# Where you aim – not how you aim – affects implicit recalibration in visuomotor adaptation

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**Abstract:** The influence of explicit strategies on implicit recalibration during visuomotor adaptation has become a central question in motor learning. Because the two systems operate in tandem, explicit strategies could indirectly influence implicit recalibration. However, explicit strategies are not unitary: they may rely on algorithmic-based computations or memory-based retrieval of cached solutions. This raises the possibility that different strategy implementations interact with the cerebellar-based implicit recalibration system in qualitatively distinct ways, especially given that these strategies likely rely on different frontoparietal networks. Here, we tested whether the type of explicit strategy modulates implicit recalibration. Across a set of experiments, we observed subtle differences in the spatial profile of implicit generalization: the algorithmic strategy produced a broader generalization pattern than the retrieval strategy, even after controlling for intertrial decay, generalization structure, and between-target interactions. While this pattern is suggestive of greater flexibility afforded by algorithmic strategy use compared to memory-based retrieval, it could instead arise from increased variability in explicit aiming, which constitutes the input data driving implicit recalibration. Indeed, when we isolated the direct contribution of each strategy to implicit recalibration by rigorously controlling for reach variability and using error-clamp feedback to ensure uniform implicit learning conditions, we found no difference in implicit recalibration across strategies. Together, these findings suggest that while algorithmic and retrieval strategies differ in their behavioral signatures and influence the movement plan, the implicit recalibration process itself remains rigid with respect to the strategy employed.

Key words: algorithmic strategy; movement retrieval; implicit generalization; visuomotor adaptation;

## Significance Statement

Whether explicit strategies influence implicit recalibration remains debated – a question complicated by the fact that different training conditions give rise to distinct forms of strategy. Because algorithmic and retrieval-based strategies engage partially dissociable frontoparietal networks, they may differentially interface with cerebellar subregions, yielding distinct effects on implicit recalibration, potentially reconciling prior mixed findings. Our results indicate that, once the first order spatial and temporal statistics that typically covary with these different strategies are matched, the strategies themselves do not directly influence implicit recalibration. Instead, the cerebellar-based implicit recalibration system faithfully updates the sensorimotor mapping simply based on the training data it is provided. These findings support prior work suggesting strong independence and stereotyped behavior of implicit recalibration.

## Introduction

The interaction between explicit and implicit processes has recently become a central focus in visuomotor adaptation, as conflicting findings across studies have left the precise influence of explicit processes on implicit recalibration unresolved. On the one hand, some studies support the view that explicit and implicit processes operate largely independently (Bond and Taylor, 2015; McDougle et al., 2015; Morehead et al., 2017), as reflected in their distinct learning signatures and their reliance on different neural systems (Mazzoni and Krakauer, 2006; Taylor and Ivry, 2011, 2014; Butcher et al., 2017; Areshenkoff et al., 2024). On the other hand, several studies suggest that explicit strategies may directly (Albert et al., 2022) or indirectly influence implicit recalibration (Day et al., 2016; McDougle et al., 2017). Evidence for such interactions includes plan-based generalization, in which implicit recalibration is centered on the explicit aiming direction (Day et al., 2016; McDougle et al., 2017), competition for a shared error signal (Albert et al., 2022), and nonlinear patterns of interaction revealed through various methodological approaches (Maresch et al., 2021; t Hart et al., 2024).

These mixed findings may arise from subtle differences in task design, which can shift the nature of the explicit strategies participants employ (McDougle and Taylor, 2019; Velazquez-Vargas and Taylor, 2024); such shifts, in turn, can modulate the expression of implicit recalibration in distinct ways (Albert et al., 2022). At least two distinct types of explicit strategies have been identified in visuomotor adaptation. The first is an algorithmic strategy, in which participants mentally rotate their intended movement vector away from the target by an amount equal in magnitude and opposite in direction to the imposed cursor rotation (Georgopoulos et al., 1986; Georgopoulos and Pellizzer, 1995; Sanes and Donoghue, 2000; McDougle and Taylor, 2019). This visuomotor mental-rotation strategy is highly flexible, but it comes with a cost: preparation time increases linearly with the size of the required rotation, paralleling the classic mental-rotation

effects (Shepard and Metzler, 1971). In contrast, once a successful solution has been identified, participants may instead rely on a retrieval strategy, in which the previously successful aiming solution is cached in working memory and retrieved at minimal computational cost (McDougle and Taylor, 2019; Fresco et al., 2023; Velazquez-Vargas and Taylor, 2024). However, this retrieval process is constrained by its reliance on previously learned stimulus–response associations (Logan, 1988). As a result, retrieval-based strategies show limited generalization and tend not to extend far beyond the specific conditions experienced during training (McDougle and Taylor, 2019).

A common method for manipulating strategy use in visuomotor rotation tasks is to vary the number of training targets (set size; (McDougle and Taylor, 2019)). A high set size overwhelms working memory, rendering retrieval strategies ineffective (McDougle and Taylor, 2019; Velazquez-Vargas and Taylor, 2024) and forcing reliance on an algorithmic strategy. Previous research has demonstrated that manipulation of set size appears to impact the magnitude of cerebellar-dependent implicit recalibration (Bond and Taylor, 2015; Neville and Cressman, 2018) and mediates the performance of patients with cerebellar-ataxia (Gibo et al., 2013; Tsay et al., 2022; Hadjiosif et al., 2023).

The effect of set size on implicit recalibration could be the result of temporal decay, which is supported by prior work finding that implicit recalibration comprises temporally persistent and temporally volatile components. As set size increases, the interval between successive visits to the same target grows, allowing the volatile component to decay before it can carry over and accumulate on the next encounter. This rapid loss would reduce net trial-to-trial buildup, yielding smaller apparent implicit recalibration at larger set sizes (Hadjiosif et al., 2023; Hadjiosif et al., 2024). Alternatively, it could be that different strategies, which are guided by set size (Miller, 1956; Oberauer et al., 2016; Cowan, 2017) and draw upon different frontoparietal networks

(D'Esposito, 2007; Engelhardt et al., 2019; Reineberg et al., 2022), lead to different interactions with the cerebellum, which, in turn, reshape the profile of implicit recalibration (Ravizza et al., 2006; Buckner et al., 2011; Bernard and Seidler, 2013).

In this study, we sought to systematically test whether algorithmic and retrieval strategies differentially shape implicit recalibration during visuomotor adaptation. To obtain an unbiased estimate of implicit learning and isolate the unique contribution of each strategy, we conducted three experiments that progressively tightened control over key confounding factors. These included: plan-based generalization, which can broaden the implicit generalization function due to variability in movement planning, and inter-trial interval, which may produce unequal levels of adaptation between groups through differential memory decay. We hypothesized that the strategy engaged during adaptation could affect both the magnitude and generalization profile of implicit recalibration. In particular, we predicted that relying on an algorithmic strategy—requiring computation on each trial—would lead to a broader implicit generalization function compared to repeatedly retrieving a well-learned solution.

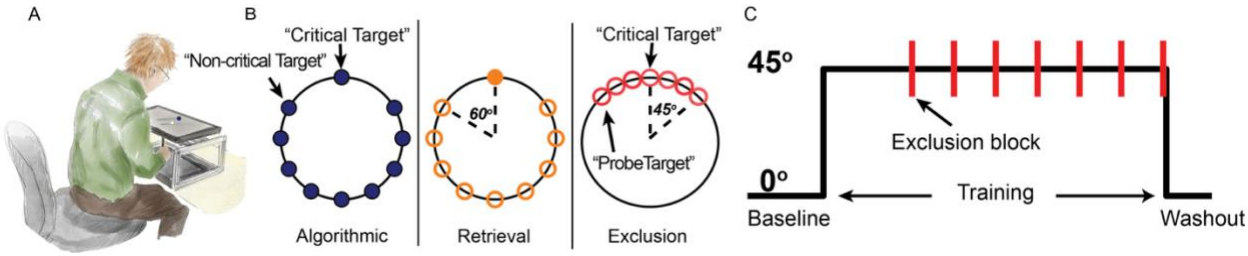


Figure 1. A) Setup for the experiment. B) Illustration of experimental workspace for groups (Algorithmic (blue) and Retrieval (orange)) during training and Exclusion conditions. A 45° visuomotor rotation was applied to all filled targets, while no rotation was applied to empty targets. C) Experimental procedures, in which red bars represent Exclusion blocks (7 trials within each block) during the training.

## Material and Methods

### Participants

A total of 164 participants (66 males, 98 females; mean age = 24.66 years, SD = 3.79) were recruited through the Princeton University psychology subject pool in exchange for course credit or from the local community in exchange for monetary reimbursement for their time. All participants were right-handed, confirmed by the Edinburgh Handedness Test (Oldfield, 1971), and reported normal or corrected-to-normal vision. The study protocol was approved by the Institutional Review Board at Princeton University, and all participants provided written informed consent prior to participation.

