Signatures of short-term and long-term strategies for visuomotor adaptation

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Abstract

Cognitive strategies are essential for visuomotor adaptation. Task set size (the number of targets) often determines which strategy is engaged: working memory (WM) is sufficient for small set size, but its capacity is often limited for more complex tasks. These WM limitations may be bypassed by retrieving a strategy from long-term motor memory (LTM), but the required repetition is unknown. To address this, participants were trained on a single target–rotation pair, establishing an LTM visuomotor solution, after which we probed LTM-based retrieval across set sizes by comparing it with WM. The results indicated that LTM-based retrieval was relatively automatic and largely insensitive to set size, whereas WM-based retrieval declined as set size increased. Initial practice of just 10 or 30 trials produced similarly robust LTM for a strategy, which outperformed strategies held in WM. Model-based analyses suggested a trend toward higher LTM precision at larger set sizes, consistent with dynamic interactions between WM and LTM.

Keywords: Sensorimotor Adaptation, Cognitive Strategy, Long term memory, Retrieval Strategy

Introduction

Visuomotor adaptation (VMR) is essential for maintaining skilled motor performance when the environment changes unexpectedly (Wolpert & Ghahramani, 2000; Shadmehr et al., 2010; Krakauer et al., 2019). Recent work increasingly indicates that cognitive strategies make a substantial contribution to adaptation, often through explicit re-aiming: deliberately aiming in the direction opposite the visual perturbation by an equal magnitude (Taylor et al., 2014; Taylor et al., 2011; McDougle et al., 2019).

Previous research indicates that cognitive strategies in VMR can take at least two forms. An algorithmic strategy continuously computes aiming solutions to counter the visual perturbation and carries high computational demands (McDougle & Taylor, 2019). In contrast, a retrieval strategy caches a previously successful aiming solution in working memory by establishing stimulus–response associations between a target location and its aiming solution, enabling movement automaticity (McDougle & Taylor, 2019; Velazquez-Vargas & Taylor, 2024). Relative to algorithmic strategies, retrieval reduces the time required to compute an aiming solution and lowers movement variance (Logan, 1988; Fresco et al., 2023). However, the success of retrieval-based strategies in VMR is significantly limited by working memory capacity (Velázquez-Vargas & Taylor, 2024).

This limitation may be mitigated by retrieving aiming solutions from a form of long-term motor memory. Unlike working memory, which holds only a few items at a time, long-term motor memory should have virtually unlimited capacity, enabling storage of aiming solutions over extended periods (Fresco et al., 2023). For a target–aiming solution to enter long-term memory, it must undergo consolidation (Shadmehr & Krakauer, 2006), which can be achieved through repeated practice (Huberdeau et al., 2015; Cowan, 2008) by solidifying direct stimulus–response associations or control policies (Logan, 1988; Haith & Krakauer, 2018). Although repetition-dependent transfer to a long-term memory store has been studied extensively in declarative memory, it remains unclear how many repetitions are needed to consolidate a visuomotor aiming strategy in long-term motor memory (Huberdeau et al., 2015; Huberdeau et al., 2019).

Previous studies have shown that long-term memory-based retrieval of motor strategies is often expressed as an automatic response without deliberate planning, even under constrained response times (Huberdeau et al., 2019; Hardwick et al., 2019). However, these signatures are typically assessed only after multiple days of practice, in which case consolidation cannot be attributed to practice alone — time and sleep may also contribute substantially (Walker & Stickgold, 2004; Huberdeau et al., 2019; McGaugh, 2000). In contrast, the primacy effect in free recall suggests that even a single exposure can be consolidated into long-term memory despite interference from subsequent items (Murdock, 1962; Glanzer & Cunitz, 1966). Given that evidence for long-term memory retrieval spans a wide range of practice schedules — from a single trial to multiple days — it becomes difficult to trace the dose-dependent relationship of long-term memory formation attributable to practice alone.

