The Time-Course of Implicit Learning

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Abstract

The implicit, or unconscious, component of motor learning has been thought to emerge slowly, but this proposition has not been adequately tested. Different forms of error feedback have been shown to reduce, and potentially slow down the implicit component in visuomotor learning. We compared two types of cursor-feedback during a reaching task: terminal and cursor jump, with our continuous feedback control. We measured reach aftereffects after each training trial, and this approach allowed us to measure the time-course and contribution of the implicit process. Our results revealed a reduction in implicit reach aftereffects for both feedback groups, but no change in the speed by which aftereffects emerge. Explicit strategy use was also measured, and greater explicit use was found for both feedback groups. Despite this pattern, a regression showed no relationship between the implicit and explicit processes. Overall, our work suggests that implicit adaptation occurs much earlier in reach training, and will take place regardless of feedback type. This highlights the potential to optimize how we can best exploit this learning system in motor adaptation.

Acknowledgements

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Introduction

People constantly adapt their movements to their changing circumstances, which is partly handled by our automatic, unaware, or "implicit" motor adaptation systems. While the time-course of these implicit processes is thought to be slow, it is largely unknown. The advantage of implicit motor learning and adaptation is that it leaves cognitive resources for other purposes. For example, when driving, we would not need to consciously control the car, allowing us to pay more attention to traffic, thus increasing safety. In contrast, explicit adaptation is effortful and, hence, not as efficient in the long run. Despite this, training regimens for activities such as sports and music often focus on our explicit motor learning processes, perhaps because there are suitable methods to track them throughout practice (e.g., Bond & Taylor, 2015). However, people likely rely on more implicit processes when carrying out well-learnt motor tasks, but it is much harder to quantify these unconscious contributions to our performance, or even identify when they emerge and under what conditions. Therefore this paper will focus on the time-course of implicit adaptation. Others in our lab have pioneered a method to assess ongoing implicit adaptation (Ruttle et al., 2021). We will use this method to quantify the time-course of implicit adaptation during visuomotor adaptation, and determine how sensitive this time-course is to various levels of visual feedback about movement performance.

Visuomotor adaptation is induced in the lab by having people reach to targets on a screen using a cursor representing their unseen hand, and then misaligning or deviating the direction of the cursor relative to the hand from a common start position, as illustrated in Fig 1. To adapt to these deviated cursor directions, that is, to move the misaligned or rotated cursor onto the target (green dot and line in Fig 1), the unseen hand has to be moved in a direction opposite to the rotation, see the dashed line in Fig 1 (Cunningham 1989, Krakauer et al., 2000, Wigmore et al., 2002, Miall et al., 2004).

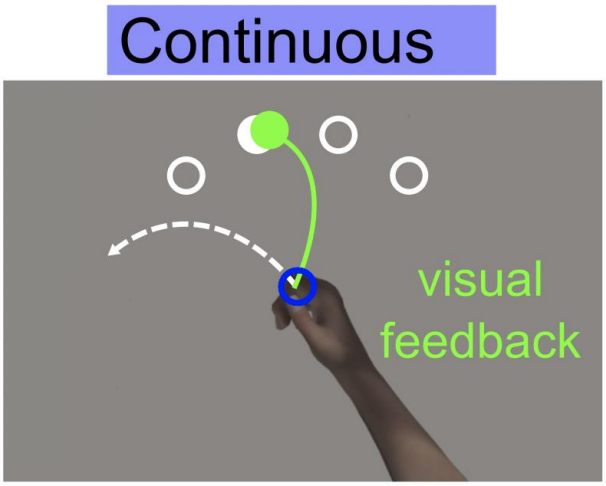

Fig 1. Participants attempted to move the green cursor to one of the four forward targets as quickly and as straight as possible. Training with continuous rotated feedback meant participants would move their hand along the dashed line, to have the visible cursor move along the green line to correctly acquire the target.

Like all types of learning, adaptation depends on a combination of explicit and implicit learning processes. Explicit learning of a visuomotor rotation involves developing a conscious strategy to counter the rotation. This is usually assumed to develop and contribute quite quickly and be responsible for much of the initial adapted change in hand direction (Mazzoni & Krakauer, 2006, Taylor et al., 2014, Miyamoto et al., 2020, Bond & Taylor, 2015, Van Es & Knapen, 2019, Benson et al., 2011). People who adapt quickly tend to have longer reaction times than those who adapt more gradually, which suggests that quick learners may be relying more on strategies (Fernandez-Ruiz et al., 2011). The implicit or unconscious component is assumed to emerge later and likely replaces cognitive strategy after sufficient training. In other words, when reaching with a misaligned cursor, people start by consciously re-aiming their hand movement to get the cursor to the target, but after a while, they move their hand in the modified direction automatically (Mazzoni & Krakauer, 2006, Taylor et al., 2014, McDougle et al., 2015, Miyamoto et al., 2020). This is consistent with our intuition, that people use a more effortful conscious strategy at the beginning of learning or adapting to a new task until the new movements become more automatic or implicit. Yet, results from our lab suggest that implicit changes in hand movement can emerge quite quickly, within the first few reaches with the

visuomotor rotation (Ruttle et al., 2021). The goal of my thesis is to replicate this surprising result and determine what factors may possibly delay or diminish the contribution of the implicit component in adaptation.

Implicit adaptation is traditionally measured by how much reaches continue to deviate even after feedback is removed or returned to vertical, called "reach aftereffects" (Fig 2). These aftereffects, usually measured after adaptation is complete, are roughly fixed to 15° in magnitude independent of the size of rotation (Bond & Taylor, 2015). And while aftereffects do gradually decay with movement repetition, they can persist even 24 hours after a perturbation is removed (Nourouzpour et al., 2014). We are unable to suppress these aftereffects as we do not have conscious access to them. Even being aware and instructed about how to compensate for the visuomotor rotation is not enough to suppress these aftereffects (Modchalingam et al., 2023; Gastrock et al., 2020). Given the assumption that implicit learning requires sufficient training to develop, most studies measure reach aftereffects after adaptation is complete, which usually entails at least 60 reach trials with the perturbation (Hinder et al., 2008, Fernandez-Ruiz et al., 2011, Taylor et al., 2014, Barkley et al., 2014, Neville & Cressman, 2018). However, Ruttle et al. (2016, 2018) were one of the first to show that substantial reach aftereffects can emerge after only 6 trials of training with a 30° rotated cursor. But to really investigate how quickly aftereffects can emerge, Ruttle and colleagues (2021) measure reach aftereffects after each single training trial. As illustrated in Fig 3, they found that not only did aftereffects emerge after the first training trial, but these deviated hand movements saturated (to the usual 15°) by the third training trial.

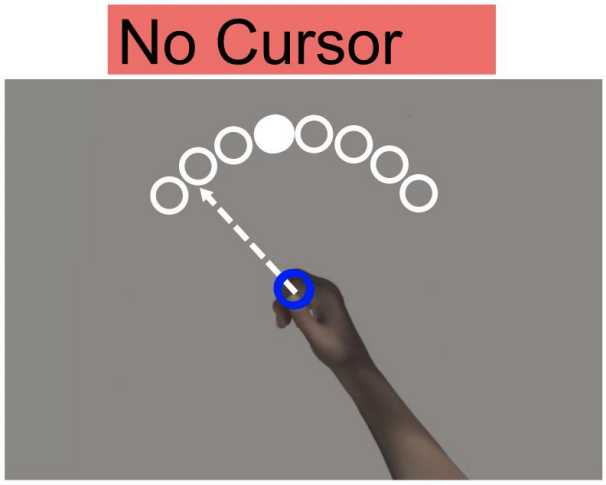

Fig 2. Participants moved their hand to one of the eight forward targets as quickly and as straight as possible. This movement had no cursor feedback, and the dashed line shows the typical hand movement path after rotated cursor training. This deviation from what should be a straight movement is what we refer to as a "reach aftereffect".

