Spatial Dynamics Shape the Interaction Between Motor Adaptation Processes

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Abstract

Motor adaptation relies on explicit aiming strategies and implicit recalibration, but their interaction and effects on implicit skill learning remain debated. While these processes were initially thought to combine linearly, recent research challenges this view, though spatial and temporal dynamics may have confounded these findings. Specifically, implicit recalibration peaks at where individuals aim their movements, and adaptation operates across multiple timescales, with both stable and volatile components. To examine whether these factors mask the true relationship between explicit strategies and implicit recalibration, we conducted a visuomotor rotation task that obtained independent measures of both processes while accounting for spatial and temporal dynamics. After controlling for task instruction clarity and spatial dynamics (plan-based generalization), we found a strong but subadditive relationship between explicit strategies and implicit recalibration, with temporal dynamics showing minimal influence. This sub-additivity may stem from methodological imprecision or nonlinear interactions between processes.

Keywords: motor adaptation; sensorimotor learning; cognitive control

Introduction

Sensorimotor calibration is essential for accurate and efficient motor control in everyday activities. Traditionally, adaptation was thought to occur solely through implicit processes, operating unconsciously to adjust movement in response to environmental changes. More recently, explicit strategies – conscious, deliberate changes in motor planning – have been shown to play a larger role than previously thought, particularly in visuomotor rotation tasks. These tasks, unlike prism adaptation, allow perturbations and solutions to be experienced in the same coordinate space, making them ideal for studying explicit strategies. One key demonstration of this came from the aim-report paradigm (Taylor et al. 2014), where participants indicated their intended aiming location before movement execution. This paradigm provided a direct measure of an explicit strategy on a trial-by-trial basis, allowing implicit recalibration to be inferred via the subtraction of the participant's reported aim and their executed reach (Fig. 1a). It revealed the stereotypical adaptation curve (e.g., power-law function) reflecting the dynamic interplay between explicit strategies and implicit recalibration (Fig. 1b), with initial aftereffects closely matching implicit recalibration measured during training, although the aftereffects appeared slightly smaller (Taylor et al. 2014).

The aim-report paradigm assumed linear additivity between these processes, supported by correlations between aftereffects and implicit recalibration (Taylor et al., 2014). Since then, many studies have adopted this assumption, though recent efforts to validate the method using the Process Dissociation Procedure (PDP) have raised questions about its accuracy (Werner et al. 2015; Gastrock et al. 2020; Maresch et al. 2021; Modchalingam et al. 2019; Vachon et al. 2020). The PDP was originally developed to distinguish between conscious and unconscious processes in memory and decision-making (Jacoby 1991; Werner et al. 2015; Maresch et al. 2021; 't Hart et al. 2024). Here, PDP dissociates explicit and implicit processes by instructing participants to suppress (Exclusion trials; Fig. 1c, left) or apply any strategy (Inclusion trials; Fig. 1c, right) they learn to counteract the rotation. In theory, the hand angle observed at the final stage of training and Inclusion should match, and the difference between Inclusion and Exclusion should provide an estimate of the explicit strategy (Fig. 1d). Despite these predictions, the measures of explicit and implicit do not appear to perfectly match, calling into question the methodological attempts to dissociate the different processes and, potentially, the assumption of linear additivity.

