2024b). Our findings shed important new light on this question. Across two experiments, we found that observers can overcome a complex set of perturbations, as long as the set size does not exceed working memory capacity. In line with prior findings, we find that implicit recalibration is unable to track multiple perturbations. Instead, adaptation seems to be driven almost entirely by the use of an explicit memory retrieval strategy. These findings further underscore the notion that in a wide range of settings, and particularly in complex situations, explicit cognitive strategies may be the dominant mode of learning.

Notably however, we found that when task complexity exceeded working memory capacity (i.e., in the 8x8 condition), participants were no longer able to counteract all the rotations appropriately. While their adaptive response was in the correct direction, it was not proportional to rotation magnitude. A *post hoc* individual difference analysis revealed that each participant's response in experiment 1 was biased toward the average rotation magnitude, with better performance for smaller rotations. This finding is suggestive of a heuristic solution to the capacity limit problem. Indeed, prior research has implicated greater cognitive costs when adapting to larger rotation magnitudes (c.f. observers avoid situations that require greater mental rotation; Kim et al., 2024, Morsella et al. 2011). However, in experiment 2, participants did not exhibit a preference for smaller rotations but rather settled for the average rotation magnitude. It is possible that the suppression of implicit recalibration in experiment 2 might have precipitated this change, as smaller rotations are more within the operating capacity of implicit learning (Al-Fawakhiri et al., 2023; Bond & Taylor, 2015; Kim et al., 2018; Morehead et al., 2017; Tsay et al., 2022). A heuristic solution of aiming toward the average rotation offers no better performance, in terms of absolute or cumulative error, but it may be perceived as a rational strategy in terms of proportional error.

Note that in our study, while the rotation magnitude varied, rotations were in the same direction, which might have promoted the usage of an algorithmic strategy. This design was chosen because, if the rotations were of different signs, implicit learning in experiment 1 would overwrite itself from trial to trial (Hutter & Taylor, 2018; Kim et al., 2018; Marko et al., 2012; Morehead et al., 2017; Tsay et al., 2022; Wei & Kording, 2009). If instead, we had opted to balance rotation magnitude and direction, adopting an algorithmic strategy would confer little benefit as participants would have to first encode and retrieve the target-rotation solution pairing on each trial. Indeed, in such a scenario, participants do not display any signs of an algorithmic strategy; however, it takes substantial training to learn retrieval strategies for even small set sizes (Velazquez-Vargas & Taylor, 2024b).

Repetition is critical to developing effective retrieval strategies (Fresco et al., 2023; Logan, 1988; Provost et al., 2013; Velazquez-Vargas & Taylor, 2024b). The amount of repetition required to learn complex sets of perturbations is currently unknown. Even prior to repetition, the task cannot exceed working memory; otherwise, learning may not take root (c.f. "desirable level of difficulty" in learning; Bjork & Bjork, 2011). Indeed, complex skills are often decomposed into components or subroutines (Correa et al., 2023; Mané & Donchin, 1989; Park et al., 2004; Velazquez-Vargas & Taylor, 2024a). Further work will be needed to determine if the limits in task complexity observed here can be overcome with prolonged or progressive training protocols. For instance, participants in our study were exposed to fewer trials *per perturbation* in the 8x8 condition and it remains to be determined if increased training may enable further learning despite the set size exceeding working memory capacity. Indeed, we know that humans can learn to perform highly complex tasks and achieve extraordinary levels of skill – our study is a step toward identifying the factors that afford or limit this remarkable capacity.

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