Here, across three experiments, we sought to determine the minimal amount of practice required to form a long-term memory aiming strategy and to establish a dose-dependency relationship between repetitions and long-term memory. Because short-term retrieval in VMR is strongly constrained

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by working memory capacity — characterized by longer reaction times and greater variability as set size increases — we developed a protocol that enables continuous assessment of long-term memory retrieval across multiple set sizes while interleaving probes of short-term retrieval within the same task. Comparing reaction time and reach performance between long-term and short-term retrieval as a function of set size allowed us to dissociate strategies held in working memory from those held in long-term memory.

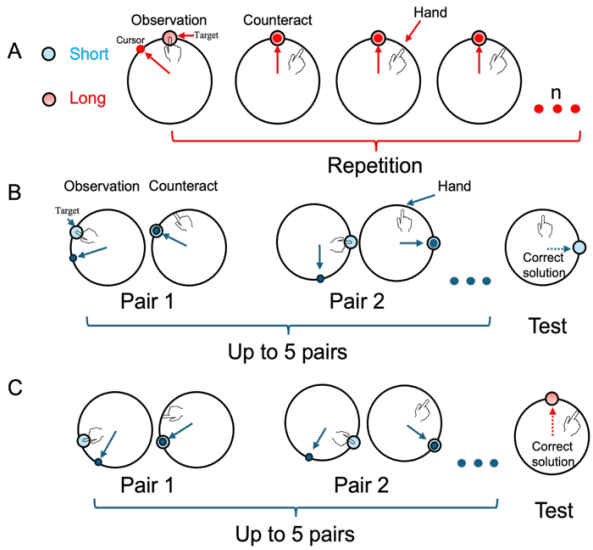

Figure 1: Experiment design. A) Initial encoding of the long-term target (red). B) An example of mini-block trial-pair design with testing a short-term target in the end. C) An example of mini-block with testing the long-term target.

Methods

Participants

One hundred and forty-three right-handed college students (mean age = 20.56 years, SD = 3.73, Female = 76) were recruited from the subject pool maintained by the Department of Psychology at Princeton University. All experimental procedures were approved by the Institutional Review Board (IRB), and written informed consent was obtained from all participants prior to participation.

Apparatus and General Procedure

The experiment was conducted online using the OnPoint-Master system, a validated platform for remotely administering visuomotor adaptation tasks in each participants' own computer (see Tsay et al., 2021). Participants used a trackpad to perform center-out reaching movements, controlling an on-screen cursor. The start position was marked by a white circle at the screen center, and the target—colored blue or red depending on condition—was placed 2.4 inches away. Participants were instructed to move quickly and accurately; movements had to be completed within 300 milliseconds. Violations triggered a "Move faster" warning. Online feedback was removed after movement initiation, and endpoint feedback was shown once the cursor exceeded the target radius. If accurate, the cursor reappeared directly over the target.

In the classic visuomotor rotation task, a constant angular mismatch was introduced between hand and cursor trajectories. To succeed, participants had to compensate by reaching in the opposite direction with equal angular magnitude. To isolate explicit strategies from implicit adaptation, endpoint feedback was delayed by 1 second after movement completion—a method known to attenuate implicit learning (Brudner et al., 2016). Feedback remained visible for 0.5 seconds, after which the program assisted in returning the cursor to the center to begin the next trial.

Task Design for Assessing Retrieval Strategy

The present study aimed to dissociate retrieval-based aiming strategies supported by working memory versus long-term memory. We embedded a visuomotor rotation task in a classic working-memory item-recognition paradigm (Pellizzer & Georgopoulos, 1993; Sternberg, 1969). Participants first completed a concentrated learning phase to promote long-term memory transfer, then performed mini-blocks alternating encoding and retrieval to probe working memory.