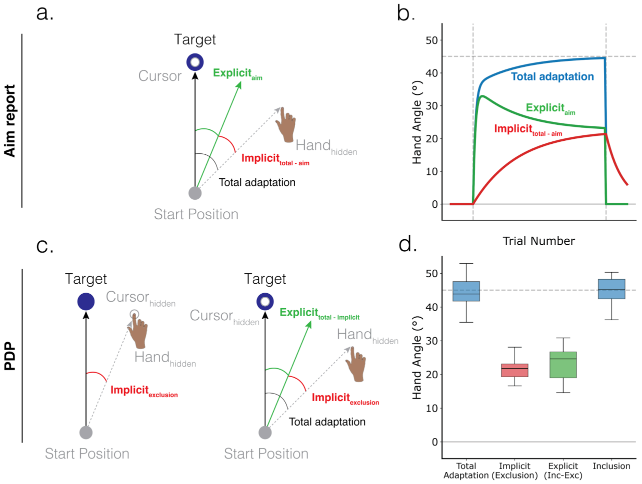

Figure 1. Aim-report paradigm: (**a**) Explicit adaptation measured via movement intention reports; implicit adaptation calculated as total adaptation minus reported aim. (**b**) Provides trial-by-trial component measures. PDP paradigm: (**c**) Inclusion trials measure total adaptation while Exclusion trials isolate implicit adaptation through strategy suppression; (**d**) Explicit adaptation is derived from differences between Inclusion and Exclusion.

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Both paradigms assume linear additivity, predicting that increases in implicit recalibration should result in proportional decreases in explicit strategy when total adaptation remains constant. Whether the relationship reflects indirect interaction between independent processes or competition between the processes remains an open question (Albert et al. 2022). Evidence from aim-report and error-clamp studies suggests that implicit recalibration operates independently, proceeding in a stereotypical fashion regardless of error size or task relevance (Bond and Taylor 2015; Morehead et al. 2017; Kim et al. 2018; Butcher and Taylor 2018). Under this view, explicit strategies simply compensate for the slack in implicit recalibration, achieving an angular value necessary for optimal performance. We should note that there is evidence for implicit recalibration also responding to changes in explicit strategies (Miyamoto et al. 2020), but these interactions could be explained by two relatively independent processes operating in series or a feedthrough arrangement (Taylor and Ivry 2011). Alternatively, their inverse relationship could be the result of a more direct interaction where implicit and explicit processes compete for error information: if one consumes the error signal, less remains available for another (Albert et al. 2022). In either case, an inverse relationship is assumed.

‘t Hart et al. (2024) tested the inverse relationship using both aim-report and PDP paradigms to obtain independent measures of each process to avoid mathematical dependencies inherent in each method (Taylor et al. 2014; Albert et al. 2022). In the aim-report paradigm, implicit adaptation is derived by subtracting explicit aim reports from the total adaptation, inherently creating a correlation between the two measures since one is mathematically dependent on the other. Likewise, in the PDP paradigm, explicit adaptation is inferred via subtraction of Exclusion from Inclusion. To test for a true correlation, at least two independent methods (e.g., aim-report and PDP) must be used. However, despite this dual-method approach, they found a lack of linear additivity using both independent and dependent measures of explicit and implicit processes, suggesting more complex interactions between the two.

While these findings are concerning, potentially invalidating more than a decade of research, there have been several studies demonstrating subtle yet complex spatial and temporal interactions that could explain the lack of relationship between implicit recalibration and explicit strategies (Day et al. 2016; McDougle et al. 2017; Poh and Taylor 2019; Hadjiosif et al. 2023; Hadjiosif et al. 2024). First, plan-based generalization shows that implicit recalibration follows a Gaussian distribution centered at the explicit aiming location rather than the target location (Fig. 2a; Day et al. 2016; McDougle et al. 2017). During Exclusion trials, participants are instructed to reach directly to the target rather than their training aim location. Consequently, the measured implicit recalibration captures only the tail of the Gaussian distribution rather than its peak. Second, implicit recalibration has been shown to comprise temporally volatile and persistent components (Hadjiosif et al. 2023), with the volatile component dropping significantly after a 30s to 1-min delay and the persistent component remaining (Fig. 2b; Zhou et al. 2017). The intertrial interval between successive reaches is often on the order of 5 seconds and studies often have more than one target. Given typical intertrial intervals of 5 seconds and multiple target locations, significant decay may occur between reaches to the same target. One or both of these factors, which arise from differences between training and probe trials, could potentially explain the apparent lack of additivity between explicit strategies and implicit recalibration.