**Task and Apparatus**

Participants performed a center-out visuomotor reaching task using a stylus on a Wacom digitizing tablet. Their goal on each trial was to bring a virtual cursor to a visually displayed target by sliding the stylus across the tablet surface. The cursor and targets were presented on a 17 inch Dell LCD monitor (1024 × 768 resolution; 60 Hz refresh rate) running Windows 7. The monitor was positioned 10 inches above the tablet, fully occluding direct vision of the hand to ensure that participants relied solely on the displayed cursor for visual feedback (Figure 1A). Each trial began with the participant being guided to a central starting location (5-mm diameter). A white ring dynamically expanded or contracted with the radial distance of the hand from the center to cue participants toward the start position without precise angular cursor feedback. When the hand came within 6 mm of the center, a white cursor (5-mm diameter) appeared, to more precisely guide the hand into the start position. Participants were required to maintain this position for 500 ms before the target appeared.

Targets (10-mm diameter) were displayed at one of several locations along a blue ring with a 70-mm radius. Upon target appearance, participants were instructed to perform a rapid, “shooting-

style" movement to try to intersect the target with the cursor. Once the hand left the start position, continuous or delayed endpoint cursor feedback was provided depending on task conditions.

To enforce fast, ballistic movements, the maximum allowed movement time was limited to 300 ms. If the movement exceeded this limit, an auditory warning ("too slow") was played. When the hand crossed the radial distance corresponding to the target location (70 mm from the start), a neutral "thunk" sound was delivered to indicate that the reach had terminated. Cursor feedback remained visible for 0.5 s following movement completion. Afterward, participants were guided back to the start location using the dynamic centering ring, and the next trial was initiated.

**Experiment 1: Does the use of either an algorithmic or retrieval strategy result in different implicit generalization?**

Participants (n=86) were randomly assigned to one of two groups designed to bias learning toward distinct cognitive strategies: an algorithmic strategy group or a retrieval strategy group (Figure 1B). Regardless of group assignment, the experiment consisted of baseline, adaptation, and washout phases, totaling 484 trials (Figure 1C).

The baseline phase comprised three components intended to familiarize participants with the task, assess inherent movement biases, and ensure stable calibration before learning began. First, participants completed a 16-trial familiarization block, during which the experimenter provided detailed instructions on performing the rapid center-out shooting movements and the goal of the task. Next, participants completed a 48-trial no-feedback block in which the cursor disappeared immediately after movement onset to obtain an unbiased estimate of each participant's movement biases that may arise without feedback (Wang et al., 2024). Participants were instructed to aim directly toward each target and maintain fast, ballistic movements despite the absence of feedback. Finally, participants completed a 16-trial feedback block, during which veridical, continuous

cursor feedback was restored. This brief block ensured that participants recalibrated the mapping between hand movement and cursor motion before entering the learning phase. Across all baseline trials, cursor feedback – when provided – accurately reflected true hand position.

Following baseline, participants assigned to the retrieval group received five training trials at a single target with a 45° visuomotor rotation. All participants were told to counteract this rotation by re-aiming in the opposite direction by 45°. This brief exposure phase was designed so that participants in the retrieval group could begin to cache an explicit aiming solution for that target, thereby reducing the discovery process (Tsay et al., 2024) and minimizing any reliance on visuomotor mental rotation later on in the experiment (McDougle and Taylor, 2019). In contrast, these trials were omitted from the algorithmic group, ensuring that algorithmic participants would rely primarily on an algorithmic (mental rotation–based) strategy during adaptation.

For each participant, the trained target was pseudo-randomly selected from 0° to 330° in 30° increments and designated as the critical target for evaluating implicit generalization. The critical target locations were yoked between the algorithmic and retrieval participants to ensure matched target locations across groups (Figure 1B).

The adaptation phase consisted of reaches to 10 target locations, including the critical target, spanning from ±60° to ±180° around the critical target in 30° increments. Critically, no training targets were located within ±45° of the critical target, creating a gap around the critical target to probe generalization with the goal of not directly contaminating error-based learning (Figure 1B).

For the algorithmic group, continuous cursor feedback with a 45° rotation was provided at all target locations (Figure 1B). Experiencing the rotation across multiple targets has been shown to pressure participants into relying on a visuomotor mental rotation strategy (McDougle and Taylor, 2019). In contrast, for the retrieval group, cursor feedback was withheld for all target locations

except the critical target (Figure 1B). Restricting rotated feedback to a single target encourages participants to retrieve a cached explicit aiming solution, rather than compute a rotation on each trial. Removing feedback at all other non-critical targets further minimized opportunities for visuomotor mental rotation and helped equate inter-trial timing across groups and control for the movement variability across the entire workspace.

During the learning phase, participants intermittently completed short sets of Exclusion trials, in which cursor feedback was withheld and participants were explicitly instructed not to use any aiming strategy (Taylor et al., 2014; Werner et al., 2015; Maresch et al., 2021; t Hart et al., 2024). These trials were designed to probe both the magnitude of implicit recalibration and its generalization function around the critical target. Specifically, seven targets spanning –45° to 45° in 15° increments, centered on the critical target, were presented once per Exclusion block (Figure 1B). Thus, each Exclusion block contained 7 trials, ensuring that each probe location received one reach. The order of target locations was counterbalanced both within blocks and across participants. Immediately before each Exclusion block, participants made a single reach to the critical target with rotated cursor feedback. This ensured that implicit recalibration was maximally engaged at the critical target before implicit generalization was assessed. After completing the seven Exclusion trials, rotated cursor feedback was restored, and participants resumed practicing to the full set of training targets in the workspace. To summarize the structure of this repeating "mini-block" within the learning phase: Participants performed 40 reaches (except during the first block) to the standard training targets –including the critical target – then made one final reach to the critical target with rotated cursor feedback before experiencing seven Exclusion trials to probe the magnitude and generalization function of implicit recalibration. This mini-block sequence was repeated periodically throughout the learning phase (Figure 1C).

A total of 356 trials were completed during the adaptation phase, encompassing all training reaches and the seven Exclusion mini-blocks (Figure 1C). Across this phase, the critical target appeared on 40% of the trials. The sequence of target presentations was pseudo-randomized by carefully controlling the intertrial intervals (ITIs), ensuring that the spacing between successive critical-target trials was consistent across participants. This approach ensured sufficient practice of the critical target while preventing the formation of stimulus–response associations in the algorithmic group and avoiding excessive decay of implicit recalibration memory (Hadjiosif et al., 2023). Following the adaptation phase, participants completed a washout phase that consisted of 48 trials. Within these trials, we ensured that each target location received three washout trials given that the total of 16 target locations were used for constructing the learning phase. The task was paused at the transition between each phase of the experiment, during which instructional text was displayed on the monitor to inform participants about the upcoming trial structure (e.g., *"During the following trials, the cursor will be removed and will not be rotated. Please stop using any strategy and reach directly to the target."*). Additional reminder text was also displayed whenever visual feedback was withheld (e.g., during non-critical targets and Exclusion trials) to further emphasize that participants should refrain from using any aiming strategy.

**Experiment 2: Is the increased breadth of implicit generalization the result of "error spill over"?**

Experiment 2 (n = 40) followed the same general structure as Experiment 1, consisting of baseline, adaptation, and washout phases; however, several key modifications were introduced to isolate implicit generalization while minimizing the effect of plan-based generalization from training at nearby target locations. All participants were equally and randomly assigned to the algorithmic and retrieval groups.

We suspected there was a greater possibility that a broader breadth of the implicit generalization curve observed in the algorithmic group from Experiment 1 was attributed to an error "spillover" effect from reaching adjacent targets, where the implicit recalibration also occurred. To reduce the influence of practicing targets adjacent to the critical target, the set of training targets was shifted away from the critical target. Specifically, all targets were sampled from ±90° to ±270°, creating a 90° gap on each side of the critical target. This large angular separation ensured that participants did not perform repeated reaches near the critical target, thereby minimizing the possibility that training at nearby directions would affect the implicit generalization profile centered on the critical target (Figure 3A and B).

In addition, endpoint feedback for all remaining targets (adjacent to critical target) was presented with a 1.5-second delay, a manipulation that has been shown to suppress implicit recalibration at those target locations, even when participants experience systematic cursor errors (Brudner et al., 2016). Thus, while the critical target continued to support implicit learning through standard online rotated feedback, all remaining (non-critical) targets were effectively prevented from accruing implicit recalibration.

Aside from these modifications, the overall experimental procedure – including the baseline structure, the implementation of strategy conditions (algorithmic and retrieval), the Exclusion blocks used to probe implicit generalization, and the washout phase – remained identical to Experiment 1.