In the learning phase, participants compensated for a fixed 75° rotation at a single red target across 1–30 repetitions (varying by experiment), with target location and rotation direction counterbalanced across participants. Each mini-block began with an encoding phase of 1–5 observation–counteract pairs at blue targets. On observation trials, participants viewed the rotation's sign and magnitude while cursor direction was clamped to the imposed rotation, removing motor variability. On the subsequent counteract trial, they aimed in the opposite direction. Rotation magnitude, direction, and target location were randomized across mini-blocks. At retrieval, either a blue target or the red learning target was presented, and participants recalled the appropriate strategy.

Each participant's long-term memory target was randomly assigned from 24 locations (15° spacing) and paired with a fixed ±75° rotation. The working-memory pool comprised the opposite-signed 75° rotation plus eight additional rotations (±30°, ±45°, ±60°, ±90°), sampled uniformly from ±90° in 15° steps to enable separation of memory-based responses from guessing (Zhang & Luck, 2008). Mini-blocks were balanced across set sizes; one encoded pair was randomly selected for retrieval after each encoding phase, and each rotation magnitude was tested twice per set size. Reaction time and reach direction were recorded.

Experiment 1

Experiment 1 (N = 79) tested whether prolonged repetition of a single strategy could transfer it to long-term memory, freeing working memory to cache new strategies. Before the first encoding block, participants completed one observation

trial followed by 29 counteracting trials at the designated long-term memory target to establish a stable movement solution. During subsequent blocks, the long-term memory target was not presented at encoding but could be randomly selected for retrieval, balanced across set sizes such that it was tested twice at each set size. Participants then completed mini-blocks comprising encoding and retrieval phases. The experiment included 463 trials in total: 38 baseline, 30 long-term memory practice, 55 mini-blocks (385 trials), and 10 washouts.

Experiment 2

Experiment 2 (N = 30) shortened the initial learning phase to begin quantifying a dose-dependency curve between repetitions and the precision of a long-term memory strategy. The task was identical to Experiment 1 except that the learning phase comprised only 10 trials (1 observation, 9 counteracting) at the fixed target–rotation pair, yielding 453 trials total.

Experiment 3

Experiment 3 (N = 34) tested whether a single instance of learning is insufficient to promote long-term memory transfer. The task was identical to the prior experiments except that the learning phase comprised only 2 trials (1 observation, 1 counteracting), yielding 445 trials total.

Data Analysis

All analyses were conducted in MATLAB R2025b and R 4.5.2. Task performance was quantified using reaction time (RT; time between target appearance and movement onset), target error (angular distance between cursor and target), unsigned error (absolute target error), reach magnitude (angular distance of the hand from the target), and reach variability (SD of target errors across trials within each set size). Measures were computed per subject, except target error distributions, which were pooled. Statistical analyses included linear mixed-effects models, correlations, and t-tests.

Non-learners were identified using counteracting trials, in which reach direction should be negatively correlated with rotation magnitude. Participants with a positive or non-significant Pearson correlation between reach angle and rotation magnitude ($r > 0$ or $p > .05$) were excluded as non-compliant, yielding final samples of 56/79 (Experiment 1), 20/30 (Experiment 2), and 26/34 (Experiment 3). Given the minimal demands of these trials, exclusions likely reflect non-compliance rather than learning failure, consistent with elevated non-compliance rates reported for online VMR tasks (Crump et al., 2013).

Model fitting

To dissociate cognitive processes underlying task performance, we used a Bayesian latent-mixture model (Lee, 2018; Shiffrin et al., 2008) in which angular errors (θ, in radians) were modeled as a mixture of memory-based responses, drawn from a von Mises distribution, and random guesses, drawn from a uniform distribution (Zhang & Luck, 2008; Velázquez-Vargas & Taylor, 2024). Memory precision was indexed by κ (higher κ = higher precision) and guessing rate by ϕ. Due to limited trials per participant, parameters were estimated at the group level for each set size using circular statistics functions in R (e.g., *dvonmises*). Posterior estimates were evaluated with 1,000 bootstrap replicates, with 95% confidence intervals defined by the 2.5th and 97.5th percentiles (Lehmann & Romano, 2010).