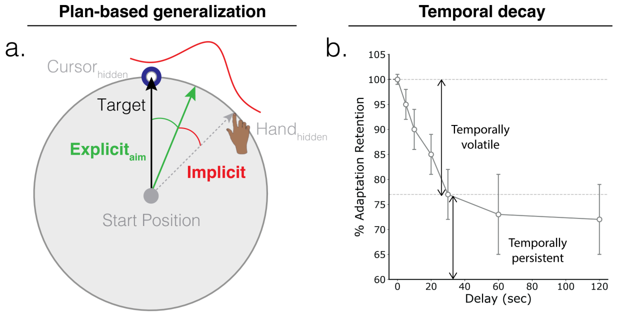


Figure 2. (**a**) Plan-based generalization: Implicit adaptation peaks at the aiming location rather than the target location. (**b**) Temporal decay: Adaptation exhibits two components: a volatile component that nearly vanishes, and a persistent component that remains after a 30s to 120s delay (recreated from Zhou et al. 2017).

The present study tested the linear additivity assumption by independently measuring explicit and implicit processes while accounting for spatial (plan-based generalization) and temporal (decay) interactions. Using a within-subject PDP design, we manipulated target location and delay as participants adapted to a 45° visuomotor rotation while reporting their aiming strategies. We found a strong inverse relationship between explicit strategies and implicit recalibration when controlling for plan-based generalization, with minimal impact from temporal decay. However, the relationship does not follow perfect linear additivity, suggesting that either more complex interactions or further methodological improvements are needed to accurately assess the two processes.

Methods

Participants

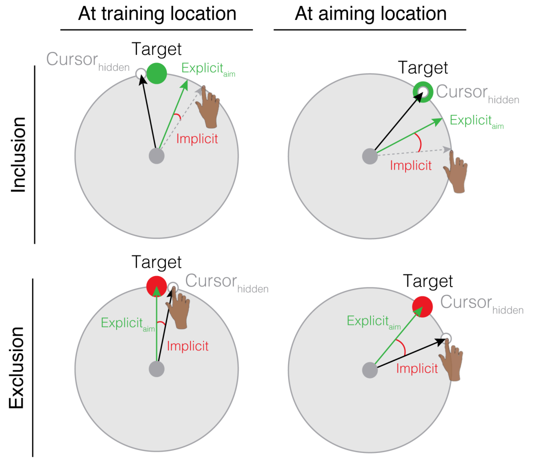
Thirty-nine (aged 18-23; 23 females, 16 males; one participant was excluded for poor performance) participants were recruited from the research participation pool managed by the Department of Psychology at Princeton University in exchange for course credit. Recruitment was limited to individuals who were right-handed, had normal or corrected vision to receive visual feedback, and did not have color blindness due to color changes in the targets.

Task and apparatus

Participants made rapid "shooting" movements with a digitizing stylus (Intuos 3, Wacom) to bring a virtual cursor (0.8 cm diameter) to a target (1 cm diameter) positioned 7 cm from the start position. An auditory warning was triggered if movements exceeded 300 ms. Visual stimuli were displayed on an LCD touchscreen monitor (Dell) mounted 23.5 cm above the tablet, preventing direct vision of the hand. Between trials, an empty circle dynamically adjusted in size based on the radial distance between the hand and the center of the tablet to guide participants back to the start position (1 cm diameter), where they held for 500 ms before proceeding. In some trials, participants indicated their intended aim location by tapping with their left hand along an "aiming" ring (7 cm diameter) centered on the starting position. A desktop PC (Dell) running custom MATLAB software (Brainard 1997) controlled the task.

