Measures of Implicit and Explicit Adaptation Do Not Linearly Add

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Abstract

Both implicit (unconscious, automatic) and explicit (effortful, strategic) processes contribute to various kinds of learning[1], including visuomotor adaptation[2–4]. Implicit adaptation may be capped at some level[5], regardless of the level of explicit adaptation, or implicit and explicit adaptation could be linearly added in total adaptation[6,7]. Both appear well accepted, but ironically contradict each other. In the latter case, the equation used is simple:

1) adaptation ~= implicit + explicit,

Which is used to "predict" that implicit adaptation is perfectly anti-correlated with explicit adaptation:

2) implicit ~= adaptation - explicit,

This derived implicit adaptation is sometimes further analyzed[8–10]. But the underlying additivity assumption is not always replicated[11] and is considered the "least robust" assumption in motor adaptation[12]. Here we directly test the additivity assumption, particularly how well it predicts implicit adaptation. We find that the relationship between explicit and implicit adaptation is not additive but more complicated and very noisy, which means that future studies should measure both implicit and explicit adaptation directly. It also highlights a challenge to the field to disentangle how various motor adaptation processes combine when producing movements.

Main Text

We test additivity both in an experiment where we elicited various levels of explicit adaptation, and by analyzing aggregate data from a series of other studies using a wide range of protocols. In our experiment, three groups of participants adapted to a 30° rotation: an "instructed" group (N=24) that was made aware of the rotation and given a counter-strategy, an "aiming" group (N=24) that reported their aiming before every training trial by orienting an arrow in 1° steps, and a "control" group (N=24). All groups repeated counterbalanced blocks of include and exclude strategy no-cursor reaches[3] to assess implicit and explicit adaptation. Aiming reports are used as a measure of explicit adaptation as well. See methods for more details.

First, we find no group difference in adaptation (Fig1A,B; $F(2,69)=1.30$, $p=.28$, $\eta^2=.036$; $BF_{10}=0.316$) nor in exclusion as measure of implicit adaptation (Fig1B; $F(2,69)=0.59$, $p=.555$, $\eta^2=.017$, $BF_{10}=0.185$). Additivity would then predict equal inclusion deviations in the three groups

(inclusion=implicit+explicit), but we find that the instructed group has higher inclusion deviations ($F(2,69)=24.72$, $p<.001$, $\eta^2=.417$, $BF_{10}=1369327$), with no difference between the other two groups. In short, the group averages do not show additivity.