**Experiment 3: Under tight control of sensory prediction errors, do differences in implicit recalibration vanish?**

Experiment 3 (n = 38) followed the same overall structure as Experiments 1 and 2, including baseline, adaptation, and washout phases. In Experiments 1 and 2, the broader implicit

generalization observed in the algorithmic group was likely driven by greater variability in reach directions, which produced an error spillover effect consistent with plan-based generalization. To increase the robustness of control for this confounding factor and isolate the contributions of algorithmic versus retrieval strategies, Experiment 3 implemented a modified task design based on the error-clamp paradigm (Morehead et al., 2017). Implicit recalibration elicited through error-clamp feedback exhibits the same qualitative characteristics as those observed in conventional visuomotor adaptation. We leveraged this paradigm to fully control for any potential differences in error feedback that may inadvertently become linked via plan-based generalization when using an algorithmic strategy, which may increase movement plan variability, versus a retrieval strategy.

A critical target was randomly selected from 12 possible locations (0° to 330° in 30° increments), with the frequency of each critical target location matched between the algorithmic and retrieval groups. During Exclusion blocks, participants executed reaches to nine generalization probe directions, spanning 45° to 165° away from the critical target in 15° increments. In addition, the angular space between the critical target and the 45° direction was used to define the probe directions (or targets) for the Exclusion trials (see Figure 4D).

For the algorithmic group, no target landmarks other than the critical target were presented to indicate the reaching directions. Instead, after participants moved the cursor to the start position, an instruction text (e.g., *"Move toward 75 degrees"*) appeared at the top of the screen, indicating the required movement direction (see Figure 4B). This required them to perform visuomotor mental rotation to re-aim their movement away from the critical target location. No cursor feedback was provided for any of these trials; instead participants received coarsely-grained performance feedback:

*"excellent"* for errors ≤ 5°,

*"good move"* for errors between 5° and 10°,

*"fair move"* for errors between 10° and 15°, and

*"poor move"* for errors > 15°.

In contrast, for the retrieval group, we wished to prevent participants from performing visuomotor mental rotation throughout training. Thus, all trials except for the critical target, were displayed as visible targets, and cursor feedback was withheld (Figure 4B, C). Participants were instructed to reach directly to these visible non-critical targets without using any additional aiming strategy and were provided with only the coarse performance feedback. However, for the critical target, participants were instructed to reach toward the 45° direction and cursor feedback was clamped to the opposite direction (see Figure 4A). To encourage caching a strategy for this target, participants experienced five pre-training trials to allow participants to cache the correct aiming strategy for reaching the 45° direction.

For both groups during training, the cursor feedback was error-clamped at 15° away from the critical target, in the opposite direction of the required aiming direction. This clamped feedback was only used for the 45° direction to maintain consistency with Experiments 1 and 2, in which participants learned to counteract a 45° rotation at the critical target with implicit recalibration ensured by error-clamp feedback. In contrast, for all other angular directions in both groups, no cursor feedback was provided. Consistent with prior experiments, Exclusion blocks were included to assess implicit recalibration, with seven probe targets positioned around the critical target at 15° increments from –45° to 45°.

**Implicit Measures and Performance**

Aftereffects, the hallmark of implicit recalibration, were assessed using Exclusion trials embedded throughout the adaptation phase (see above). Each Exclusion block began with a top-up reach to the critical target to prevent decay of the adaptation (Hadjiosif et al., 2023). Within each block, targets used for probing implicit recalibration (including the critical target) were presented in a randomized order and counterbalanced across blocks and participants (Figure 1B). Participants were instructed not to use explicit aiming strategies, but instead to reach directly toward each target. During these trials, both online cursor feedback and visual perturbations were withheld. The hand angle at movement completion served as the measure of implicit recalibration. This same measure was also used to estimate the degree of adaptation on every trial throughout the task.

**Analyses**

**Performance**

Two primary dependent variables were analyzed: endpoint hand angles and reaction time (RT). Endpoint hand angles were computed as the angular deviation between the final hand position at reach completion and the target location. These angles were used to quantify performance during training, as well as the magnitude and spatial extent of implicit generalization during Exclusion trials. RT was defined as the interval between target onset and the moment the hand moved more than 5mm from the starting position. Prior work suggests that RT reflects the computational demands of planning, which differ between algorithmic and retrieval strategies (McDougle and Taylor, 2019; Velazquez-Vargas and Taylor, 2024).

To evaluate group- and time-related differences, we conducted a linear mixed model analysis with group (algorithmic vs retrieval) as the between-subjects factor and time (Early vs Late) as the within-subject factor for hand angle and RT for all trials. More specifically, we conducted separate

analyses for the critical target and non-critical targets. The adaptation performance for non-critical target locations was computed as the absolute error in hand angle, defined as the absolute value of the difference between the hand angle and the rotation size (45°). Early training was defined as the average across the first training block, while late training was defined as the average across the last training block. By conducting these analyses, we sought to verify that our paradigm successfully dissociated the algorithmic and retrieval strategies into two distinct groups, as evidenced by their differing RT profiles, while ensuring that both groups achieved comparable levels of adaptation. RT was used as an indicator of the cognitive strategy engaged during task performance. Based on prior research, we expected the algorithmic group to exhibit significantly longer RTs than the retrieval group, reflecting the greater computational demands of algorithmic planning (McDougle and Taylor, 2019).

To assess whether the two groups exhibited comparable levels of adaptation prior to the Exclusion trials across all seven blocks, we conducted a linear mixed-effects model on hand angle with group (algorithmic vs. retrieval) as the between-subjects factor and time (Blocks 1–7) as the within-subjects factor. Additionally, to verify that strategy use was indeed withheld in the algorithmic group during the Exclusion blocks, we ran a separate analysis on RT, using the same model structure. If strategy use was successfully withheld, the algorithmic and retrieval groups should show similar RT profiles across these blocks.

To quantify and compare implicit recalibration across all non-critical target locations, we conducted an independent-samples t-test on the magnitude of the aftereffect measured during the washout phase. This analysis ensured that any residual implicit recalibration arising from non-critical locations was equivalent between groups. Controlling for this factor strengthens the

interpretability of the present findings by confirming that group differences cannot be attributed to variations in implicit learning at non-critical target locations.

**Generalization Analyses**

Generalization functions were estimated by fitting the endpoint hand angles from the seven Exclusion targets with Gaussian tuning curves (Tanaka et al., 2009; Brayanov et al., 2012; Poh and Taylor, 2019):

$$g\,(\theta) = k \cdot e^{\frac{(\theta-\theta_0)^2}{2\sigma^2}} \qquad (1)$$

Where $\theta_0$ denotes the target direction that produced the greatest shift in reach direction, k represents the amplitude of generalization, and $\sigma$ characterizes the width of the tuning function. We used a bootstrapping procedure (1000 iterations), drawing from the population with exclusion and replacement, to estimate the generalization function (Poh and Taylor, 2019). This approach leverages the full distribution of samples (1000 total fits) and assesses parameter significance using 95% confidence intervals derived from the bootstrap distribution ($\alpha$= .05; (Fisher, 1995)). Curve fitting was performed using MATLAB's fmincon optimizer.

To control for the potential influence of plan-based generalization on the breadth of implicit generalization, we performed a separate analysis on movement variability at the critical target location. Specifically, we quantified variability by calculating the standard deviation of the reaching directions for each bootstrap sample across 1000 resamplings. Greater variability in reaching direction suggests that participants generated more variable re-aiming plans. This dispersion in planned movement directions may broaden the resulting implicit generalization function (Day et al., 2016; McDougle et al., 2017; Chen and Taylor, 2025).

## Results

### Experiment 1: Does the use of either an algorithmic or retrieval strategy result in different implicit generalization?

*Adaptation performance*

The primary goal of this study was to test whether the higher-order explicit strategy participants adopt modulates lower-level implicit recalibration, which has become a central question in visuomotor adaptation research. To test for this potential interaction, we created conditions that favored the use of an algorithmic-based or retrieval-based strategy to counteract a visuomotor rotation, and tested for their impact on implicit recalibration while attempting to hold all other mediating variables constant.

Both groups had little difficulty in following instructions to reach directly to the targets during the familiarization phase, as reflected by no difference in error ($t(84) = -0.192$, $p = 0.848$). When the visuomotor rotation was introduced during the adaptation phase both groups adapted quickly to the imposed 45° rotation, with reach angles increasing from early to late training and approaching near-complete compensation by the end of training (Figure 2A). To determine if there were any differences in the learning function between the groups, given the differences in our imposed task demands, the hand angles were submitted using a linear mixed-effect model with Group (algorithmic and retrieval) and Time (early and late) as factors. As expected, we found a main effect of Time ($b = 3.99$, $SE = 0.94$, $t(168) = 4.24$, $p < .001$), suggesting a continuous improvement in reach performance in the course of practice. We also found a main effect of Group ($b = 3.40$, $SE = 1.09$, $t(168) = 3.13$, $p = .002$), suggesting a distinct learning pattern associated with each strategy. More interestingly, however, we found there was an interaction between Group and Time ($b = –2.97$, $SE = 1.33$, $t(168) = –2.23$, $p = .027$), with post-hoc analyses revealing that the

retrieval group displayed faster learning than the algorithmic group. During the early phase of training, the retrieval group (42.21 ± 4.62°) exhibited significantly greater hand angles than the algorithmic group (38.82 ± 8.44°; $p = .002$), but by the end of training both groups achieved similar levels of performance (Retrieval 43.23 ± 2.12°; Algorithmic 42.81 ± 2.59°, $p = .695$). At a minimum, this suggests that storing and retrieving a memory from a short-term memory cache confers more rapid performance improvements than executing an algorithmic strategy. Furthermore, the stability of a cached memory is more stable or precise than executing an algorithmic strategy, as reflected by a main effect of Group (variability for retrieval - algorithmic: $b = -2.05$, $SE = 0.73$, $t(168) = -2.80$, $p = .005$).