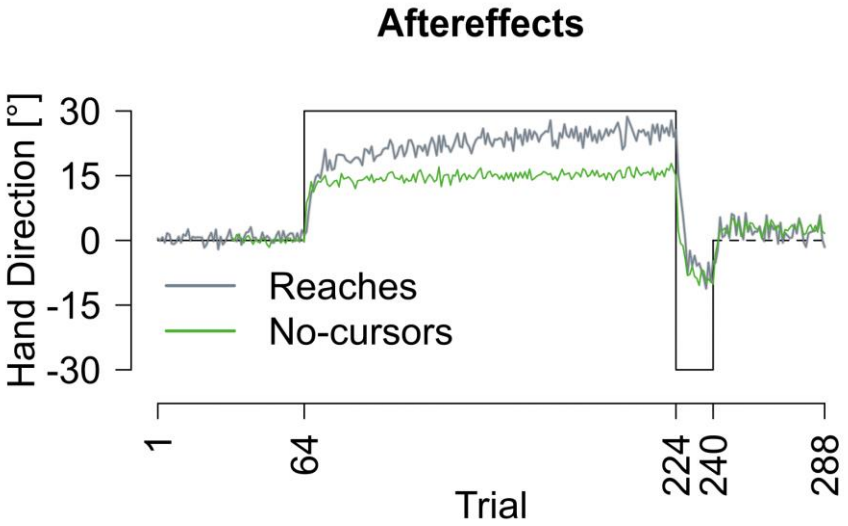

Fig 3. Adapted from Ruttle et al (2021) showing the aftereffects visible when performing the task. Reach training performance is in grey, and no-cursor testing is in green. All solid lines are an average of all participants in that group.

This recent finding from our lab challenges a long-held notion that implicit learning emerges slowly after pioneering a method to assess ongoing implicit adaptation of sensory processes (Ruttle et al., 2021). They measured reach aftereffects after every reach-training trial with a 30° visuomotor rotation in order to qualify and model the rate of these implicit measures of learning. They found these intervening reach aftereffects saturated after only 3 reaching trials (green line in Fig 4), well before that of reach adaptation which in the same study took 9

trials for asymptote, see black line Fig 4. This suggests that the implicit aspects of adaptation do not necessarily emerge after explicit-driven changes in movement (Ruttle et al., 2021). Our goal is to replicate this finding that implicit motor changes occur rapidly and to test the extent by which cognitive strategy or reduced visual feedback of the hand could possibly slow down or reduce the onset of this implicit component of learning.

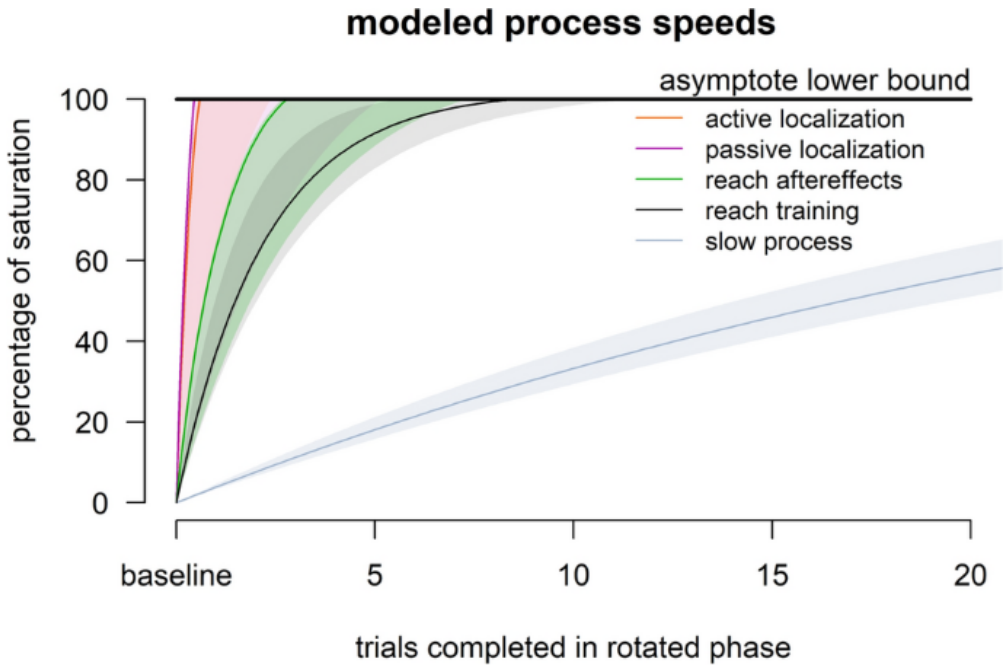

Fig 4. From Ruttle et al., (2021) showing the amount of rotated session trials it took for each process to saturate. Here, we see the baseline (0%) to the lower limit of the 95% confidence interval of the asymptote (100%). For reach adaptation, the highest rate of change is used. Measures of implicit adaptation (reach aftereffects and hand localization shifts) are faster than adaptation.

To determine whether the visual feedback about movement performance affects the time-course of implicit learning, we will manipulate visual feedback of the misaligned cursor in two ways. First, we will impoverish visual feedback to decrease or slow down implicit learning, e.g., by only providing a cursor at the very end of the reach, also known as terminal feedback, and illustrated in Fig 8B. Second, we will provide visual feedback that shows the source and nature of the perturbation on each trial, to decrease implicit learning by increasing explicit learning. This could be done by jumping the cursor halfway through the reach, from

normal to perturbed (Gastrock et al., 2020), as illustrated in Fig 8C. Each kind of manipulation changes the visual error signals available for motor adaptation. This should affect the time-course of implicit adaptation to the perturbation. To test, we will include a control group where participants received the typical visual feedback, i.e. the hand-cursor was continuously visible, but deviated 45° during the reach as in the terminal and cursor-jump paradigms. Our hypothesis is that reach aftereffects, which we will measure after every single training trial, should again saturate quickly for participants who adapted to a continuous visible cursor (control group), but take longer to emerge for participants training with terminal feedback and those who train with a cursor that jumps to its misaligned direction in the middle of every trial.

When comparing terminal and continuous cursor training, we can better understand how the different error signals drive learning. Given the terminal feedback provides less visual information about the movement, we hypothesize that implicit aftereffects may require more trials to saturate and may be smaller; that is the rate of implicit learning should be slower when training with terminal feedback. Studies have found that the magnitude of adaptation to terminal feedback is similar to that of continuous control (Taylor et al., 2014, Hinder et al., 2008, 2009, Brudner et al., 2016, Heuer & Hegele, 2008, Schween & Hegele, 2017, Song et al., 2020), but requires more training to attain the same level (Taylor et al., 2014, Song et al., 2020). However, other studies show that terminal feedback also slows down or reduces overall adaptation and subsequent aftereffects compared to when continuous feedback about the misaligned cursor is given (Taylor et al., 2014, Barkley et al., 2014). But again, all of these studies measure reach aftereffects after at least 60 trials and usually only after a hundred trials (Hinder et al., 2008, Fernandez-Ruiz et al., 2011, Taylor et al., 2014). Many of them have found these aftereffects to be smaller for terminal (Taylor et al., 2014, Barkley et al., 2014, Hinder et al., 2008, Brudner et al., 2016, Schween & Hegele, 2017), while others find no difference

(Heuer & Hegele, 2008, Song et al., 2020). Thus, it is unknown whether reach aftereffects also emerge slower in these conditions.