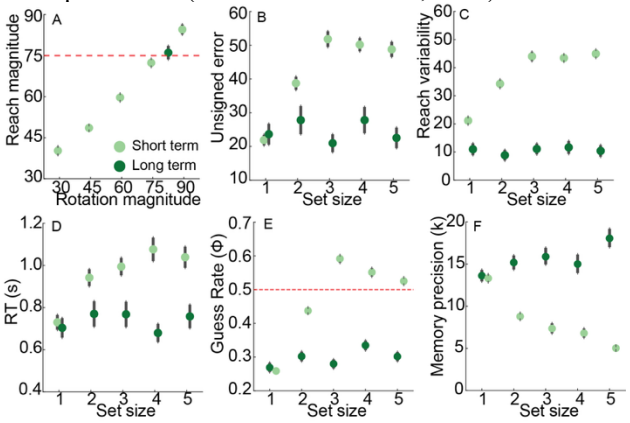

Figure 2: Experiment 1. Encoding with 30 repetitions. A) Reach angle at encoding phase for working memory targets (light green) and the long-term memory target during the learning phase (dark green). B) Absolute error during retrieval tests. C) Reach variance during retrieval tests. D) Reaction time during retrieval tests. E) Guessing rate with greater than 0.5 indicating a bias towards uniform distribution. F) Memory precision with larger numbers indicating more precise retrieval.

Results

Experiment 1

Experiment 1 tested whether extensive practice (30 repetitions) of counteracting a single rotation at a fixed target could establish a long-term memory strategy with distinct behavioral signatures relative to working-memory strategies. Participants counteracted rotations accurately: reach angle scaled with rotation magnitude for working memory targets [$r(278) = 0.82$, $p < 0.001$, Fig. 2A], and did not differ from rotation magnitude for the long-term memory target [$t(55) = 0.43$, $p = 0.67$], confirming successful encoding. However, working-memory performance degraded with set size, with larger unsigned error [$r(278) = 0.49$, $p < 0.001$, Fig. 2B] and greater reach variability [$r(278) = 0.57$, $p < 0.001$, Fig. 2C], whereas long-term target performance remained stable [unsigned error: $r(278) = -0.01$, $p = 0.83$; variability: $r(278) = 0.02$, $p = 0.81$]. Collapsed across set sizes, the long-term target was more accurate [$F(1, 55) = 74.55$, $p < 0.001$] and less variable [$F(1, 55) = 151.47$, $p < 0.001$] than working memory targets, though the accuracy advantage was absent at set size 1 [$p = 0.94$].

Consistent with automatic, set-size-insensitive retrieval, RTs for the long-term target were stable across set sizes [$r(278) = 0.01$, $p = 0.92$, Fig. 2D], whereas working-memory RTs increased with set size [$r(278) = 0.30$, $p < 0.001$]. Overall, responses were faster for the long-term target [$F(1, 55) = 6.80$, $p < 0.001$], with no difference at set size 1 [$p = 0.59$].

Mixture-model analyses supported these patterns. Guessing increased with set size for working memory targets [$r = 0.73$, 95% CI (0.70, 0.76), Fig. 2E] but remained stable for the long-term target [$r = 0.24$, 95% CI (0.14, 0.34)], with higher guessing for working memory targets at all set sizes [ps < 0.001] except set size 1 [$p = 0.13$]. Memory precision declined with set size for working memory targets [$r = -0.79$, 95% CI (-0.82, -0.75), Fig. 2F] but increased for the long-term target [$r = 0.31$, 95% CI (0.21, 0.40)], with the long-term target exceeding working memory targets at all set sizes [bootstrap, ps < 0.001] except set size 1 [$p = 0.42$].