At the non-critical targets, hand angles for the algorithmic group progressively increased from early to late training to offset the visuomotor rotation ($b = -7.88$, $SE = 0.98$, $t(168) = -8.01$, $p < .001$), ultimately, diminishing reach error to 4.14 ± 2.32° from 12.02 ± 9.79° during the Early training (Figure 2B). In contrast, for the retrieval group, because they were instructed to aim directly toward these non-critical ("dummy") targets and no rotation was applied, their hand angles remained stable across training (Early: 2.54 ± 2.44°, Late: 3.92 ± 2.84°; $p = .163$).

*Preparation time*

Preparation time, operationalized here as RT, provides a window into the underlying strategic processes for visuomotor adaptation (McDougle and Taylor, 2019). Despite both groups achieving similar performance at the critical target, there were clear differences in their RT (Figure 2C). Indeed, a linear mixed-effects model examining reaction time revealed a significant main effect of Group ($b = -0.18$, $SE = 0.03$, $t(168) = -5.49$, $p < .001$), indicating that the retrieval group responded faster than the algorithmic group across training. There was also a significant main effect of Time ($b = -0.14$, $SE = 0.02$, $t(168) = -5.75$, $p < .001$), showing that reaction times

decreased from early to late practice; however, the group × time interaction was significant ($b = 0.12$, $SE = 0.03$, $t(168) = 3.56$, $p < .001$) with only the algorithmic group showing improvements in RT over the course of training (Early: 0.58 ± 0.25 s; Late 0.44 ± 0.10 s; $p < .001$). In contrast, the retrieval group maintained stable reaction times from early (0.41 ± 0.11 s) to late (0.39 ± 0.08 s) ($p = .478$, 95% CI [−0.04, 0.02]). This pattern of results supports the interpretation that participants in the retrieval group cached a strategy in working memory, while the algorithmic group relied primarily on mental-rotation strategies (McDougle and Taylor, 2019; Velazquez-Vargas and Taylor, 2024).

Further validation that our experimental design was effective in guiding the two groups toward different strategies, is revealed by RT at the non-critical target locations (Figure 2D). We found a significant main effect of Group ($b = -0.27$, $SE = 0.04$, $t(168) = -6.30$, $p < .001$), Time ($b = -0.13$, $SE = 0.04$, $t(168) = -3.74$, $p < .001$), and interaction ($b = 0.13$, $SE = 0.05$, $t(168) = 2.67$, $p = .008$). This suggests that the algorithmic group had to use a visuomotor mental rotation strategy at all targets – both critical and non-critical.

*Implicit recalibration*

The primary goal of this study was to determine if different kinds of explicit strategies have downstream consequences for implicit recalibration. To quantify implicit recalibration in relative isolation of strategies, we periodically leveraged Exclusion probe target trials around the critical target. Here, participants were instructed to refrain from using any strategies they may have developed and, instead, simply reach straight to the presented target without any cursor feedback. Because plan-based generalization can shift the center of the implicit generalization function, these Exclusion trials were drawn from -45° to 45° centered around the critical target.

Prior work has shown that implicit recalibration is reduced when adaptation must be learned for multiple targets, raising the possibility that strategy use may differentially shape implicit generalization (Bond and Taylor, 2015). To test this idea, we first compared hand angles during Exclusion trials at the critical target and observed no difference in the amplitude of implicit recalibration between retrieval (17.09 ± 9.51°) and algorithmic strategy (16.37 ± 9.09°, $t(84) = -0.47$, $p = 0.64$) (Figure 2E). Inspection of the full generalization function indicated that strategy type did not affect the overall amplitude of implicit recalibration (Figures 2G and 6C, algorithmic: 15.91; retrieval: 16.14; bootstrap, $p = 0.42$). Likewise, the center of the generalization function did not differ between groups (Figures 2G and 6D, algorithmic: 12.35; retrieval: 8.91; bootstrap, $p = .35$). At first glance, these results suggest that strategy type does not influence implicit recalibration. However, a different pattern emerged when we examined the breadth of the generalization function. The generalization function was significantly broader for the algorithmic group ($\sigma = 75.41°$) than for the retrieval group ($\sigma = 32.97°$) (Figures 2G and 6E, bootstrap, $p < .001$), indicating that strategy type selectively modulated the spatial extent of implicit generalization. Beyond the potential influence of strategy use, several other factors could inflate hand angles observed on Exclusion trials: 1) unequal adaptation magnitude prior to the assessments of implicit recalibration, 2) incomplete strategy withholding during Exclusion trials, and 3) differences in reach angle variability between the algorithmic and retrieval groups.

First, we administered a "top-up" trial at the critical target location prior to each Exclusion assessment to ensure that the levels of adaptation were similar between groups, as well as minimize the effects of temporal decay (Hadjiosif et al., 2023). Indeed, analysis of hand angles across all "top-up" trials revealed no significant main effect of Group ($F(1, 575) = 0.35$, $p = .554$), indicating that overall adaptation did not differ between the two groups across top-up trials. There was also

no significant main effect of the trial ($F(6, 575) = 1.31$, $p = .249$), showing that adaptation levels remained stable across repeated top-up trials. Critically, the group × trial interaction was not significant ($F(6, 575) = 0.37$, $p = .896$), demonstrating that the two groups exhibited highly similar patterns of adaptation across all seven blocks.

Second, the observed differences in the generalization function are also not well explained by a failure to follow the instructions to withhold their learned strategy during the Exclusion block. Analysis of RTs revealed no overall difference between groups during the Exclusion block ($F(1, 588) = 0.64$, $p = .423$), suggesting that participants in the algorithmic group did not engage the high-cost mental-rotation strategy typically associated with slower responses. This result also serves as a manipulation check, indicating that participants in both groups followed the instruction to withhold their strategies. Although reaction times exhibited small fluctuations across the seven blocks (main effect of trial: $F(6, 588) = 3.15$, $p = .005$), these variations were modest and, importantly, did not differ between groups (trial × group interaction: $F(6, 588) = 1.17$, $p = .318$).

Finally, upon closer inspection, the reach distributions during training were not identical between the groups as the algorithmic group produced more variability than the retrieval group (Figures 2G and 6B; bootstrap, $p < .001$). Based on the notion of plan-based generalization, the greater variability in the reach distributions observed in the algorithmic group suggests that their re-aiming plans were more variable, which likely contributed to a broader generalization function. Supporting this interpretation, the analysis of aftereffects at non-critical target locations showed that the algorithmic group exhibited substantially larger implicit recalibration than the retrieval group (algorithmic: 15.00 ± 8.36°; retrieval: 4.59 ± 3.05°), $t(84) = 7.68$, $p < .001$). This elevated aftereffect pattern suggests that the broader generalization observed in the algorithmic group may have been driven, at least in part, by error spillover across adjacent targets. Consequently,

Experiment 1 did not provide sufficient evidence to determine whether algorithmic and retrieval strategies differentially influence implicit recalibration.

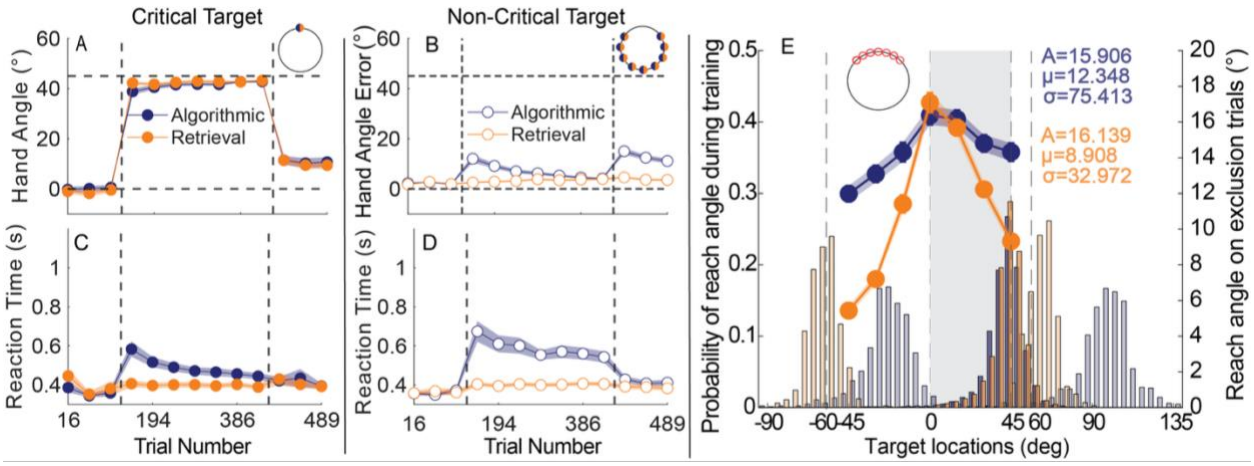


Figure 2. A) Adaptation performance measured at the critical target location, reflected by the hand angles reaching near 45°. Vertical dashed lines indicate onset and offset of the training phase. Each data point represents binned hand angles for one cycle of training. B) Absolute hand angle error is calculated for all non-critical target locations. C) Reaction time for the critical target and D) Reaction time for non-critical target locations. E) Two generalization curves (right y-axis) for the algorithmic (blue) and retrieval (orange) groups are shown across the corresponding target locations (x-axis). Beneath these curves, bar plots illustrate the distribution of reach directions for each group (left y-axis), with darker colors indicating reaches to the critical target and lighter colors representing reaches to adjacent locations. The shaded gray region marks the "aiming zone," where participants were most likely to aim when counteracting the 45° rotation at the critical target. The amplitude, mean, and width parameters displayed in the figure were derived from Gaussian function fits.