We also hypothesize that implicit learning could be slower for the cursor jump. In this task, the cursor begins by moving in alignment with the unseen hand but then jumps to a deviated direction of 45° CCW, as illustrated in Fig 8C. The purpose of this manipulation is to make participants aware that the cursor error is caused externally. Our lab has found evidence for this (Gastrock et al., 2020) using a similar cursor jump condition. They found that participants who trained in this cursor-jump condition, could elicit the strategy when asked, and almost to the same extent as another group of participants who were given explicit instructions about the nature of the perturbation and how to compensate for it. But non-instructed participants who trained with a misaligned cursor that did not jump could not elicit any strategy when asked. This suggests that only those given instructions or shown the nature of the manipulation (i.e. cursor jump) were likely relying more on explicit strategy. Nonetheless, all groups showed implicit reach aftereffects following 90 trials of training, although aftereffects were slightly but significantly smaller in the cursor jump compared to the control group. Thus, developing an explicit strategy during cursor-jump training could lead to a reduction in implicit-driven changes, and it is possible that it could also delay the onset of reach aftereffects. This is what we will test in the current study - whether reach aftereffects produced when adapting to a cursor jump are slower than for those that adapt to a continuous rotation. To explore whether adaptation that depends on cognitive strategy reduces and slows down implicit reach aftereffects, we will also include some aiming trials near the end of training for all three training groups. Aiming trials (see methods for a description, and Fig 5) are a common way of measuring the contribution of cognitive strategy or explicit processes to adaptation (Taylor et al., 2014, McDougle et al., 2015, Witterson & Taylor, 2021, Yin & Wei,

2020) and we will use these trials to assess whether the cursor-jump paradigms did elicit more strategy use in this study compared to the other paradigms.

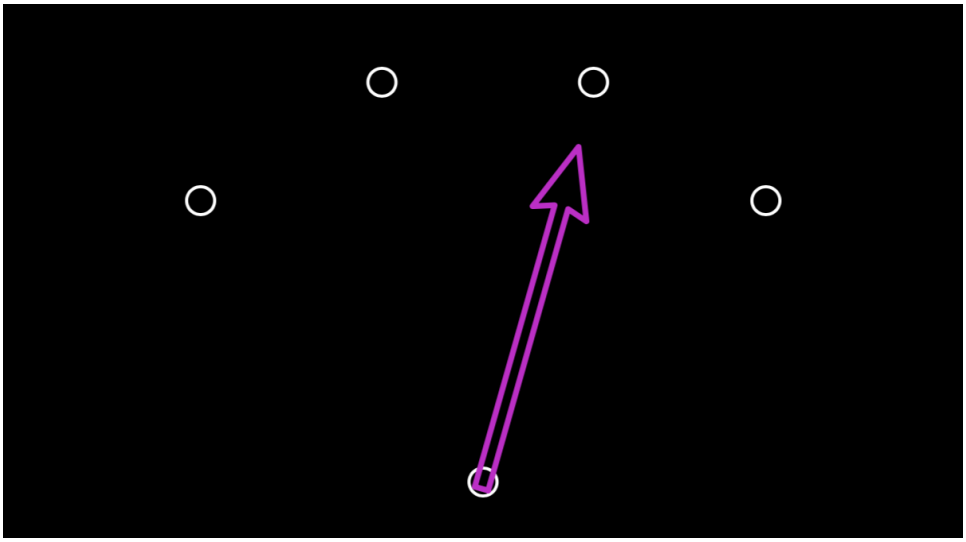

Fig 5. Aiming Trial in the experiment. One of the above four targets was shown to the participant, and they used the left and right arrow keys on the keyboard to manually adjust where the arrow was pointed to indicate the direction they were moving their hand on a rotated trial. The direction they would point the arrow informed us if they were consciously aware of the adaptation strategy being used. If the arrow was pointed directly to the target (as shown above) we expect full implicit use, and pointed 45° CCW, which directly counters the rotation, we expect full explicit use.

In the current study, we will further confirm the time-course of implicit motor changes and whether altered visual feedback can potentially delay the onset of implicit learning. We will do this by measuring reach aftereffects after every training trial, and by using two forms of visuomotor adaptation. The first provides endpoint position feedback only, and the second uses an imposed 45° rotation mid-reach. Our hypothesis is that these feedback types may slow down implicit learning while reducing the ensuing aftereffects. Overall, we will examine the possibility that implicit learning develops much faster than originally assumed.

Methods

Participants

One hundred eleven right-handed participants from York University took part in the experiment (mean age = 22.75, range = 18-56, females = 70). All participants provided written, informed consent before beginning the study. All participation was voluntary and taken from the Undergraduate Research Participation Pool (URPP) for credit, the Kinesiology Undergraduate Research Experience (KURE) group for credit, and also from Undergraduate Neuroscience Students. All participants reported having normal or corrected-to-normal vision.

Experimental Set-up

Apparatus

Participants sat on a height-adjustable chair facing a digitizing tablet (Wacom Intuos3, 12" x 12" surface, resolution of 5080 lines/inch, sampled on every frame refresh) and screen (Fig 6). The tablet was positioned at waist level so hand movements could be made along a horizontal plane (See Fig 6 for detail). Visual feedback was shown on a computer screen located approximately 60 cm from the tablet workspace (22" monitor, 1680x1050 pixels, 60 fps). A wooden shield was placed above the tablet work surface to obstruct participants view of their arm movements. All conditions had four forward targets (0.5 cm in diameter) located at 45˚, 75˚, 105˚, and 135˚ as shown in Figure 1. Participants used a digital stylus to move the cursor (0.5 cm in diameter) onto the target displayed on a vertical screen (Fig 6). The trial began when the cursor was moved to the home position, at which point a target appeared 12 cm away. The trial ended when the cursor moved the full distance of 12 cm away from the home position, or just before for the terminal experimental group. On top of the tablet there was a stencil with a circular portion cut-out measuring 20 cm in diameter to constrain the amplitude of outward reaches (further details found on OSF: https://osf.io/7pzrb/). If participants attempted to move the cursor farther than the target distance, the stencil placed over the touchpad would physically block their movement. The relationship between the hand

and cursor was similar to using a desktop computer where a 1 cm movement of the hand leads to a 1 cm movement of the cursor.

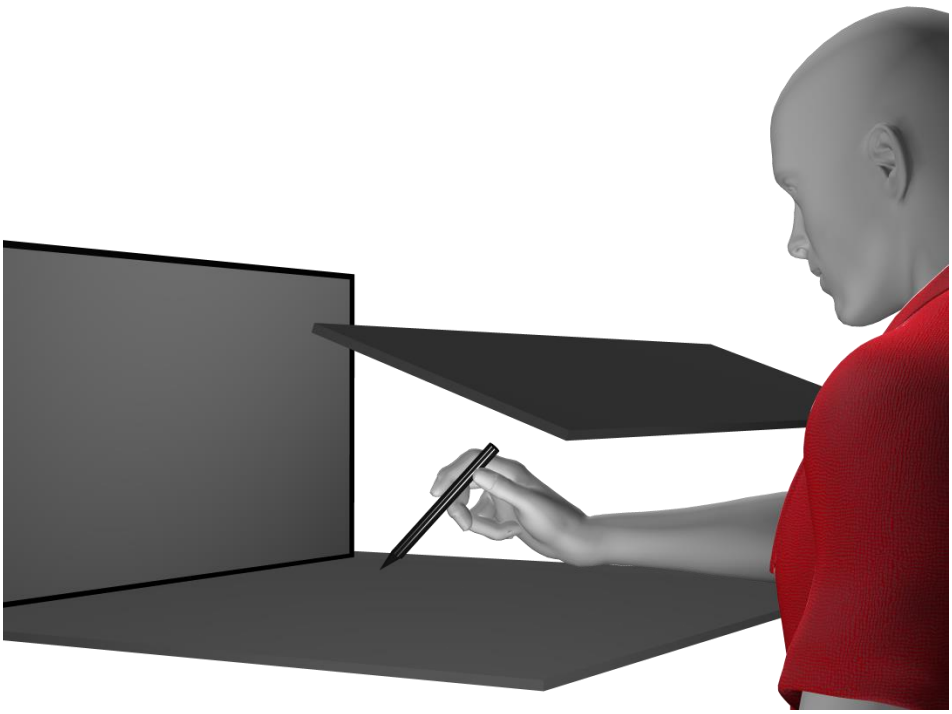

Fig 6. Apparatus which participants used to complete the experiment. The stylus hovers over a digitized tablet where movements with the pen can be seen on the connected upright screen. Hand view is blocked by a wooden pane shown in front of the participant's face.