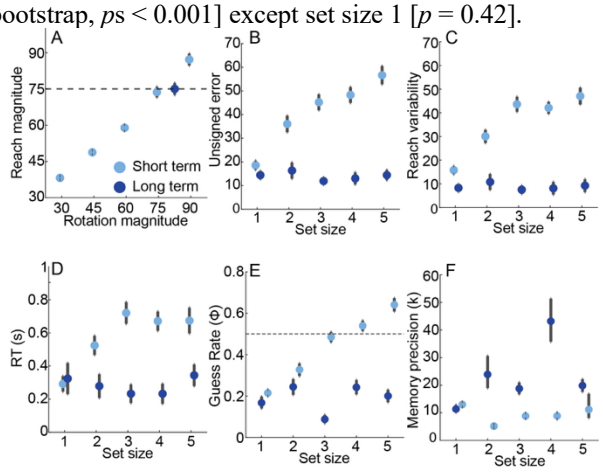

Figure 3: Experiment 2. Encoding with 10 repetitions. A) Reaching angle during encoding phase. B) Unsigned error during retrieval tests. C) Reach variability during retrieval tests. D) Reaction time during retrieval tests. E) A guessing rate greater than 0.5 indicates a bias towards uniform distribution. F) Memory precision with larger numbers indicating more precise retrieval.

Experiment 2

Extending Experiment 1, Experiment 2 tested whether 10 repetitions of a single target–rotation association were sufficient to establish long-term memory-based retrieval. Participants successfully counteracted rotations, with reach angle scaling with rotation magnitude [r(98) = 0.92, p < 0.001, Fig. 3A] and not differing from rotation magnitude at the long-term memory target [t(19) = -0.001, p = 0.99]. Working-memory performance declined with set size, with larger unsigned error [r(98) = 0.65, p < 0.001, Fig. 3B] and greater reach variability [r(98) = 0.63, p < 0.001, Fig. 3C], whereas long-term target performance remained stable [unsigned error: r(78) = -0.05, p = 0.66; variability: r(78) = -0.01, p = 0.91]. Collapsed across set sizes, the long-term target was more accurate [F(1, 18) = 202.45, p < 0.001] and less variable [F(1, 18) = 239.62, p < 0.001] than working memory targets, though the accuracy advantage was absent at set size 1 [p = 0.15]. Thus, 10 repetitions were sufficient to establish long-term retrieval that was more accurate and stable than working-memory retrieval as set size increased.

RTs further supported set-size–insensitive retrieval: long-term target RTs did not vary with set size [$r(98) = -0.01$, $p = 0.96$, Fig. 3D], whereas working-memory RTs increased [$r(98) = 0.41$, $p < 0.01$]. Overall, responses were faster for the long-term target [$F(1, 18) = 30.86$, $p < 0.001$], with no difference at set size 1 [$p = 0.66$]. Mixture-model results converged: guessing increased with set size for working memory targets [$r = 0.92$, 95% CI (0.89, 0.95), Fig. 3E] but remained stable for the long-term target [$r = 0.10$, 95% CI (-0.05, 0.25)], with higher guessing for working memory targets at all set sizes [ps < 0.001]. The long-term target also showed higher precision than working memory targets at all set sizes [ps < 0.001]; although precision appeared to increase with set size for the long-term target, this trend was not reliable [$r = 0.35$, 95% CI (0.24, 0.45)].

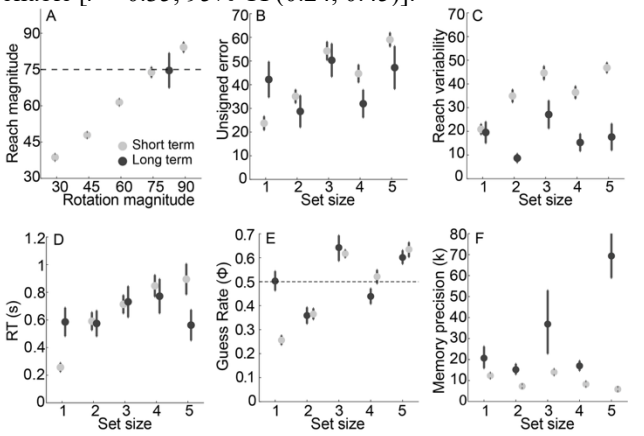

Figure 4: Experiment 3. Practice with 1 trial. A) Reaching angle during encoding phase. B) Unsigned error during retrieval tests. C) Reach variability during retrieval tests. D) Reaction time during retrieval tests. E) Guessing rate from the mixture model. F) Memory precision from the mixture model.