## Experiment 2

To resolve the key confounds identified in Experiment 1, we designed Experiment 2 to directly limit error spillover and better isolate implicit recalibration. We did so by increasing the spatial separation between neighboring targets around the critical target and by providing delayed endpoint feedback at all non-critical locations, a manipulation known to suppress implicit recalibration (Figure 3A, B). Aside from these changes, the experimental protocol was kept identical to Experiment 1. The primary goal of Experiment 2 was to build on Experiment 1 by testing whether algorithmic and retrieval strategies yield different levels of implicit recalibration under stricter experimental constraints.

*Adaptation performance*

Because feedback type was manipulated at all non-critical targets, we first asked whether this manipulation changed performance in either group. As in Experiment 1, participants adapted rapidly when the visuomotor rotation was introduced, and hand angles remained largely stable from early to late training (Figure 3C). Using the same analysis as Experiment 1 to compare learning functions, we found an overall group difference: the retrieval group produced smaller hand angles than the algorithmic group (main effect of Group: $b = -5.34$, $SE = 2.33$, $t(76) = -2.30$, $p = .024$). This effect was driven primarily by early training. The algorithmic group initially overshot the required compensation (50.18 ± 9.43°), producing larger hand angles than the retrieval group (44.84 ± 6.98°; $p = .024$). By late training, the groups converged, with both showing slight undershoot relative to the imposed 45° rotation (algorithmic: 46.58 ± 8.96°; retrieval: 42.10 ± 3.16°), and the between-group difference was reduced to a marginal trend ($p = .058$). We did not observe clear evidence that adaptation changed over time (main effect of Time: $b = -3.60$, $SE = 2.00$, $t(76) = -1.80$, $p = .076$) between the groups (Group x Time interaction: $b = 0.87$, $SE = 2.83$, $t(76) = 0.31$, $p = .760$) Furthermore, the stability of a cached memory was more stable or precise than executing an algorithmic strategy, as reflected by a main effect of Group (variability for retrieval - algorithmic: $b = -5.48$, $SE = 1.96$, $t(76) = -2.79$, $p = .006$).

At the non-critical target locations, performance improved over practice overall, reflected by a significant main effect of Time ($b = -3.06$, $SE = 1.37$, $t(76) = -2.23$, $p = .029$). This improvement was driven mainly by the algorithmic group: reach errors decreased from early to late training (9.10 ± 10.08° to 6.04 ± 4.76°; $p = .03$). In contrast, the retrieval group showed stable accuracy across practice (3.39 ± 3.13° early; 4.44 ± 3.07° late), consistent with the fact that participants were simply instructed to reach straight to these targets (Figure 3D).

*Preparation time*

Consistent with Experiment 1, both groups reached a comparable level of performance, but did so with different computational costs, as reflected in reaction time (Figure 3E). Indeed, the main effect of Group indicated that the retrieval group responded faster than the algorithmic group across training ($b = -0.55$, $SE = 0.10$, $t(76) = -5.41$, $p < .001$). There was also a significant main effect of Time ($b = -0.42$, $SE = 0.08$, $t(76) = -5.14$, $p < .001$), indicating that reaction times decreased from early to late practice. This overall speeding was driven mainly by the algorithmic group, whose responses became markedly faster with training (early: 1.15 ± 0.54 s; late: 0.88 ± 0.27 s; $p < .001$). In contrast, the retrieval group showed little change over time, with reaction times remaining stable from early to late practice (0.56 ± 0.15 s to 0.49 ± 0.12 s; $p = .320$). This pattern of results indicated that the behavioral signatures were consistent with those observed in Experiment 1 despite the stricter controls.

Further, we analyzed reaction times at the non-critical targets as an additional check that the revised design continued to elicit distinct strategies in the two groups. We found a significant main effect of Group ($b = -0.55$, $SE = 0.10$, $t(76) = -5.41$, $p < .001$), Time ($b = -0.42$, $SE = 0.08$, $t(76) = -5.14$, $p < .001$), and interaction ($b = 0.26$, $SE = 0.12$, $t(76) = 2.23$, $p = .029$; Figure 3F). These results show that the RT signatures were consistent across target locations, reinforcing that our design manipulation successfully induced distinct strategies in the two groups.

*Implicit recalibration*

The primary goal of this study was to test whether different forms of explicit strategy differentially shape implicit recalibration when controlling for error spillover. We first compared implicit recalibration between the algorithmic and retrieval groups to test whether strategy use directly modulates its magnitude. Numerically, implicit recalibration was larger in the retrieval group (15.49 ± 8.99°) than in the algorithmic group (11.43 ± 6.43°), but this difference did not

reach significance ($t(38) = -1.65$, $p = .11$; Figure 3G). When the generalization functions were fit with Gaussians, the estimated amplitude of the generalization function was similar across groups (Algorithmic: 14.99°; Retrieval: 16.20°; bootstrap, $p = .28$; Figures 3G and 6C). Interestingly, the algorithmic ($\mu = 28.69°$) and retrieval groups ($\mu = 10.94°$; bootstrap, $p = .01$, Figure 6A, D) showed distinct centers of generalization, a difference that may reflect the groups' markedly different distributions of aiming directions and is consistent with the principle of plan-based generalization. More importantly, by imposing stricter controls on plan-based generalization, we reduced the breadth of the algorithmic group's generalization function ($\sigma = 53.06°$) compared with Experiment 1 ($\sigma = 75.41°$). This narrowing was consistent with our feedback manipulation effectively constraining implicit recalibration at non-critical target locations, yielding negligible aftereffects in both groups (Algorithmic: 5.66 ± 4.31°; Retrieval: 4.05 ± 3.58°; $t(38) = 1.28$, $p = .21$; Figure 3G, Figure 6A, B). In contrast, the breadth of the generalization function for the retrieval group ($\sigma = 37.12°$) remained relatively unchanged from what we observed in Experiment 1 ($\sigma = 32.97°$), as participants only needed to reach directly towards assigned target locations. This narrowing in the algorithmic group provides clear evidence that statistics of planned aiming direction reshapes implicit recalibration via plan-based generalization. Nevertheless, the difference in the breadth of generalization function between algorithmic and retrieval groups still remained modest (Figures 3G and 6A, D, E; bootstrap, $p = .02$).

First, this modest difference in generalization breadth cannot be explained by overall adaptation level: adaptation was comparable between groups immediately before each Exclusion block ($F(1, 256) = 0.86$, $p = .354$) and did not change reliably across practice ($F(6, 256) = 1.89$, $p = .083$). Second, the group difference in generalization is unlikely to reflect continued use of algorithmic strategies during the Exclusion blocks. Consistent with this, Exclusion-block reaction

times showed no main effects of Group ($F(1, 266) = 0.20$, $p = .651$) or Time ($F(6, 266) = 1.05$, $p = .395$), indicating that both groups responded comparably quickly. This difference in generalization function could only be explained by reach variability at the critical target location, as the algorithmic group produced more variability than the retrieval group (Figures 3G and 6A; bootstrap, $p < .001$). Consequently, stricter control of plan-based generalization from the non-critical targets by restricting online feedback yielded broadly comparable generalization functions in the algorithmic and retrieval groups. However, these constraints were insufficient to equalize reach variability at the critical target, which likely contributed to the remaining modest group difference.