The experiment consisted of 400 trials spread over four blocks. The first block was designed to familiarize participants with all aspects of the task, which incrementally became more complex and consisted of four 10-trial phases (Baseline block). For the first 10 trials, participants were provided with veridical continuous feedback of the cursor location. Cursor feedback was removed for the next 10 trials to measure any movement bias, before being reintroduced for an additional 10 trials. For the last 10 trials, participants practiced reporting their intended aiming location with their left hand prior to executing each reach with their right hand. Following this Baseline block, a 45° rotation was introduced between movements of the hand and the visual feedback, and participants were trained to overcome this rotation for 200 trials while continuing to report their aim (Training block). The direction of rotation was counterbalanced across participants (20 clockwise, 19 counterclockwise). The location of the target was always at 90° (north) for the Baseline and Training blocks.

Following the Training block, participants were introduced to the Process Dissociation Procedure (PDP), which unfolded over four phases of 30 trials (PDP blocks). Each PDP block included 5 Exclusion trials, 10 Top-up trials, 5 Inclusion trials, and another set of Top-up trials. During Exclusion trials, cursor feedback was removed, and participants were instructed to reach directly toward the target without using any compensatory strategies (Fig. 3, bottom panels). The target turned from green to red to further indicate that participants should refrain from implementing any strategy. Exclusion trials are designed to assay implicit recalibration in relative isolation from explicit strategies (Werner et al. 2015; Maresch et al. 2021; 't Hart et al. 2024). During Inclusion trials, cursor feedback was removed and participants were instructed to use any explicit strategy they had developed to counteract the perturbation in order to get their now unseen cursor on the target (Fig. 3, top panels). Inclusion trials are assumed to assay the joint operation of explicit strategies and implicit recalibration (Werner et al. 2015; Maresch et al. 2021; 't Hart et al. 2024). In between the Exclusion and Inclusion trials were Top-up trials where cursor feedback was restored, and participants were instructed to try to get the rotated cursor on the 90° training target. These trials were designed to recover any adaptation that may have decayed during Exclusion/Inclusion trials since cursor feedback was removed. The order of the Exclusion and Inclusion sets alternated after each PDP block, and they were always separated by Top-up trials. Throughout the PDP blocks, participants continued to report their aiming location by tapping on the monitor.



*1-min delay before the Exclusion/Inclusion set for **delayed** condition

Figure 3. Example schematic of Inclusion trials (top) and Exclusion trials (bottom) for target at the training location (left) and at the aiming location (right).

The four PDP blocks were designed to test if plan-based generalization and temporal decay affect linear additivity. Here, we used a within-subject 2x2 factorial design with factors of Target Location (at training location or aiming location) and Delay (no delay or 1-min delay). In the training location condition, the target appeared at 90° (north), which is the same target location as during the training block, for both Inclusion (Fig. 3, top-left) and Exclusion (Fig. 3, bottom-left). In the aiming location condition, the target appeared at the average aiming angle from the five most recent Top-up/adaptation trials before the current Inclusion/Exclusion set (Inclusion example: Fig. 3, top-right; Exclusion example: Fig. 3, bottom-right). To test for the effects of temporal decay, a 1-min delay was introduced between the final trial of Top-up and the onset of Exclusion/Inclusion in the Delay condition. The order of the four PDP blocks (Target Location and Delay combinations) was randomized for each participant.

The experiment ended with 40 no-feedback no-aim-report trials to wash out any adaptation (Washout block).

Data Analysis

Hand angles were calculated as the angular distances between the target and the hand's endpoint position. Aim reports were calculated based on the angular distances between where participants tapped on the screen relative to the target. To standardize the data, we flipped all hand angles and aim reports in the same direction, ensuring that positive values always reflected the direction of counteracting the rotation, regardless of whether the rotation was clockwise (-) or counterclockwise (+).

To investigate whether explicit and implicit adaptation linearly add up to total adaptation, we focused on the Exclusion, Inclusion, and Top-up trials. The first trials of all exclusion and inclusion sets were excluded to account for potential failures to adjust to the changing demands throughout the PDP blocks. To keep consistency in the number of trials included from different conditions, only the last 4 trials of each condition were included.