Experiment 3

Having established that both 10 and 30 repetitions are sufficient to support long-term memory-based retrieval, Experiment 3 tested whether a single repetition could do the same. Participants accurately compensated for rotations, with reach angle correlating strongly with rotation magnitude [$r(128) = 0.89$, $p < 0.001$, Fig. 4A] and not differing from rotation magnitude at the long-term memory target [$t(25) = -0.10$, $p = 0.96$], confirming successful encoding. Working-memory accuracy declined with set size [unsigned error: $r = 0.55$, $p < 0.001$, Fig. 4B] while long-term target accuracy did not [$r = 0.05$, $p = 0.57$], and unsigned errors did not differ between conditions overall [$F(1, 25) = 0.42$, $p = 0.52$]. Working-memory variability also increased with set size [$r = 0.49$, $p < 0.001$, Fig. 4C] but remained stable for the long-term target [$r = 0.16$, $p = 0.85$], with the long-term target less variable overall [$F(1, 25) = 60.13$, $p < 0.001$]. RTs increased

with set size for working memory targets [$r = 0.50$, $p < 0.001$] but not the long-term target [$r = 0.04$, $p = 0.66$, Fig. 4D], with no overall difference [$F(1, 25) = 0.05$, $p = 0.83$].

Mixture-model results converged: guessing increased with set size for both working memory [r = 0.81, 95% CI (0.75, 0.85), Fig. 4E] and long-term targets [r = 0.27, 95% CI (0.17, 0.38)], with the long-term target showing a slightly higher guessing rate overall [long − short: 0.03, 95% CI (0.01, 0.05)]. Memory precision decreased with set size for working memory targets [r = -0.38, 95% CI (-0.48, -0.26), Fig. 4F] but increased for the long-term target [r = 0.46, 95% CI (0.35, 0.55)], with higher overall precision for the long-term target [long − short: 22.39, 95% CI (18.22, 26.81)]. Together, these results indicate that a single exposure is insufficient to establish a stable long-term memory capable of supporting retrieval.

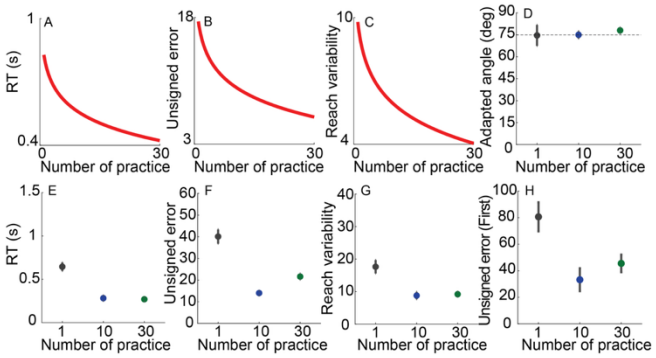

Figure 5: A) Simulation of dose-dependent reaction time. B) Simulation of dose-dependent accuracy. C) Simulation of dose-dependent reach variability. D) Performance after the initial encoding. E) Mean reaction time by group. F) Mean accuracy by group. G) Mean reach variability by group. H) Mean accuracy at the first retrieval test trial.