Trial Types

Cursor Trials

This type of trial, also referred to as a reach-training trial, is one where participants make out-and-back reaching movements in order to hit a target. Participants would reach to one of the four aforementioned targets, and once this was accomplished the cursor and target would disappear. Participants then needed to return their hand back to the home position, and a green disc (shaded filled circle) was used to assist them as they made this return movement with no feedback. The ring was centred on the home position and the radius of this ring represented the distance from the home position to the participant's unseen hand position. Therefore, the ring would decrease in size the closer they would move to the centre. When the participants came within 2.4 cm of the home position, their cursor would be visible again to

precisely land back at home. Although, also noted by Taylor et al. (2014), subjects became proficient in home-to-target reach movements over the course of the experiment and used the guiding ring less. This reaching accuracy largely sped up the experimental procedure.

No-Cursor Trials

These trials worked very similarly to the *Cursor Trials* with a couple notable differences. The first being that participants were unable to see their cursor, which represented their hand position, during the entire reaching movement. The second being that because they were unable to see their cursor, the previously mentioned green disc was used to assist them with reaching to-and-back from the target. The target alternated between eight different locations, which differed by ± 7.5˚ degrees of the four aforementioned target locations. These locations were 37.5˚, 52.5˚, 67.5˚, 82.5˚, 97.5˚, 112.5˚, 127.5˚ and 142.5˚. As mentioned above, within a 2.4 cm distance of the home position, the cursor became visible on the return movement to assist with accurate repositioning for the subsequent trial.

Aiming Trials

These trials, shown in Fig 5, are used to measure explicit adaptation. Participants would need to press the left-and-right arrow keys to move the angle that the arrow was pointed to. Participants were instructed to point the arrow to the direction they would move their hand so that the cursor would hit the target. Once they got to the desired position, they would press the spacebar. Using this form of an explicit judgement test will allow us to examine if adaptation dependent on cognitive strategy can lower implicit adaptation by increasing explicit adaptation.

Procedure

After providing informed consent and demographic information, all participants watched a basic instruction video in an effort to standardize the instructions received. They were allowed an opportunity to ask questions if something in the video was unclear, but if not, then participants began by completing a practice session of the experiment. The ‘Reach with

Cursor' phase alternated every trial with the 'Reach with No Cursor' phase. In both phases the cursor was white, and in the 'Reach with No Cursor' task the target was green. In the 'Reach with Cursor' task, the target was green when the cursor was aligned, and purple when the cursor was rotated. Throughout the entire experiment, the target would turn blue if participants performed the trial correctly, and turn orange if it was done incorrectly (criteria outlined below). For trials with the 'Reach with No Cursor' task, aside from a small space around the home position, participants would see a big green disc appear instead of regular cursor feedback. This was so that participants could not see where they were moving. The green disc was also shown for the return movement. The participants' position of their unseen right-hand holding the stylus was synced with the cursor displayed, and this represented their right hand through all tasks in the practice session and in the following 'Aligned' session.

While in the practice session, participants received information regarding the quality of their movement. They would see "too slow!" if they did not complete the reach within 1500ms, and "missed target!" if the cursor did not hit the target within ±15˚. Once participants completed 16 pairs of practice trials, they moved on to complete 20 pairs of 'Aligned' trials with each pair consisting of a 'Reach with Cursor' trial and a 'Reach with No Cursor' trial. The practice session was used to familiarize participants to the tasks that would be presented, and the 'Aligned' session was used to establish baseline data. After participants completed the 16th 'Aligned' pair of trials, a warning screen with instructions was shown telling them that in eight trials the target was going to turn purple and that they were going to have to move a bit differently for the cursor to hit the target. This was also mentioned to them in the instruction video prior to beginning the experiment. They were informed to create a strategy that would compensate for the deviation. This strategy would be used to counteract the rotation so that they could still move the cursor in a straight line to their targets. This colour change to purple marked the beginning of the 'Rotated' session. In this, they would complete 100 pairs of trials

again with alternating ‘Reach with Cursor’ trials and ‘Reach with No Cursor’ trials. The ‘Reach with Cursor’ task presented in this session was rotated about the starting position such that the cursor representing the participants unseen right hand was distorted 45° CCW. The ‘Reach with No Cursor’ task was the same as before and participants were told to ignore the deviation and reach directly to the target. Before beginning the 56th pair of ‘Rotated” trials, we performed the aiming trial mentioned prior, and did so 8 times in total after every 4 pairs of trials. Constantly alternating between a cursor and a no-cursor trial helped emphasize the necessity of using a developed strategy. The total number of trials performed in the experiment is 240.

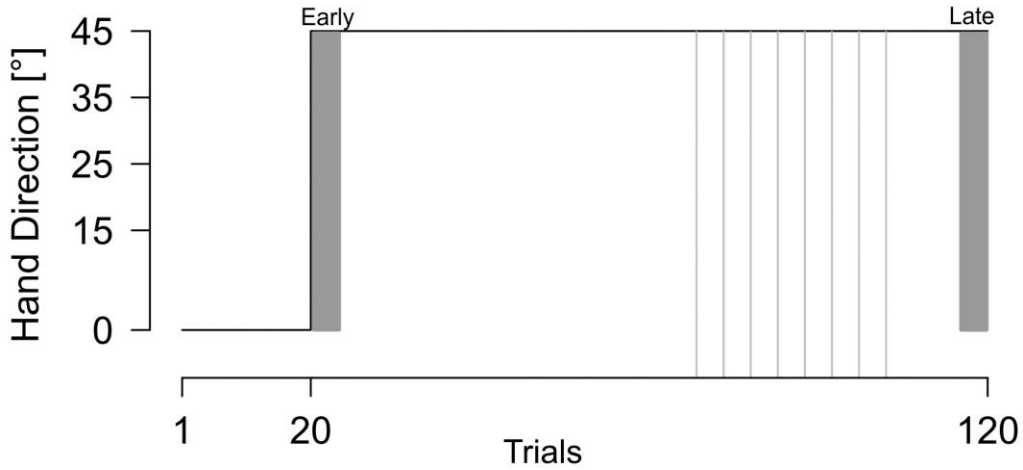

Fig 7. Schedule of perturbation introduction for our experiment. All participants followed the same sequence of design for all reach trials, note this does not include aftereffect trials. Practice session is not shown but the two major sessions include: ‘Aligned’ - trials 1-20, and ‘Rotated’ - trials 20-120. Gray boxes represent early and late phases of rotated training used in analysis, and gray lines represent when an aiming trial was performed.

Experimental Groups

There are three different experimental groups in this experiment: Continuous, Terminal and Cursor Jump (Fig 8). The reaching conditions will be the same for all groups during the ‘Aligned’ session, but will differ beginning in the ‘Rotated’ session. Further, all received instructions to ensure appropriate strategies were developed in order to counter the given perturbation. All experiments were visually inspected to confirm that participants followed the instructions provided.

Continuous Group

Thirty-five participants adapted to a 45° CCW visuomotor rotation with regular cursor feedback (Fig 8A). The cursor which represented their unseen hand position was shown to them throughout the entire movement.

Terminal Group

Thirty-nine participants adapted to a 45° CCW visuomotor rotation with terminal cursor feedback (Fig 8B). Similar to the Continuous Group except that no cursor displaying their hand position was shown to them. Participants would only receive end-point position feedback once their hand had moved 12cm away from the home position. This means that the only time participants were given an idea of how they performed the reach movement, would be a static position where they ended at. i.e. no cursor displaying their hand position was shown; only end-point position feedback.