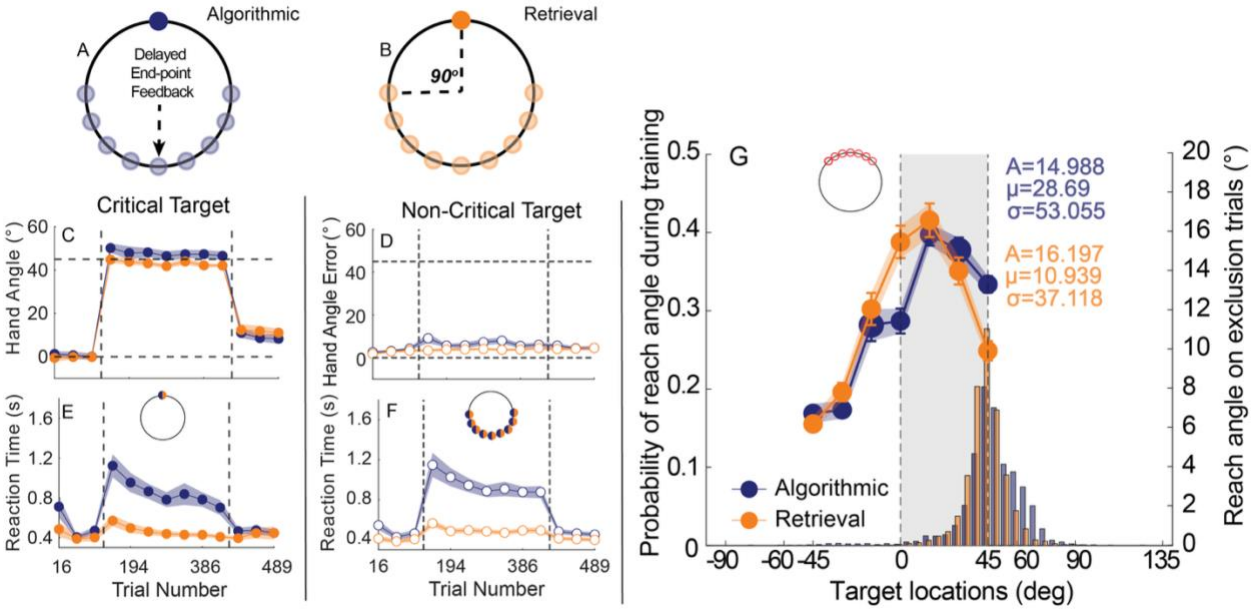


Figure 3. A) Diagram of workspace setup and target locations for algorithmic strategies in Experiment 2. Participants receive delayed endpoint feedback at all non-critical targets. B) Diagram of workspace setup and target locations for retrieval strategies in Experiment 2. C) Hand angle for the critical target locations. D) Absolute hand angle error for the non-critical target location. E) Reaction time for the critical target location. F) Reaction time for the non-critical target location. G) Generalization curves for algorithmic and retrieval strategies. Beneath the curves, bars represent the distribution of reach direction for each group. The shaded gray region marks the "aiming zone," where participants were most likely to aim when counteracting the 45° rotation at the critical target. The amplitude, mean, and width parameters displayed in the figure were derived from Gaussian function fits.

## Experiment 3

In Experiments 1 and 2, we found that variability in reaching direction strongly shaped the breadth of implicit generalization. This created a key interpretive challenge: when variance changes, the generalization profile can change with it, making it hard to isolate what each explicit strategy contributes. Here, we used an error-clamp to generate sensory prediction errors that were incidental to task goals, thereby isolating implicit recalibration while minimizing strategy-specific influences from plan-based generalization (Morehead et al., 2017; Poh and Taylor, 2019). Specifically, participants in the algorithmic group had to compute the appropriate aiming direction relative to the critical target on each trial based on verbal (or text) based instructions, whereas participants in the retrieval group reached directly to the non-critical targets and only needed to retrieve a cached aiming solution for a single, 45° target (see. Figure 4). When participants were instructed to reach the 45° direction, we constrained cursor feedback to a fixed 15° trajectory, effectively removing trial-to-trial variability in the experienced error (Figure 4A). To restrict implicit recalibration at other probing locations, no error-clamp feedback was displayed (Figure 4B, C). With the impact of reach variability largely eliminated, the resulting generalization function is minimally influenced by movement dispersion, allowing a more direct test of how algorithmic versus retrieval strategies uniquely shape implicit recalibration.

*Adaptation performance*

Replicating the pattern from Experiments 1 and 2, hand angles were comparable across groups, with no main effect of Group ($b = -1.21$, $SE = 2.09$, $t(72) = -0.58$, $p = .565$). Participants did show a modest decline in hand angle from early to late practice ($b = -4.42$, $SE = 2.01$, $t(72) = -2.20$, $p = .031$), but this drift was similar in both groups (group × time: $b = 3.60$, $SE = 2.85$, $t(72) = 1.27$, $p = .210$). In other words, despite the design differences from all previous experiments, the algorithmic and retrieval groups ultimately reached an essentially identical level of adaptation at

the critical target (Figure 5A). Furthermore, the stability of a cached memory is more stable or precise than executing an algorithmic strategy, as reflected by a main effect of Group (variability for retrieval - algorithmic: $b = -2.73$, $SE = 1.17$, $t(72) = -2.35$, $p = .021$).

To provide an additional check that performance was matched across groups under error-clamp conditions, we also examined hand-angle errors at the non-critical targets from early to late practice. The algorithmic and retrieval groups performed similarly (no main effect of Group: $b = 1.68$, $SE = 1.73$, $t(72) = 0.97$, $p = .336$), and errors remained stable over time (no main effect of Time: $b = -0.88$, $SE = 1.63$, $t(72) = -0.54$, $p = .591$), with no group differences in change across practice (Group × Time: $b = 1.34$, $SE = 2.30$, $t(72) = 0.58$, $p = .563$) (Figure 5B).

*Preparation time*

Despite the major redesign in Experiment 3, the reaction-time pattern closely matched what we observed in earlier experiments (Figure 5C). Across groups, responses became faster from early to late training, yielding a reliable main effect of Time ($b = -0.21$, $SE = 0.04$, $t(72) = -6.05$, $p < .001$). We also observed a strong main effect of Group ($b = -0.46$, $SE = 0.06$, $t(72) = -8.08$, $p < .001$), indicating that the retrieval group responded markedly faster than the algorithmic group overall. At the same time, the magnitude of improvement differed between groups, as reflected by a significant Group × Time interaction ($b = 0.15$, $SE = 0.05$, $t(72) = 2.98$, $p = .004$). This interaction was driven primarily by a pronounced reduction in reaction time for the algorithmic group from early ($0.98 \pm 0.29$ s) to late training ($0.76 \pm 0.14$ s, $p < .001$), whereas reaction time in the retrieval group changed little (early: $0.52 \pm 0.13$ s; late: $0.45 \pm 0.09$ s, $p = .07$). Notably, this dissociation persisted even without a visible target at 45° relative to the critical target. The retrieval group's consistently fast responses are consistent with caching a stable aiming solution, whereas the algorithmic group appeared to rely on trial-by-trial computation of the appropriate aiming direction.

Further, we validate this interpretation that the two groups relied on distinct explicit strategies to plan their aiming solutions by comparing their reaction-time profiles at the non-critical target locations (Figure 5D). The reaction time profile largely mirrored what we observed when aiming in the 45° direction. In particular, both groups increased their response speed from early to late training (main effect of Time: $b = -0.48$, $SE = 0.09$, $t(72) = -5.14$, $p < .001$), with the retrieval group having an overall faster reaction time than the algorithmic group (main effect of Group: $b = -1.10$, $SE = 0.13$, $t(72) = -8.80$, $p < .001$). In addition, the amount of improvement differed by Group (Group × Time: $b = 0.45$, $SE = 0.13$, $t(72) = 3.39$, $p = .001$): the algorithmic group showed a clear reduction in RT across practice (early: 1.56 ± 0.75 s; late: 1.08 ± 0.21 s; $p < .001$), whereas the retrieval group remained consistently fast with little change (early: 0.46 ± 0.10 s; late: 0.42 ± 0.08 s; $p = .73$). This replication at non-critical targets provides converging evidence that Experiment 3 successfully dissociated the explicit strategies used by the two groups.

*Implicit recalibration*

Like the first two experiments, the primary goal was to determine if different kinds of explicit strategies have downstream effects on implicit recalibration (Figure 4D).

We first examined whether different kinds of strategies differentiate their impact on the amplitude of implicit recalibration. As a result, we found there was no significant difference in amplitude of implicit recalibration arising from different kinds of explicit strategies (Figure 5E; algorithmic: 7.21± 3.36°, retrieval: 8.08 ± 4.24°, $t(36) = -0.70$, $p = 0.49$). This result was further supported by fitting hand angles from Exclusion trials to Gaussian function, indicating that the amplitude between algorithmic ($A = 9.05°$) and retrieval groups ($A = 9.87°$) was comparable (Figure 6C). Likewise, the center of the generalization function was statistically indistinguishable between groups (Figures 5E and 6D; algorithmic: $\mu = 41.43°$, retrieval: $\mu = 51.61°$; bootstrap, p =

0.37). Notably, under the error-clamp design, the breadth of generalization also converged: the algorithmic group (σ = 69.62°) and retrieval group (σ = 75.67°) showed comparable breadths (Figures 5E and 6E; bootstrap, p = 0.39). Because the algorithmic group continued to generate more variable aiming solutions than the retrieval group, the fact that both groups nevertheless showed comparable generalization breadth suggests that plan-based generalization did not meaningfully contribute to the present effect. This stands in contrast to Experiments 1 and 2, where differences in aiming variability were accompanied by broader generalization in the algorithmic group.