Comparing long-term strategy across All Experiments

To characterize how long-term memory scales with repetitions, we compared retrieval behavior across experiments. Groups reached comparable adaptation at the end of initial practice [F(2, 97) = 0.27, p = 0.76, Fig. 5D]. During retrieval tests, unsigned error showed a main effect of experiment [F(2, 97) = 8.06, p < .001, Fig. 5E], driven by larger errors in Experiment 3 (single-trial practice) than Experiment 1 [p = .0048] or Experiment 2 [p < .001]. Reach variability showed the same pattern [F(2, 97) = 21.84, p < .001, Fig. 5F], with Experiment 3 greater than Experiments 1 and 2 [both ps < .0041], as did RTs [F(2, 97) = 7.29, p ≤ .001, Fig. 5G], which were slower in Experiment 3 than Experiment 1 [p ≤ .001] or Experiment 2 [p = .0014]. To control for practice-related improvement across retrieval tests, we restricted the comparison to the first retrieval test and observed the same pattern [F(2, 97) = 6.51, p = 0.002, Fig. 5H], with reduced accuracy in Experiment 3 relative to Experiment 1 [p = 0.009] and Experiment 2 [p = 0.004]. Across all measures, performance did not differ between Experiments 1 and 2, indicating that 10 repetitions were sufficient to match the retrieval performance of 30 repetitions, whereas a single trial yielded weaker, less stable retrieval. These findings suggest that transfer of a visuomotor adaptation strategy to long-term memory requires more than one repetition but as few as 10, consistent with Huberdeau and colleagues (2015), and that such transfer may bypass the working memory capacity constraints that limit strategy use in more complex sensorimotor mappings (Bejjanki & Taylor, 2026).

Discussion

The present study asked simple but unresolved questions in sensorimotor adaptation: can an explicit visuomotor strategy be cached and stored in a long-term motor memory store and, if so, how much practice is needed for consolidation? Across three experiments, we found converging behavioral signatures that were consistent with encoding and retrieving an explicit re-aiming strategy in long-term memory, and that 10 repetitions were sufficient to establish a long-term memory. Unlike strategies held in working memory, those held in long-term memory were executed quickly and accurately and were insensitive to set-size manipulations. Mixture modeling confirmed these findings, suggesting that the precision for strategies held in long-term memory remained stable as set size increased, but the precision for strategies progressively decreased with greater demands on working memory. Together, these results suggest that long-term memory-based retrieval of an aiming solution can emerge rapidly – potentially requiring less than 10 repetitions. Once a strategy is established in long-term memory, it can support stable performance even when working memory is under significant strain from holding new, interfering strategies or other task demands.

These findings align with a growing consensus that strategic processes contribute substantially to VMR, particularly through explicit re-aiming (Taylor et al., 2014; McDougle et al., 2015). Prior work has argued for at least two distinct cognitive strategies: an algorithmic strategy involves actively computing an aiming solution, often referred to as computational expense processes (McDougle & Taylor, 2019). Whereas a retrieval strategy relies on recalling a previously successful solution associated with a given stimulus (target location) (Velázquez-Vargas & Taylor, 2024), enabling lower computation and potentially more automatic performance (Logan, 1988; Fresco et al., 2023).

A key motivation for this current study is that recent work has revealed that retrieval strategies appear to be strongly constrained by working memory capacity, particularly as the number of target–rotation mappings increases (Velázquez-Vargas & Taylor, 2024). This limitation was also highlighted in a recent study finding that working memory constraints limit participants' ability to learn multiple motor mappings in a complex visuomotor adaptation task (Bejjanki & Taylor, 2026). Consistent with these concerns, our data showed that once working memory approaches its capacity limit, short-term retrieval becomes unreliable and is increasingly accompanied by behavior consistent with guessing (Fig.2E,

3E). However, our results identified a plausible route around this bottleneck: when repetitions were sufficient to support long-term memory, retrieval no longer exhibited meaningful sensitivity to set size, and remained comparatively fast and stable. In this sense, long-term memory retrieval can break through the hard capacity constraints imposed by working memory, enabling multiple short-term solutions to be managed while a well learned long-term solution remains accessible.