Cursor Jump Group

Thirty-seven participants adapted to a 45° CCW visuomotor rotation with cursor jump feedback (Fig 8C). The 'Rotated' session of these trials began like one in the 'Aligned' session. However, when the cursor which displayed their hand position moved halfway of the distance to the target, the cursor would jump 45° CCW. i.e. when the cursor which displayed their hand position moved 50% of the distance to the target, the cursor would jump 45° CCW.

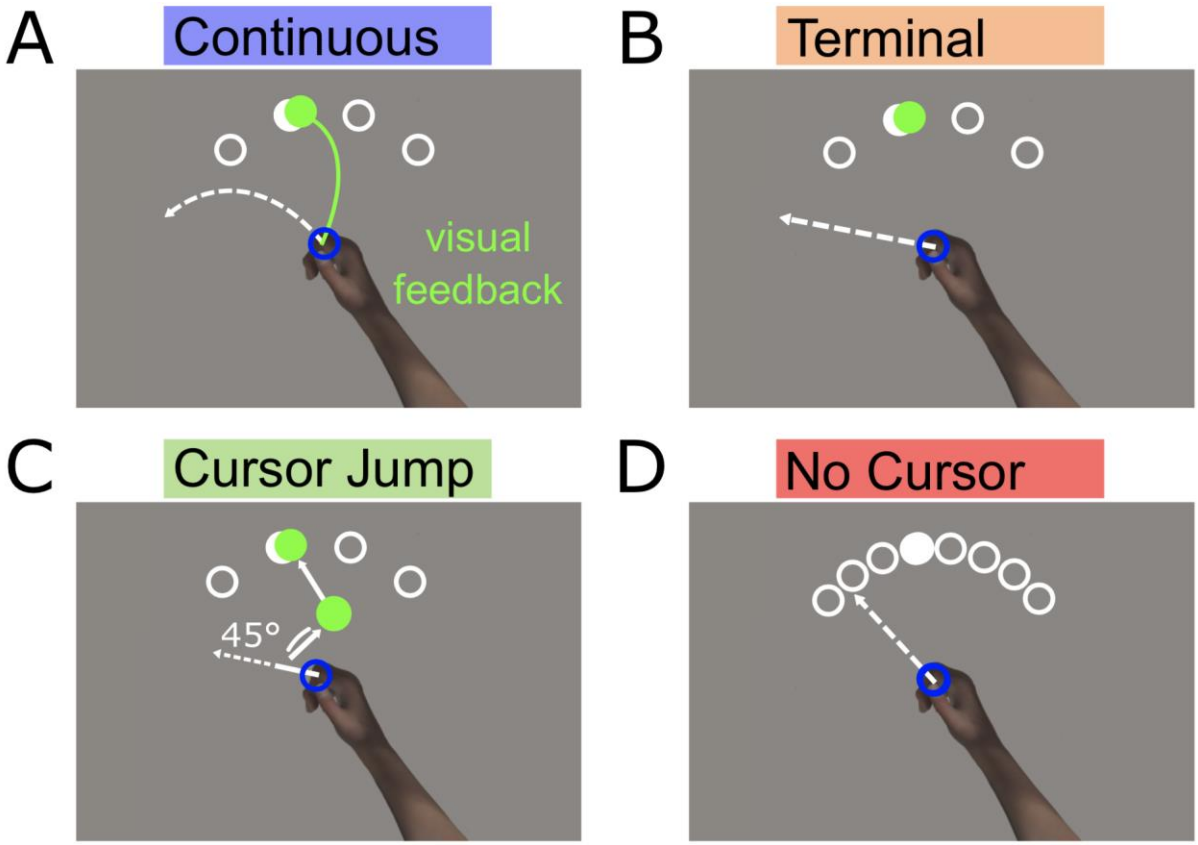

Fig 8. Four different trial types of cursor movement. Participants attempted to move the cursor to one of the four or eight forward targets as quickly and as straight as possible. A. Training with continuous rotated feedback B. Training with terminal rotated feedback; cursor only shown at end of reach trial C. Training with cursor jump feedback, cursor jumps 45° CCW mid-reach on every trial D. Training with continuous rotated feedback; albeit with no cursor feedback. Depending on which condition a participant was assigned they would perform either A., B. or C. interlaced with D. after every trial.

Data Analysis

Our experiment has two different trial types with similar analysis methods used in each. Both 'Reach with Cursor' and 'Reach with No Cursor' trials involved measuring reach deviation.

Reaching with a cursor

To assess reach performance during training, we calculated the error by comparing the angular deviation measured at one-third of the reach distance with the target location, relative to the home position.

Reaching without a cursor

To determine if participants exhibit reach aftereffects as a result of training, we measured angular eSrror a third of the way into the reach during no-cursor trials. To calculate the error, we measured the angular deviation a third of the way into the reach and compared it with the target location, relative to the home position.

Analyses

The main goal of our study was to identify the time-course of implicit learning and reach aftereffects in various conditions. To measure the speed of implicit learning, we must first ensure that participants adequately learned the task. Our cutoff criteria for participant inclusion involved adapting to at least 50% of the exposed rotation by the end of the experiment, and thus twenty participants did not meet the outlined criteria and were removed. We measured reach trials and no-cursor trials separately and looked at them individually regardless of the type of measure. We performed four 1-factor ANOVAs, two for reach training and two for reach aftereffects, using a between-subjects factor (Continuous, Terminal, Cursor Jump) design at both the early (trials 21-24) and late (trials 125-129) time points. We followed significance up with Welch t-tests. To counteract any family-wise error (inflation of Type 1 error), we used an fdr correction using the p.adjust function in R.

Exponential Decay Function for Rate of Change

To more precisely examine the time-course of the implicit process we used an exponential decay function with an asymptote to identify a rate of change for each trial type in each feedback condition. As conducted in Ruttle et al. 2021, we followed the equation below. The value of each process on the next trial (Pt1) is the current process' value (Pt0) minus the product of the rate of change (L) multiplied by the error on the current trial, which is the difference between the asymptote (A) and the process' value on the current trial (Pt0).

$$P_{t1} = P_{t0} - L * (A - P_{t0})$$

The parameter L was constrained to the range [0,1], and the parameter A to [0,2·max(data)]. This model was fit to the rotated reach data and reach aftereffect data for all three groups after they had been properly baselined. Baselining meant taking the 'Aligned' data, calculating the average, and then subtracting that average from all the values to result in the data being centred around zero. For aftereffects, a zero was prepended to account for the fact that responses in these trials already changed through the previous training trial. Each parameter was bootstrapped (1k resamples per fit) across participants to get a 95% confidence interval which was then compared for overlap. The first trial where the modelled process based on the group average fell inside the bootstrapped confidence interval for the asymptote is taken as the saturation trial.

Results

To examine the effect of feedback type on the rate of implicit learning, 111 participants completed a 45-degree adaptation paradigm with interleaved no-cursor trials. We investigated the amount and speed of adaptation for both reach training trials and reach aftereffect test trials across all three feedback conditions. We then tested the effect of different feedback on explicit adaptation, measured directly using aiming trials.

Speed of Training Adaptation

The time-course of adaptation is shown in Figure 9A, and evidently, it seems like there might be a difference in the speed of learning between groups, but perhaps not in extent of learning. To test the rate of learning, we look at the reach deviations in the early phase and the rate of change from the asymptotic decay model (Fig 9B). First, we performed a 1-factor ANOVA with group (continuous, terminal, cursor jump) in order to investigate reach training performance across the early rotated session (trials 21-24, left gray shaded region in Fig 9A).

We found no effect of group during the early phase of the rotated period [$F(2, 108) = 3.003$, $p = 0.054$, $\eta 2 = 0.05$]. To more rigorously quantify the rate of change, we used an exponential decay function to fit the changes both for reach training and reach aftereffects separately for each group. After confidence intervals were obtained by bootstrapping the fits with 1000 resamples, we found that reach training for terminal has the highest rate of change of 33% (CI 22.9-46.8%), followed by continuous with 20% (CI 12.2-30.7%), and then cursor jump with 16% (CI 9.95-22.9%) (Table 1). These rates of change are illustrated in Fig 9B and suggest that participants who received terminal feedback adapted to the perturbation more quickly.