To test the assumption of linear additivity, we examined whether implicit and explicit components exhibit an inverse relationship when total adaptation reaches a similar level (45°). According to the strict linear additivity model, an increase in one component should correspond to a proportional decrease in the other, yielding a predictable slope. We modeled this relationship using linear regression:

$$\beta \times Implicit \ + \ Intercept \ = \ Total\ Adap.$$

Explicit adaptation was measured as the average of the four Top-up aim reports immediately preceding the Exclusion trials, while implicit adaptation was calculated as the average of four Exclusion trial hand angles, ensuring independence between the two measures.

To evaluate whether the observed slopes align with the linear additivity model, we first simulated data based on empirical data. Using the means and standard deviations of participants' total adaptation and explicit aim reports during late adaptation (last 10 trials of the training block), we generated simulated data as follows:

$$Explicit_{sim} \sim N\left(\mu_{Explicit},\ \sigma_{Explicit}\right)$$

$$Total\ Adap_{sim} \sim N\left(\mu_{Total\ Adap},\ \sigma_{Total\ Adap}\right).$$

Next, we calculated simulated implicit adaptation using the linear additivity equation:

$$Implicit_{sim} = Total\ Adap_{sim} - Explicit_{sim}.$$

Finally, we fit a linear regression model to the simulated data to derive the predicted slope under the linear additivity model. This provided a benchmark for comparison with the observed slopes.

To assess how plan-based generalization and temporal decay influence the implicit-explicit relationship, we compared slopes across experimental conditions (Target Location and Decay combinations). We evaluated alignment with the linear additivity model by comparing observed slopes to the predicted slope. All slope comparisons utilized bootstrapping (1000 resamples) to generate sampling distributions of slope differences, from which we computed two-tailed p-values and 95% confidence intervals.

As the dissociation and test of additivity between explicit and implicit critically hinge upon participants' understanding of the specific instructions, we performed subgroup analysis on participants who showed a clear understanding of the instructions based on three criteria. First, reported aims during Exclusion trials (instructed to aim directly at the target) had to fall within 0.8 cm of the target (the target's diameter). Aiming at a location other than the target in Exclusion trials shows that they did not understand the instructions. Second, aim reports from the last 4 trials of Top-up and Inclusion sets (without delay, at the training location) should not differ significantly, as these phases were identical except for cursor feedback presence. We should note that we did not consider Inclusion trials from PDP blocks where a delay was imposed or the target appeared at the aiming location, as differences in aim reports could stem from the change in conditions rather than from not following the instructions. Third, participants needed to demonstrate explicit strategy use, verified by a significant directional difference in aiming between the last 10 Training trials and Baseline trials.

Results

Task Performance

Participants showed significant adaptation to the perturbation, as indicated by an appropriate change in hand angle to counteract the perturbation over the last 10 trials of the Training block compared to Baseline (43.98 ± 0.37°, $t(38) = 67.82$, $p < 0.001$). Furthermore, participants exhibited the same level of adaptation during Top-up and Inclusion trials where the probe-target was presented at the training target location without a delay, indicating that adaptation was maintained throughout the PDP blocks (Fig. 4, Top-up: 44.91 ± 1.25°; Inclusion: 45.69 ± 5.62°; $t(38) = -0.79$, $p = 0.434$).

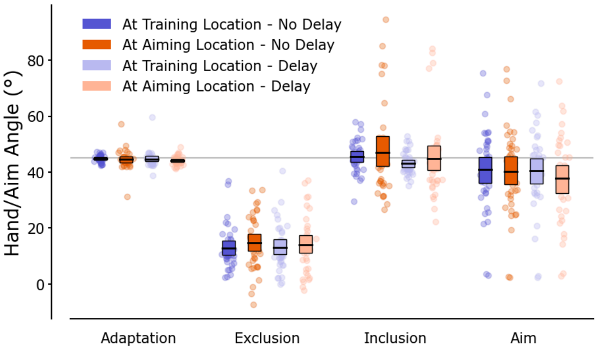


Figure 4. Mean hand angles during Top-up, Exclusion, Inclusion trials, and aim reports (N = 39, one outlier is excluded for visualization). Boxes represent 95% CIs.