Interestingly, the advantage of long-term memory retrieval became more pronounced under high working memory load (set size = 5), as evidenced by a linear increase in memory precision. One possibility is that achieving comparable precision under low load requires additional preparatory processing when multiple alternatives must be evaluated. Alternatively, at low set sizes, a strategy in long-term memory may compete for selection with strategies concurrently held in working memory. However, RTs for long-term memory strategies were similar across set sizes, arguing against both accounts. A third possibility is that a working-memory strategy slated for transfer to long-term memory interferes with the existing long-term representation — a possibility that could be tested by manipulating the similarity or spatial overlap between strategies held in the two systems.

Logan's instance theory proposed that responses can shift from computation to memory retrieval with repetitions, yielding faster and less variable performance (Logan, 1988). Instance theory also implies a key limitation: stored representations are often tightly bound to specific stimulus–response (S–R) associations. Accordingly, our long-term memory effects may primarily reflect strengthened association between the target and aiming-solution, rather than acquisition of a broadly generalizable rule. Nevertheless, this raises another concern that it may be impractical for learning to resemble an ever-expanding lookup table, especially when task complexity increases (Houk, Buckingham et al., 1996; Mussa-Ivaldi 1999). Alternatively, generalized motor program accounts (Schmidt, 1975) and internal model theories (Kawato, 1990; Wolpert et al., 1995) propose that learning can be supported by parameterizing and updating internally stored control policies, which supports flexible generalization of motor skills to some extent. But it remains unclear how such representations become stabilized in memory in a way that supports fast and accurate execution. This tension between instance-like specificity and model-like generality becomes especially salient in *de novo* skill learning, where performance improvements appear to require building new control policies rather than simply recalibrating an existing internal model. For example, learning under mirror-reversal transformation (Telgen, Parvin, & Diedrichsen 2015), novel bimanual mapping (Yang et al. 2021; Haith et al., 2022), and arbitrary keypress-grid mapping (Velázquez-Vargas et al., 2024; Velázquez-Vargas & Taylor 2025) require extensive practice to form novel control policies that are compatible for task demands.

These considerations point to an open question raised by our findings: what is the representational format of the stored "strategy" in long-term motor memory? Our data provide strong behavioral signatures of retrieval, but they are indistinguishable whether the stored content is a discrete aiming vector (Taylor et al., 2014), an abstract effector independent trajectory held in motor working memory (Hillman et al., 2024; Hillman & McDougle, 2025; McDougle & Hillman 2025), or another form of somatosensory memory (Ostry & Gribble, 2016). During encoding, participants first observed the cursor–target spatial mismatch, generate a compensatory reach plan, and hold these in memory. Because of its inherent spatial nature, it likely recruits visual short-term memory (VSTM) to encode and maintain the observed mismatch (Zhang & Luck, 2008) before the representation is operated on by motor working memory to generate a compensatory solution. Classic visual short-term memory approaches suggest that memory can be characterized by graded precision and failure mode (guessing) that scale with working memory load (Zhang & Luck, 2008). In our task, retrieval responses were ballistic and time-constrained, and the observed set-size effects on working memory resembled capacity-limited memory readout more than continuous computation. This resemblance implies that the stored aiming solutions may be more reliant on VSTM-like representations rather than an abstract internal model, even when they become accessible from long-term memory after repetition. Given the simplicity of our task it is difficult to draw definitive conclusions about the precise representational format of long-term motor memory from our data. At a minimum, this representation appears more durable than motor working memory, given its insensitivity to set-size manipulations, but its precise format remains unclear, as does its relationship to other forms of long-term memory. Future research should aim to implement tasks that require more abstract forms of strategic planning or involve goal-directed movements that can be achieved through multiple combinations of muscles and joints. Such designs would better test whether long-term motor memory encodes generalized control policies or remains tied to specific stimulus-response associations.

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