Extent of Training Adaptation

To compare the extent of learning across the three groups (continuous, terminal, cursor jump), we ran a one-factor ANOVA on reach deviations in the late phase (averaged across trials 117-120, grey bars in Fig 9A) with group as a between-subject factor. We found the reach deviations by the end of training led to almost complete compensation for the 45° visuomotor rotation, with averages of 42.4° for cursor-jump, 40.7° for terminal and 37.8° for continuous. These deviations did not significantly vary across the three groups during the late phase of the rotated period [$F(2, 108) = 1.079$, $p = 0.343$, $\eta 2 = 0.02$]. But the asymptotic values from the first 56 pairs of trials of training (prior to the aiming trials) did vary across groups: with a lower asymptote of 31.5° (28.4°-34.9°) for continuous compared to cursor jump at 38.2° (35.3°-41.1°), but no asymptotic difference for terminal to both at 36.6° (33.6°-39.9°) when using the confidence intervals (Table 1). The analysis shows that cursor jump feedback seems to lead to a larger amount of adaptation as compared to the continuous feedback group by the end of the rotated phase.

To sum up, terminal feedback seems to lead to faster adaptation, and cursor jump feedback seems to increase the extent of adaptation. Overall, we can conclude that for each

type of feedback, participants were able to adapt to the rotation at a relatively quick speed. This provides us with the foundation to now examine the respective implicit processes.

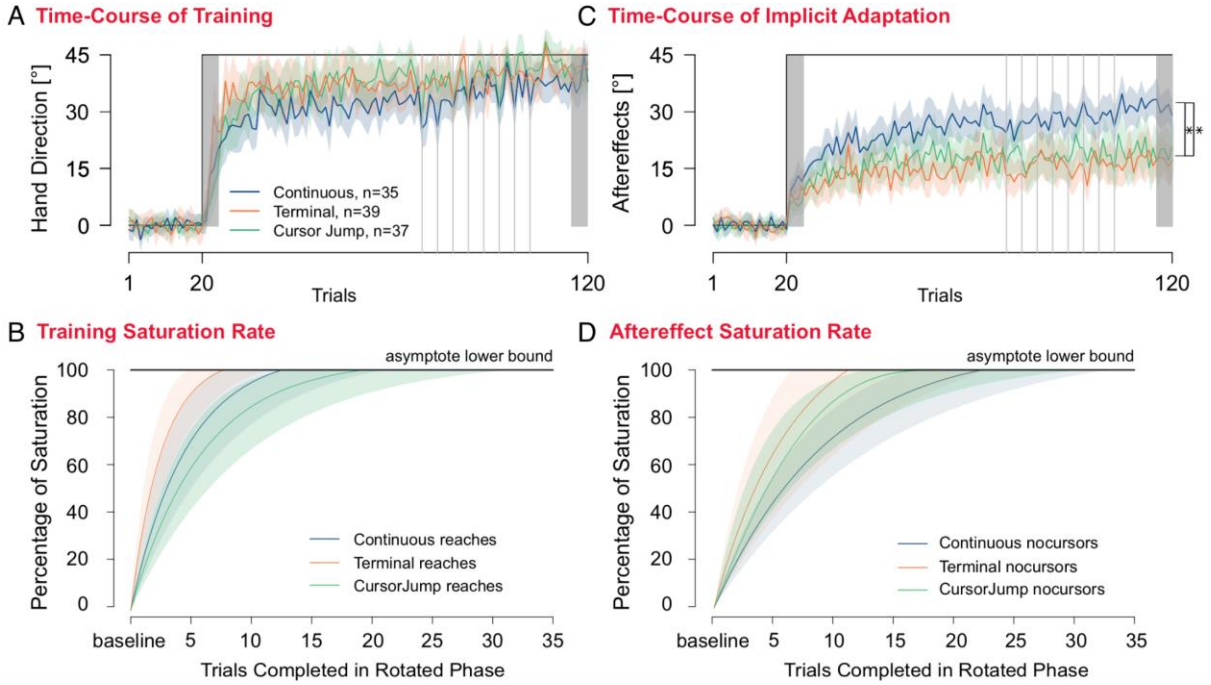

Fig 9. Summary of Results **A & C.** Reach deviations across all cursor trials (A) and no-cursor trials (C) for continuous (blue), terminal (orange), and cursor jump (green) groups. Grey bars denote early and late epochs used for analysis, and thin grey bars represent aiming trials. Thin grey bars represent aiming trials. **B & D.** Saturation curves for cursor-reaches (B) and reach aftereffects (D) showing the change from baseline (0%) to the lower limit of the 95% confidence interval of the asymptote (100%). Shaded regions are confidence intervals.

Rate of Change						
	Reach Training			Implicit Aftereffects		
	Continuous	Terminal	Cursor Jump	Continuous	Terminal	Cursor Jump
Rate of Change	25% [16.8-37.8%]	36% [25.3-50.3%]	17% [11.4-23.2%]	14% [8.98-17.6%]	17% [8.50-36.5%]	11% [6.24-16.4%]
Asymptote	31.5° [28.4°-34.9°]	36.6° [33.6°-39.9°]	38.2° [35.3°-41.1°]	25.9° [23.1°-29.4°]	14.9° [11.9°-18.4°]	15.8° [12.2°-20.0°]
Saturation Trial	10 [6-14]	7 [5-10]	15 [11-23]	16 [13-25]	10 [5-20]	14 [10-24]

Table 1. Rate of change, asymptote, and saturation trial for both reach training and implicit reach aftereffects, shown for each of the experimental groups with the rotation, before aiming. Reach training trials are shown for continuous (blue), terminal (orange), and cursor jump (green) in the first three columns and reach aftereffect test trials which is our measure of implicit are also shown for all three groups in the last three columns. Averages with 95% CI are reported for all values.

Explicit Aiming Trials

We hypothesized that our terminal and cursor jump feedback conditions would evoke lower implicit adaptation if these conditions are more dependent on cognitive strategy. This is

because they would increase explicit adaptation, leaving less room for implicit adaptation to develop. Hence, we also compare explicit adaptation between the three conditions. We measured explicit adaptation with an aiming task (see Methods) and take the angular planned movement direction (relative to the target direction) indicated by participants. Since the goal is to reach straight to the target with the cursor, this measure should only deviate from zero when participants have any consciously accessible strategies. To start, we checked if each group actually developed an aiming strategy, and single sample t-tests showed all groups aiming angles significantly deviated from zero ($p < 0.001$). We then compared our three feedback type groups (continuous, terminal, cursor jump) to determine which displayed more explicit strategy (Fig 10). We found that aiming direction was significantly lower for continuous (median of 14°) compared to terminal (median of 25°) [$t(71.79) = -5.265$, $p < 0.001$, $\eta 2 = 0.28$] and cursor jump (median of 25°) [$t(67.77) = -4.204$, $p < 0.001$, $\eta 2 = 0.20$]. This suggests that feedback type also had an impact on our magnitude of explicit adaptation.