To assess the effects of Target Location (plan-based generalization) and Delay (temporal decay) on adaptation, we submitted the observed hand angles in the PDP blocks to a repeated-measures ANOVA. For Exclusion trials, neither Target Location (Fig. 4, $F = 0.411$, $p = 0.526$), Delay (Fig. 4, $F = 0.219$, $p = 0.643$), nor their interaction (Fig. 4, $F = 0.137$, $p = 0.713$) showed significant effects. For Inclusion trials, there was no effect of Target Location ($F = 0.334$, $p = 0.566$) nor their interaction (Fig. 4, $F = 0.047$, $p = 0.829$), but a significant effect of Delay (Fig. 4, $F = 6.465$, $p = 0.015$). The effect is consistent with recent studies that have found rapid forgetting in implicit recalibration (Hadjiosif et al. 2023; Zhou et al. 2017).

Significant Relationship Between Implicit and Explicit Adaptation at Aiming Location

To investigate whether implicit and explicit adaptation exhibit a linear relationship, we examined their relationship across the four PDP conditions (Fig. 5). In the standard condition of the PDP paradigm – the probe target at the training target, regardless of delay – we found significant correlations between implicit recalibration and explicit strategies (No Delay: $\beta = -0.323$, $p < 0.001$, 95% CI [-0.496, -0.108]; Delay: $\beta = -0.305$, $p = 0.001$, 95% CI [-0.476, -0.123]). While this correlation contrasts with ‘t Hart et al. (2024)'s null relationships, the strength of the relationships was notably weaker than what would be predicted by linear additivity, aligning with their findings. Presentation of the target at the aiming location revealed no relationship, which seems to suggest that plan-based generalization does not explain the absence of the inverse relationship, contrary to our hypothesis.

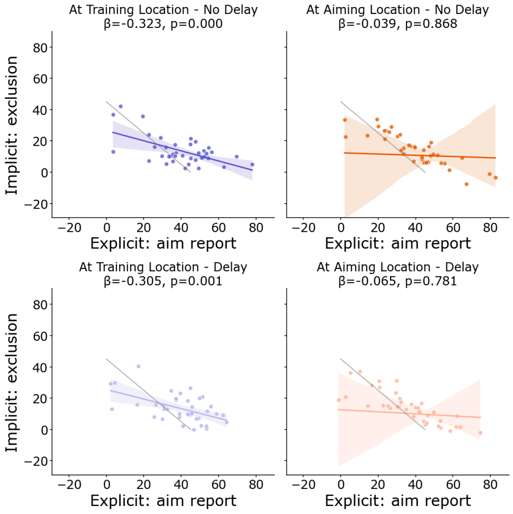


Figure 5. The relationships between explicit and implicit measures for all participants (N = 39, one outlier is excluded for visualization).

As the dissociation and test of additivity between explicit and implicit critically hinges upon participants’ understanding of the specific instructions, we performed a subgroup analysis on participants who showed a clear understanding of the instructions (N = 26, see Methods). In contrast with the whole-group analysis, there was now a significant relationship only when the probe target was at the aiming location on Exclusion trials regardless of delay, suggesting that plan-based generalization could potentially mask observation of the relationship between explicit and implicit (Fig. 6; No Delay: $\beta = -0.479$, $p < 0.001$, 95% CI [-0.604, -0.389]; Delay: $\beta = -0.426$, $p < 0.001$, 95% CI [-0.638, -0.294]). The relationship between explicit and implicit was not significant when the target was presented at the training location, and delay appeared to have no effect (No Delay: $\beta = -0.109$, $p = 0.154$, 95% CI [-0.252, 0.052]; Delay: $\beta = -0.186$, $p = 0.064$, 95% CI [-0.337, -0.033]). As can be observed in Fig. 6, it is clear that the between-subject variance is greatly reduced when considering only participants who appeared to display a reasonable understanding of the instructions. Nonetheless, the strength of the relationship is, again, far below what would be expected from a purely linear combination.