Again, this comparison of generalization function was based upon the fact that both groups reach comparable levels of adaptation prior to Exclusion trials ($F(1, 243) = 0.50$, $p = .48$), which was sustained throughout the entire training period ($F(6, 243) = 0.48$, $p = .82$). In addition, explicit strategies were successfully withheld during the assessment of implicit recalibration ($F(1, 252) = 4.19$, $p = .042$). Overall, these results showed that when plan-based generalization is minimized with error-clamp feedback, algorithmic and retrieval strategies yield indistinguishable implicit recalibration (amplitude/center/breadth), despite more variable aiming plans preserved in the algorithmic group (Figure 5E).

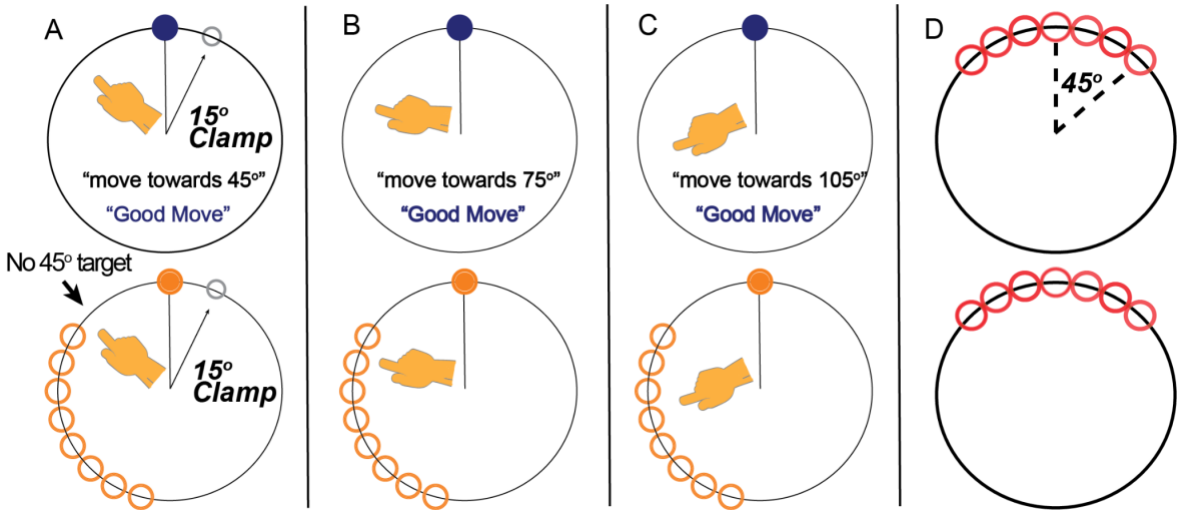

Figure 4. A) The example for trials reaching toward the 45º direction with an 15° error-clamp feedback. B) The example for trials reaching toward the 75º direction with no error-clamp feedback. C) The example for trials requiring reaching toward 105º direction with no error-clamp feedback. For any non-critical locations, no error-clamp feedback was imposed. D) The critical target and probing target locations for Exclusion trials.

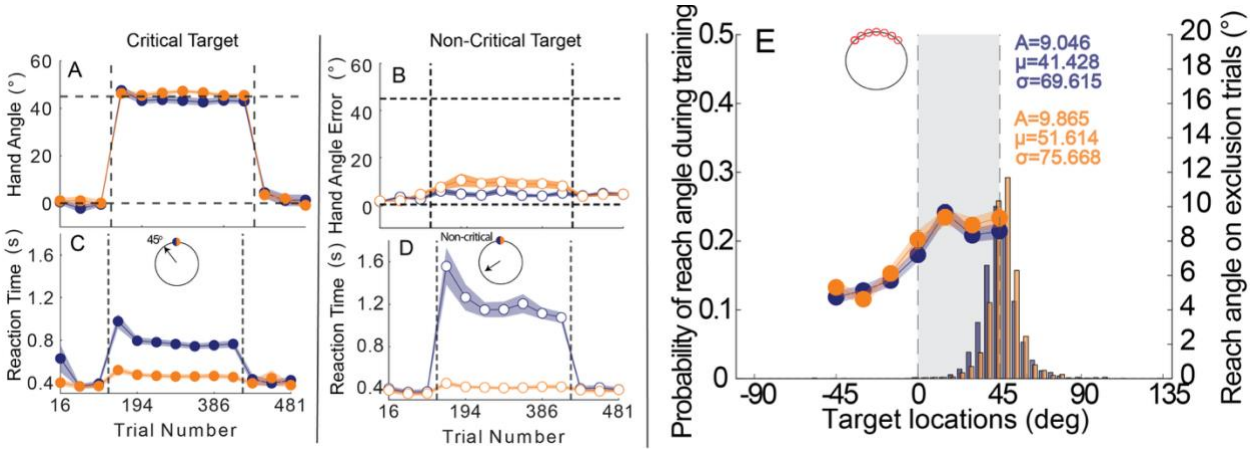


Figure 5. A) Hand angles at the critical target location. B) Absolute hand angle errors at the non-critical target locations. C) Reaction times at the critical target locations. D) Reaction time at the non-critical target locations. E) Generalization curves for algorithmic and retrieval strategies. Beneath the curves, bars represent the distribution of reach direction for each group. The shaded gray region marks the "aiming zone," where participants were most likely to aim when counteracting the 45° rotation at the critical target. The amplitude, mean, and width parameters displayed in the figure were derived from Gaussian function fits.

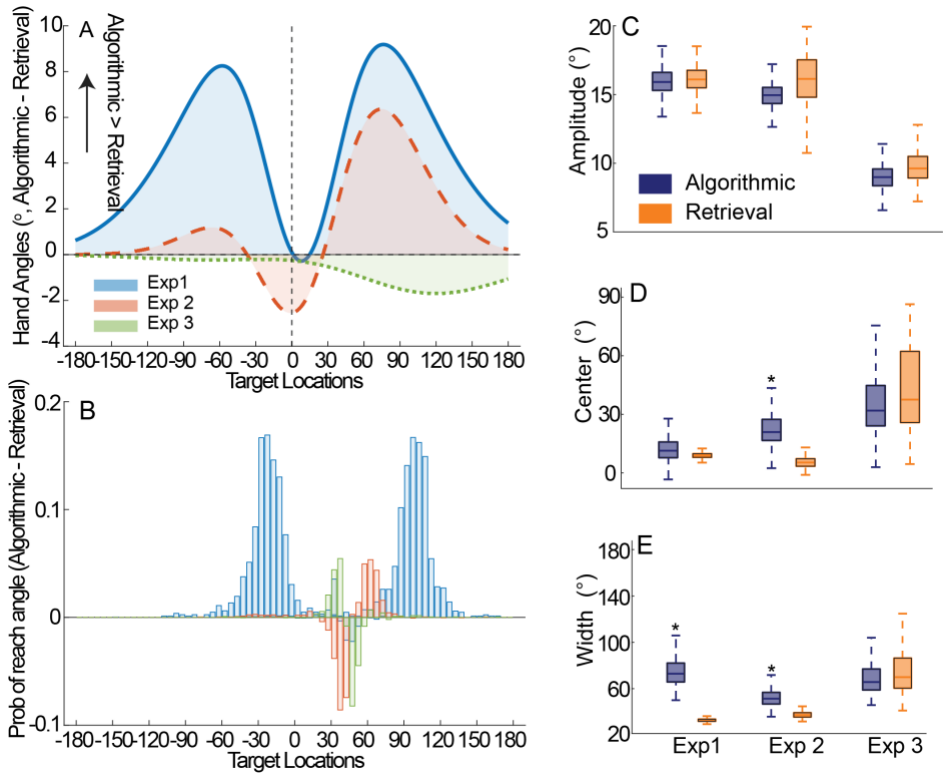

Figure 6. Summary of fitting Gaussian function across three experiments. A) Contrast of generalization function after fitting the model using algorithmic - retrieval strategies. X axis represents probing target locations, and Y axis represents the magnitude of hand angle. B) The difference in probability of reach angle. Positive value indicates that algorithmic strategies reach more frequently within that area. In Exp1, we did not compare reach-angle probabilities between the algorithmic and retrieval groups because the retrieval group showed no implicit recalibration at the non-critical targets. Therefore, we report reach angles to the non-critical targets for the algorithmic group only. C) Amplitude of generalization function across all three experiments. D) Center of the generalization function across all three experiments. E) Width of the generalization function across all three experiments.