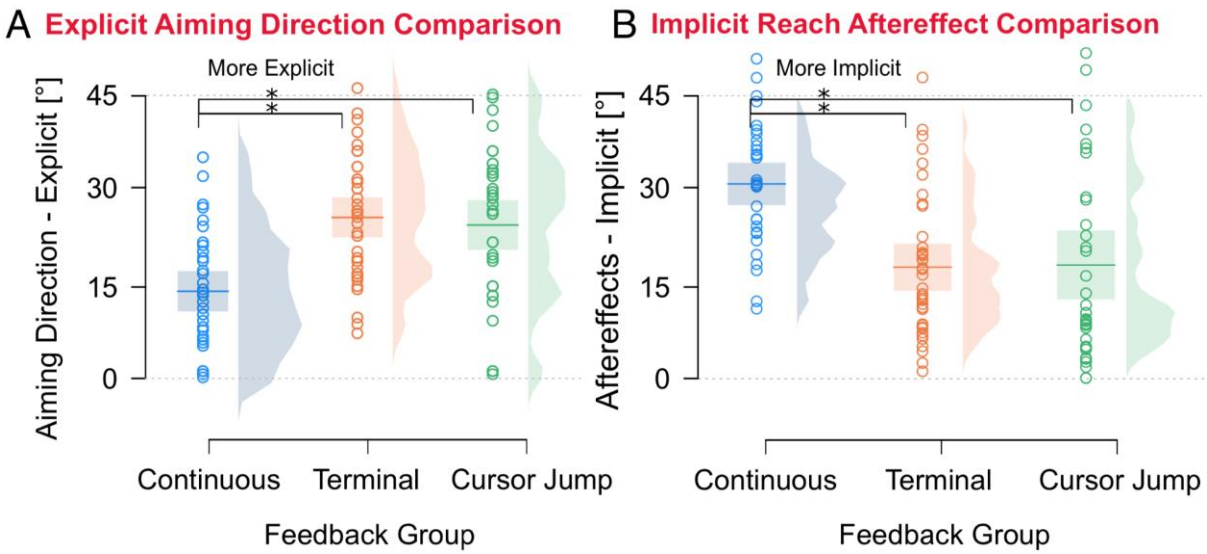

Fig 10. Magnitude of explicit and implicit measures during adaptation for Continuous (blue, terminal (orange), and cursor jump (green) groups. Dots are individual means, horizontal bars are medians. Distributions are also included. **A.** Explicit strategy as measured by having participants aim the arrow in the direction when they plan to move this unseen hand to get the cursor on the target. Dots are individual participants mean data, median of the entire group, and density plots are included. Higher values indicate more explicit awareness of the rotation. Stars indicate that the Terminal and Cursor Jump groups showed significantly larger explicit aiming than the Continuous group. **B.** Implicit adaptation measured by reach aftereffects:

Individual mean data, median of the entire group, and density plots are included. Stars indicate that Continuous showed significantly larger implicit reach aftereffects than Terminal and Cursor Jump.

Speed of Implicit Adaptation

Our main objective involves characterizing the time-course of the implicit components of adaptation, and thus determine how quickly this implicit component emerges as a function of visual information. To quantify implicit, we measure aftereffects after every single reach-training trial in order to finely measure the rate of changes. Figure 9C illustrates that reach aftereffects are emerging very quickly, even within the early phases of training for all three groups. Nonetheless, we found an effect of group on the amount of aftereffects in this early phase [$F(2, 108) = 9.204$, $p < 0.001$, $\eta 2 = 0.15$]. Welch post-hoc t-tests revealed differences between all three groups: the continuous groups producing larger aftereffects (average: 12.1°) than both terminal (average: 7.5°) ($t(62.86) = -2.424$, $p = 0.027$), and cursor jump (average: 3.9°) ($t(63.40) = -4.194$, $p < 0.001$). Reach aftereffects in this early phase were also larger in the terminal compared than the cursor-jump group ($t(71.65) = -2.116$, $p = 0.038$). To more rigorously quantify the rate of change for these implicit processes, we used the rate of change parameter from an exponential decay function (Fig 9D). These reach aftereffects have a rate of change of 9% (CI 6.81-13.2%) for continuous, a rate of change of 12% (CI 7.40-23.6%) for terminal, and a rate of change of 10% for cursor jump (CI 5.82-15.6%), but the confidence intervals overlapped suggesting these fast rates did not vary across groups. These rates of change indicate that saturation occurred at the 22nd trial for continuous, the 13th trial for terminal, and the 15th trial for cursor jump (see Table 1). Altogether, the results suggest that implicit processes are engaged quickly during adaptation, emerging much quicker than originally assumed.

Extent of Implicit Adaptation

Next, we examined how feedback type (continuous, terminal, cursor jump) affects the magnitude of aftereffects in the last phase of training (Fig 9C and 10B), and found that training feedback made a significant difference [$F(2, 108) = 12.448$, $p < 0.001$, $\eta 2 = 0.19$]. Follow-up Welch t-tests (also illustrated in Fig 10B) indicated that these final aftereffects were larger for continuous (average: 31.2°) than terminal (average: 17.6°) ($t(69.51) = -4.142$, $p < 0.001$) and than cursor jump (average: 18.0°) ($t(62.02) = -3.966$, $p < 0.001$). We found the same pattern of results when comparing the asymptotes across these groups. Together, the results suggest that feedback training type can influence the overall magnitude of aftereffects.

Given that effect of feedback type during training on explicit aiming (Fig 10A) was opposite to that for reach aftereffects (Fig 10B), we wanted to see if these two processes were related (Fig 11). That is, if implicit and explicit processes do sum together to contribute to adaptation as assumed by most researchers investigating motor learning, these two components should be highly correlated. Yet, we surprisingly found no correlation between aftereffects and aiming either in all of the groups: continuous group [$F(1, 33) = 0.642$, $p = 0.429$], in terminal [$F(1, 35) = 0.703$, $p = 0.407$], or in cursor jump [$F(1, 37) = 2.842$, $p = 0.100$] with $R < 0.07$ and slopes near zero. This could suggest that although these processes appear to work together or compete with one another, they may really be working independently but with the same adaptive objective. Given an additive relationship would require a perfect negative correlation, this may even point us to the potential that these two processes do not add to total adaptation.

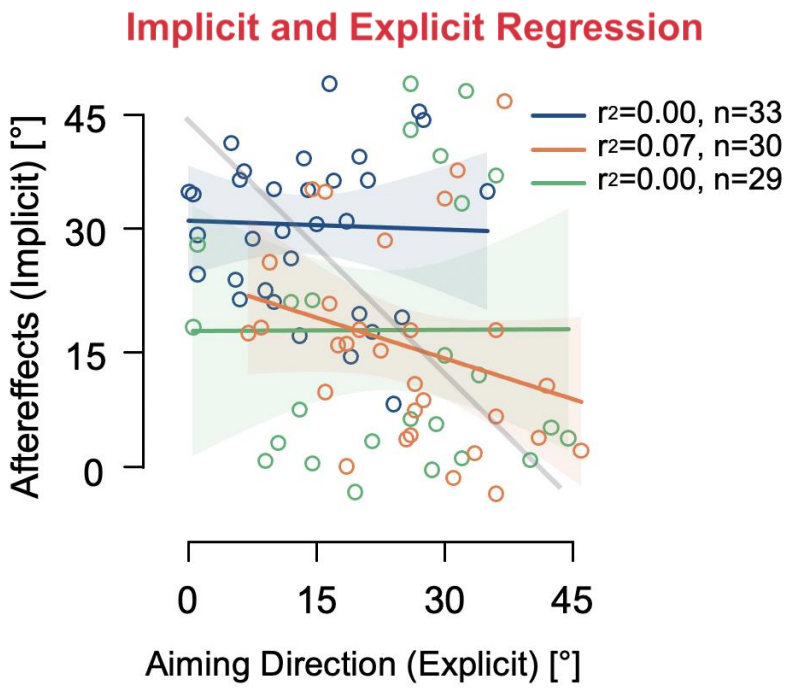

Fig 11. Regression of implicit and explicit processes. Our measure of implicit, aftereffects, is plotted against our measure of explicit, aiming direction. Light grey line indicates perfect negative correlation. Data in degrees with R-squared values provided.