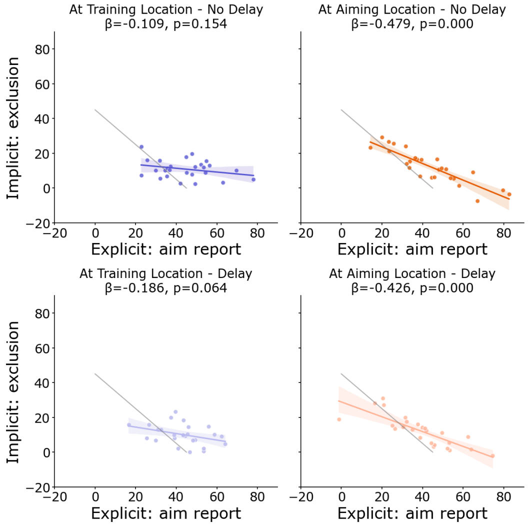


Figure 6. The relationships between explicit and implicit measures for instruction followers (N = 26).

To quantify how much the observed relationship deviates from linear additivity, we conducted a parameter recovery analysis simulating slopes under the assumption of a linear relationship between explicit and implicit adaptation. Using variance estimates from our subgroup's explicit aim reports and implicit recalibration measures, we simulated the distribution of slopes that would be expected if total adaptation were a direct sum of explicit and implicit components, subject to measurement noise. We found virtually no overlap between the simulated slope distribution and the slopes observed on PDP blocks, regardless of the target location and delay. The observed significant slopes for the aiming location conditions (No Delay: β 95% CI [-0.604, -0.389]; Delay: β CI [-0.638, -0.294]) were significantly less steep than the predicted slopes ($p < 0.001$ in both comparisons) from the subgroup (Fig. 7).

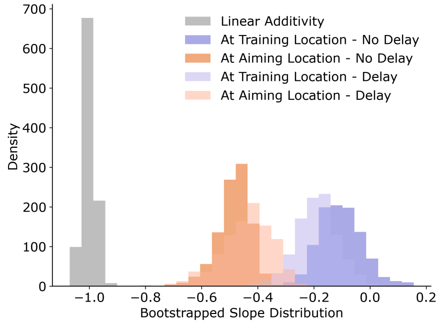


Figure 7. Distribution of bootstrapped slopes across conditions vs the linear additivity model (N = 26).

Discussion

This study aimed to investigate whether implicit and explicit adaptation linearly combine to explain total adaptation in motor learning while accounting for plan-based generalization and temporal decay. Using a within-subjects design, we systematically manipulated target location (training vs. aiming) and the presence of a 1-minute delay across four experimental conditions to obtain independent measures of explicit and implicit adaptation. We find a significant inverse relationship between explicit strategies and implicit recalibration, but this relationship did not perfectly follow linear additivity, challenging prior assumptions (Taylor et al. 2014; Bond and Taylor 2015; McDougle et al. 2015).

Recent work has questioned the linear relationship between explicit and implicit processes, with some studies finding no relationship at all (Maresch et al. 2021; 't Hart et al. 2024). Our study, however, reveals a significant inverse relationship, though not perfectly linear. When participants fail to understand the instructions, a weak or no relationship may be found. By applying minimally lenient criteria to distinguish participants who understood the instructions, a more complex relationship emerges between explicit and implicit processes, along with the effects of plan-based generalization. As implicit recalibration peaks at the aiming location rather than the target, measuring it at the training target location does not accurately capture how these processes work during training (Day et al. 2016; McDougle et al. 2017; Poh and Taylor 2019). While this plan-based generalization effect could not fully explain previous reports of sub-additivity, such subtle interaction effects may have led to misinterpretations of various phenomena, such as spontaneous recovery, savings, and interference (Schween et al. 2018; Morehead et al. 2015). It is important to consider indirect and low-level interactions that may more parsimoniously explain sub-additivity. Nonetheless, probing explicit strategies may fundamentally change how learning would have proceeded naturally, whether it is an indirect (Taylor et al. 2014; Leow et al. 2017) or direct effect (Neville and Cressman 2018; Albert et al. 2022).