## Discussion

*Summary*

In this study, we tested whether algorithmic and retrieval-based strategies, both of which are known to improve performance in visuomotor adaptation, differentially affect implicit recalibration – a central debate in the field. Given that these two strategies likely rely on distinct neural circuits, they could interact with the cerebellar-based recalibration system in different ways. Furthermore, retrieval strategies form stricter stimulus-response associations compared to algorithmic strategies, which could reshape implicit recalibration at a more process level. Indeed, a prior study has found greater generalization of the strategy under algorithmic compared to retrieval strategies but the study deliberately minimized implicit recalibration, leaving open the question of whether such strategy differences truly penetrate implicit recalibration (McDougle and Taylor, 2019).

To address this question, we manipulated the target set size to bias participants towards algorithmic and retrieval strategies (McDougle and Taylor, 2019; Velazquez-Vargas and Taylor, 2024), while controlling for several confounding factors such as inter-trial interval and memory decay (Hadjiosif et al., 2023), plan-based generalization (Day et al., 2016; McDougle et al., 2017; Chen and Taylor, 2025), and unequal training exposure (Bond and Taylor, 2015). To quantify implicit recalibration, we interleaved periodic Exclusion trials in which error feedback was withheld and participants were instructed to withhold any explicit strategy (Werner et al., 2015;

Maresch et al., 2021; t Hart et al., 2024; Chen and Taylor, 2025). Our experimental design across a set of experiments was successful in dissociating type of strategy use, with reliably slower RTs in the algorithmic group, yet both groups reached comparable asymptotic adaptation (~45°). These important experimental controls were essential in supporting that any observed differences in implicit recalibration reflected only differences in strategic demands rather than differences in exposure or target statistics.

In Experiments 1 and 2, we observed a broader implicit generalization function under algorithmic than retrieval strategies. Although this pattern could be construed as consistent with classic accounts in which stimulus variability promotes generalization (Estes and Burke, 1953; Schmidt, 1975), we do not think it reflects a fundamental change in implicit recalibration per se. Instead, we interpret the apparent broadening as a consequence of plan-based generalization: because algorithmic strategies generate more variable movement plans, implicit recalibration may accrue across variable aiming locations, producing error spillover that inflates the measured breadth of the implicit generalization function around the critical target. Critically, in Experiment 2, we imposed stricter constraints to minimize implicit recalibration at non-critical targets. This manipulation substantially reduced the distribution of learning-relevant errors (training inputs) across the workspace, and the measured implicit generalization function narrowed accordingly. Because implicit recalibration has been shown to generalize around the planned movement (Day et al., 2016; McDougle and Taylor, 2019; Poh and Taylor, 2019), any residual broadening under algorithmic strategies would be expected if participants continued to produce more variable aiming solutions at the critical target. Consistent with this account, our complementary analyses of reaching distribution showed that hand angles at the critical target were more dispersed under algorithmic than retrieval strategies. This pattern supports the perspective that explicit strategy

functions as a controller that shapes the training inputs received by the implicit system (Schween et al., 2018; Poh et al., 2021). Once variability characterized by explicit strategies becomes irrelevant (Experiment 3), the difference in generalization function becomes negligible. Modern probabilistic accounts similarly argue that generalization reflects inference about error sources and the relevance of disturbances, again emphasizing statistics of experience rather than the subjective strategy used to generate actions (Berniker and Kording, 2008). Our results support this account: the use of algorithmic and retrieval strategies can produce differing spatial distributions of these re-aiming plans and, as a consequence, implicit generalization follows those plan statistics. When we removed such a feedthrough pathway with error clamp, the implicit map no longer differed across groups (Figure 4G). Again, our results reinforce the view that explicit and implicit learning operate relatively independently, besides the indirect effects of being in tandem with one another (Taylor and Ivry, 2011; Miyamoto et al., 2020). On this account, explicit strategies need not exert any "special" influence over implicit recalibration beyond their role in shaping the state the learner occupies.

*The interaction of explicit and implicit adaptation*

The literature offers compelling, yet mixed, accounts of how explicit and implicit processes interact. One prominent view is that explicit re-aiming strategies and implicit recalibration reflect largely independent learning processes, such that overall adaptation can be approximated as the sum of these components (Mazzoni and Krakauer, 2006; Taylor and Ivry, 2011, 2014). Support for this account comes from aiming-report and error-clamp paradigms, which suggest that implicit recalibration often unfolds in a relatively stereotyped manner and shows limited sensitivity to factors such as task relevance and error size (Bond and Taylor, 2015; Morehead et al., 2017; Kim et al., 2018). Under this view, the explicit component acts as a flexible compensatory controller,

adjusting in response to any residual task performance error (Taylor and Ivry, 2011). Implicit recalibration can also respond to errors produced by explicit re-aiming (Miyamoto et al., 2020). Furthermore, implicit recalibration appears to be inextricably yoked to where explicit re-aiming strategies operate – referred to as plan-based generalization (Day et al., 2016; McDougle et al., 2017). These findings suggest that potential interactions between explicit strategies and implicit recalibration are simply indirect because they are operating in series (Taylor and Ivry, 2011; McDougle et al., 2017; Miyamoto et al., 2020).

An alternative view puts forth that explicit and implicit processes compete for a common error signal, where, reducing one component is often accompanied by a compensatory increase in the other, yielding an inverse relationship between explicit and implicit contributions (Albert et al., 2022). This pattern is typically interpreted as evidence for a direct interaction – rather than independence – between the two processes, which can lead to more complex or, at least, nonlinear interactions when explicit strategies are at play in visuomotor rotations tasks (Neville and Cressman, 2018; t Hart et al., 2024) The nature of this potential interaction is especially complicated because it depends on how these components are operationalized and measured during adaptation. Multiple studies argue that common assessment methods can bias or distort estimates of explicit and implicit contributions, complicating inferences about their interaction (Maresch et al., 2021; t Hart et al., 2024). At present, we do not have a way to probe explicit strategies or implicit recalibration that does not result in some sort of an intervention or observer effect. Even leveraging approaches, such as limiting preparation time (Haith et al., 2015), do not offer a way to independently measure explicit and implicit learning without breaking the fourth wall (Chen and Taylor, 2025).

Here, we attempted to, at least avoid, these potential intervention problems by first letting training to unfold naturally under our different task demands before introducing the Exclusion trials to probe implicit recalibration. Target set size alone was sufficient in biasing participants towards different strategies, as measured indirectly from RT. We then implemented a stepwise set of increasingly stringent controls across Experiments 1–3 and ultimately found that algorithmic and retrieval strategies produced progressively indistinguishable functions of implicit recalibration. Under error-clamp conditions – where implicit updating is largely insulated from plan-based generalization – implicit recalibration showed little sensitivity to the underlying form of the strategy, consistent with an independent account of explicit and implicit processes in sensorimotor adaptation (Mazzoni and Krakauer, 2006; Taylor and Ivry, 2011; Taylor et al., 2014; Morehead et al., 2017).

Beyond directly affecting implicit recalibration, a number of studies have demonstrated alternative routes through which explicit strategies could act as contextual cues to create, select, and update a different motor memory (Heald et al., 2021). In particular, the motor system appears to segment experience into latent causes and uses available cues to infer which memory should be expressed and updated; a strategy could therefore become part of the cue set only if it shifts the inferred latent structure of the task (Heald et al., 2021). For example, the study showed broader generalization when targets were rated as highly similar, suggesting that explicit strategy selection effectively treated them as the same context (Poh et al., 2021). Moreover, when participants were encouraged to prioritize one contextual cue over another, generalization increased specifically along the dimension that was emphasized (Poh et al., 2021). In our experiments, participants always faced the same overarching aiming problem under a stable task framing, and the key manipulation was whether the solution was computed online or retrieved from memory. That

distinction may not have constituted a salient contextual boundary for implicit learning to assign error to distinct latent causes (Heald et al., 2021). However, if different strategies were embedded within meaningfully different inferred task states, such as distinct goals, rules, mappings, or conceptually separable contexts, then strategy adoption could become a strong contextual signal, potentially supporting more separable implicit memories even when movement plans overlap (Heald et al., 2021; Poh et al., 2021). This possibility is especially relevant for paradigms in which implicit adaptation contributes a larger fraction of behavior (e.g., dynamic force-field adaptation; (Forano et al., 2021)). If the form of strategy can serve as a contextually-bound cue to retrieve the appropriate implicit mapping, then the degree to which strategies directly or indirectly affect implicit recalibration becomes more of a categorical or philosophical distinction.

**Conclusion**

By rigorously controlling multiple confounds that influence implicit recalibration across three experiments, our findings suggest that the strategies employed during visuomotor adaptation do not differentially reshape the implicit recalibration landscape. Explicit strategies do not appear to directly impact implicit recalibration beyond the observation that they simply act as a gate to control the data inflow that is used to update the implicit mapping. Simply put, the implicit recalibration system will faithfully update its mapping with whatever training data it is provided. Our findings offer a more pedestrian explanation for the role of training variability or, more broadly, guidance theories for generalization (Schmidt, 1975) – it is just the sampling distribution when it pertains to implicit sensorimotor adaptation.

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