Discussion

The purpose of this study was to characterize the time-course of implicit learning and investigate how different visual feedback influences the rate at which it emerges. We measured the implicit component using reach aftereffects at a fine temporal resolution, by inserting a no-cursor trial after each rotated training trial. Our findings indicate that implicit learning occurs quickly, saturating around the first dozen trials, and is present in the early stages of reach training. Aftereffects were largest when training with continuous feedback (31.2°), while explicit strategy appears to be greater for those training with terminal and cursor jump feedback. However, after a follow-up regression, we found that explicit training and implicit reach aftereffects were not related. Overall, implicit learning occurs regardless of the type of error feedback and emerges more rapidly than previously thought.

Comparing overall adaptation for our three types of error feedback allows us to gauge learning with the visible cursor. Our results align with previous studies on terminal feedback,

which have shown similar magnitudes of adaptation compared to continuous feedback (Taylor et al., 2014, Hinder et al., 2008, 2009, Brudner et al., 2016, Heuer & Hegele, 2008, Schween & Hegele, 2017, Song et al., 2020). In terms of comparing overall adaptation rate findings using terminal feedback, we find a faster rate of change of 36% (CI 25.3-50.3%) compared to Ruttle et al. (2022) finding of 14.2% (CI 10.0-20.0%). For cursor jump feedback, we found a higher asymptote, or a larger magnitude of adaptation, compared to continuous. Although, training with cursor jump feedback had a lower rate of change of 17% (11.4-23.2%) compared to continuous 25% (16.8-37.8%). Despite this, we can conclude that all groups adapted to the rotation by the end of the rotated session, and that terminal and cursor jump feedback does not largely influence our ability to learn overall.

Comparing aftereffects for our three types of visual feedback provides valuable insight into the factors that affect the progression of implicit learning. The present study confirms the findings of Ruttle et al. (2021), who also measure aftereffects throughout early reach training, with some minor differences. Our results show that targets separated by 30° in the forward direction are still capable of provoking implicit learning and adaptation, although at a slower rate. We find our continuous reach aftereffects had a rate of change of 14% (CI 8.98-17.6%), while Ruttle et al. (2021) found a value of 56.9% (CI 27.4–58.5%). Implicit reach aftereffects in our study saturated at around 13 trials (averaged for all three groups), in contrast to their finding of 3 trials. Despite this variation, our results provide additional support for the notion that implicit adaptation occurs rather quickly, and much faster than typically expected. Although we did not observe faster reach aftereffect saturation with our continuous control, we did find a significantly higher extent of aftereffects compared to the other feedback conditions. While the rate of implicit learning is not slower with terminal feedback, the extent of implicit adaptation is similarly reduced when compared to continuous feedback (Taylor et al., 2014, Barkley et al., 2014, Hinder et al., 2008, Brudner et al., 2016, Schween & Hegele, 2017),

although this is not always the case (Heuer & Hegele, 2008, Song et al., 2020). While we did not find a slower rate, we did replicate the finding in Gastrock et al. (2020) of cursor jump showing reduced aftereffects. Essentially, while terminal and cursor jump feedback does not influence the rate that implicit adaptation emerges, they certainly elicit a lower implicit adaptive response.

It is commonly assumed that motor learning begins with a more explicit or declarative phase, with an implicit or unconscious process emerging later (Mazzoni & Krakauer, 2006, Taylor et al., 2014, McDougle et al., 2015, Miyamoto et al., 2020). This assumption has led researchers to only measure implicit learning typically after 60-100 reach training trials (Hinder et al., 2008, Fernandez-Ruiz et al., 2011, Taylor et al., 2014, Barkley et al., 2014, Neville & Cressman, 2018). Our paradigm is the first to test this assumption by repeatedly measuring aftereffects throughout perturbation training. We also used an exponential decay function to detect when these aftereffects emerged and saturated, and compared this time-course across feedback type. And while the data might appear to better fit a double-exponential model, for our purposes, using the decay function allowed us to gauge the onset of implicit adaptation, and indicate the types of feedback to facilitate this unconscious type of learning. Our results also debunk the assumption that the implicit part of learning emerges much later and only after declarative or explicit learning

While our study primarily focused on implicit components of adaptation, we also examined the extent of explicit adaptation. We utilized an aiming task to determine the explicit contribution to adaptation across our feedback types. Our results reveal that the extent of explicit adaptation was significantly greater for both terminal feedback and cursor jump feedback compared to our continuous control, although with no difference between terminal and cursor jump. These findings suggest that error feedback type can increase the amount of explicit control over the task. This interpretation coincides with previous research that has

shown high explicit adaptation with different forms of error feedback (Taylor et al., 2014, Gastrock et al., 2020). The field has conducted substantial research on the speed of explicit processes, with the consensus being this form of adaptation is very fast (McDougle et al., 2015, Taylor et al., 2014, Smith et al., 2006, Huberdeau et al., 2015). Consequently, our study highlights the importance of considering the speed of implicit adaptation, and that further exploration of implicit learning is warranted.

We also examine how implicit and explicit processes interact with one another in these different forms of visual error conditions. For implicit, we used an asymptote measure of reach aftereffects during the late phase of the rotated period. For quantifying our explicit system, we conducted a judgment task with an arrow, where we averaged all aiming trials for each individual. There has been a long-standing untested assumption that both processes add together to denote total adaptation. Yet, we found no significant correlation between aftereffects and aiming direction across our large sample. This suggests that implicit and explicit processes are largely independent. There is an ongoing discussion about how these processes are connected, with some studies focusing on their competing function, while others examine the order of elicitation (e.g. changes in implicit learning following explicit) (Leow et al., 2020; Yin and Wei, 2020; Albert et al., 2021). There is some evidence of competition between sensorimotor learning systems, particularly in paradigms involving task error (McDougle et al., 2015, Kim et al., 2019; Leow et al., 2020; Miyamoto et al., 2020). Although this competing functioning may also be occurring within each learning process (e.g. (parallel implicit learning systems interfering in overall implicit adaptation) or even in the broader network at hand (Albert et al., 2022). Also, recent work suggests that learning processes may not be additive (Maresch et al., 2021; ‘t Hart et al., 2022), which is why it is important to directly measure them rather than inferring one from the other. Not only is directly measuring better, but it is also necessary in order to test this assumption. This collective research on these

processes helps us understand how the two components work together to achieve rapid, large adaptation. Moreover, while implicit and explicit processes may be related, they are to some degree independent of each other due to the lack of summation.

To gain a more comprehensive understanding of the time-course of implicit learning, various forms of visual feedback could be explored in future research. For instance, incorporating a pause condition, where we provide delayed error feedback, or a target-jump condition, where the target moves mid-reach instead of the cursor, could be valuable. The pause condition has been suggested to attenuate the implicit component (Kitazawa et al., 1995; Brudner et al., 2016; Schween & Hegele, 2017; Parvin et al., 2018; McDougle & Taylor, 2019), and by sampling aftereffects after each training trial, like employed in this study, we could test whether this is so at a fine temporal resolution. The target-jump condition can be used to manipulate the contribution of task error, which is linked to explicit processes (Leow et al., 2018). Task error is commonly compared to sensory prediction error, which is the implicit counterpart, and research suggests that task error contributes significantly to implicit learning (Mazzoni & Krakauer, 2006; Taylor & Ivry, 2011). More recently, task error has been further associated with implicit recalibration (Tsay et al., 2022). Nevertheless, exploring the temporal progression of implicit adaptation under various visual error conditions would yield valuable insights.

Conclusion

Our work has shown the value of measuring implicit adaptation early in reach training, as it appears quickly and irrespective of feedback type. While terminal and cursor jump feedback led to smaller implicit aftereffects, they did not affect the speed of adaptation. More specifically, we were unable to slow down the emergence of these reach aftereffects. Both error conditions elicit a higher explicit task control, however, a regression found no relationship between implicit and explicit measures. Our study underscores the importance of considering

both the speed and the extent of implicit adaptation across different feedback conditions in future research on visuomotor learning. Furthermore, our results indicate that altered visual feedback does not delay the onset of implicit learning, and provide additional evidence that implicit adaptation occurs much quicker than commonly assumed.

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