Temporal decay is another factor that could complicate the relationship between explicit and implicit processes. While explicit strategies remain stable, implicit recalibration decays over time: a volatile component that nearly vanishes within 1 min and a persistent component that remains stable (Hadjiosif et al. 2023; Zhou et al. 2017). While we did not find a significant effect of temporal decay on the relationship, it is important to note that we had to exclude the first trial following every phase change of the PDP blocks, as participants often carried over habitual behaviors from previous phases. This increased the time between the last training trial and the second probe trial, potentially allowing significant forgetting to occur. We suspect that the null finding here reflects an absence of evidence as opposed to evidence of absence.

With the comprehension of instructions, plan-based generalization, and temporal decay taken into account, total adaptation still appears more complex than a simple linear combination. As sensorimotor adaptation is not driven by unitary processes, this standard may be too strict. Like memory systems, motor adaptation represents a hierarchical taxonomy with multiple components (Squire 2004). Explicit adaptation can reflect the outcome of an algorithmic strategy involving mental rotation of movement plans, or a retrieval strategy that caches successful stimulus-response associations in memory (Pellizzer and Georgopoulos 1993; McDougle and Taylor 2019; Velázquez-Vargas and Taylor 2024). Similarly, implicit adaptation encompasses or is modulated by multiple processes, including use-dependent learning, reinforcement learning, and proprioceptive recalibration (Cressman and Henriques 2009; Ostry et al. 2010; Izawa and Shadmehr 2011; Huang et al. 2011; Kim et al. 2019; Tsay et al. 2022). These different processes could account for the apparent sub-additivity. Future work will need to develop methods to dissociate or isolate the contribution of these other processes. Higher-order interactions between the two processes may also exist. It is important to note that the use of an explicit strategy may not differ fundamentally from planning movements in typical reaching tasks, except for the need to aim away from the cued target. While this shift has measurable effects, presumably requiring overcoming an express or prepotent response triggered by target onset (Haith et al. 2016; Simon and Rudell 1967; Contemori et al. 2021; Contemori et al. 2021; Contemori et al. 2022; Contemori et al. 2023), it seems unlikely that it would have a profound effect on the operation of implicit recalibration *per se*.

Another likely possibility is that probing explicit and implicit processes is exceedingly difficult, and each method that has been attempted is not without its drawbacks (Maresch et al. 2021; Hadjiosif and Krakauer 2021). An accurate assessment of the contribution of each process demands that participants fully comprehend the instructions. What's more, once probed, it could shape the way participants respond. For example, asking participants to explicitly report their aiming directions might interfere with the natural learning process or alter participants' strategies (Maresch et al. 2021). It is also unclear whether participants are capable of accurately reporting their aiming intentions (Maresch et al. 2021; Taylor et al. 2014; Werner et al. 2015). This is especially problematic in other sensorimotor adaptation tasks, such as force field adaptation, where asking a participant to report a complex force pattern they are applying is beyond the limits of language to fully describe (McDougle et al. 2015; Schween et al. 2020; Forano et al. 2021; Forano and Franklin 2024).

While our findings are consistent with previous reports on sub-additivity between explicit and implicit adaptation, we suspect that this sub-additivity is likely due to the operation of other learning processes that interact in interesting yet pedestrian ways, which are currently obscured by available experimental techniques and subject variance. Future efforts will require novel and careful methodologies to uncover if the multiplicity of learning processes truly adds up.

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