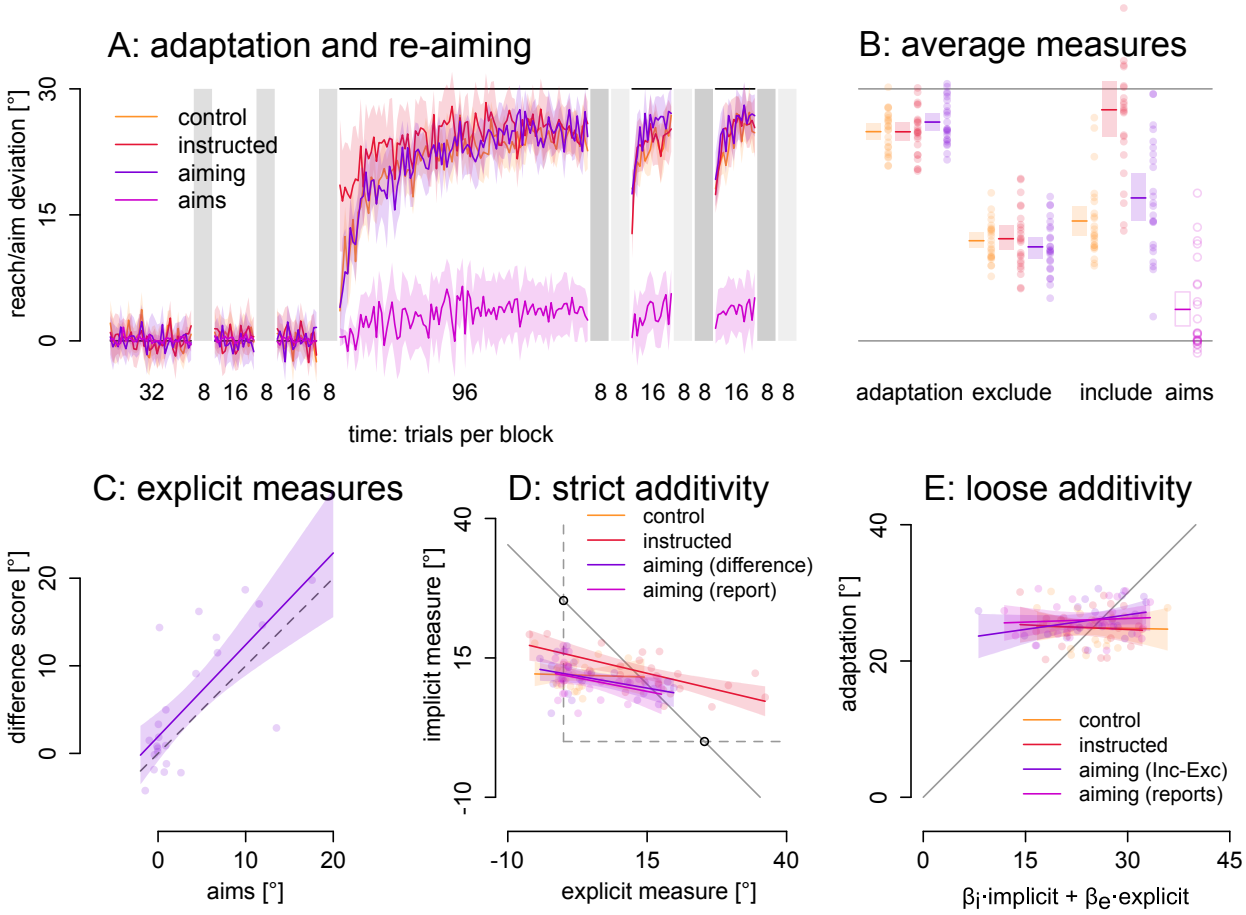

Fig 1. Adaptation measures and additivity. *Areas in color denote 95% confidence intervals of the mean. Dots are individual participants.* **A:** *Adaptation and aiming responses throughout the perturbation schedule. No-cursor blocks in gray with inclusion and exclusion trials in the rotated phase.* **B:** *Averaged estimates of adaptation, exclusion and inclusion, and aiming reports.* **C:** *Linear regression shows that aiming reports and include-exclude difference scores agree.* **D:** *Strict additivity predicts that individual data lie on the gray diagonal with slope -1, and intercept equal to average adaptation.* **E:** *Loose additivity would allow a weighted sum to predict total adaptation, with data over predictions on the gray unity line.*

But maybe additivity can be shown across individual participants instead. We find a small re-aiming strategy in the aiming group (Fig 1B: 3.74°; $t(23)=3.38$, $p=.001$, $\eta^2=0.497$). Since the reported aims and the inclusion-exclusion difference scores largely agree on explicit adaptation (Fig 1C; $R^2=0.519$, $p<.001$, intercept=1.9, slope=1.05) in contrast to other work[13,14], we will use both as estimates of explicit adaptation. Strict additivity would predict that measures of implicit and explicit adaptation would fall on a line with slope -1 and an intercept equal to

average adaptation (Fig 1D: gray diagonal line) but the 95% confidence intervals of linear regression coefficients on all four subsets of data exclude these values. As an alternative, we test loose additivity as well, by fitting weights for measures of implicit and explicit adaptation as free parameters for each of the 4 subsets of data, before being added to predict total adaptation. Actual adaptation over predictions should lie on the identity line (Fig 1E: gray diagonal), but they don't (slopes 95% CIs exclude 1). In short, neither strict nor loose additivity predict adaptation across individual participants.

Based on a striking similarity between the fast process of a common state-space model[15] and aiming reports, this model's slow and fast processes are assumed to map onto implicit and explicit adaptation respectively[8]. However, given that the model's processes are strictly additive and that the previous data analysis assumes strict additivity as well, the match between the slow process and the subtractive estimate of implicit adaptation automatically follows from the match between the fast process and the measure of explicit adaptation, and is fully dependent on the largely untested assumption of strict linear additivity.

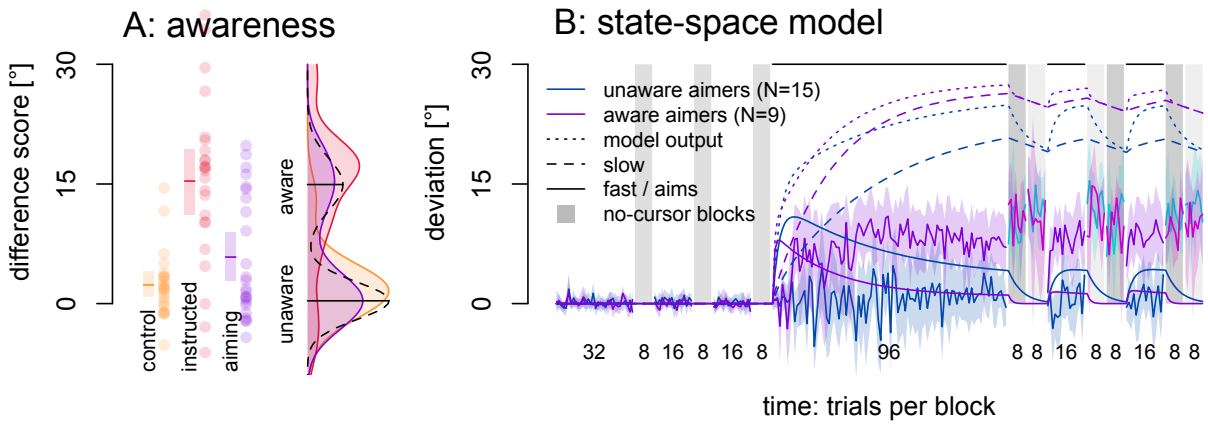

Fig 2. Additive state-space model. A: *Aware and unaware sub-groups in the aiming condition.* **B:** *The two subgroups have similar model fits. In neither subgroup does the fast process predict aiming responses, or the slow process strategy exclusion reach deviations.*

We test if the state-space model's slow process maps onto exclusion trials (implicit) and if the fast process maps onto aiming responses (explicit). We can only test this in the aiming group, and first confirmed that the paradigm used here is suitable for fitting the model at the group level[16] with a parameter recovery simulation. We also notice that the inclusion-exclusion difference scores in the aiming group are distributed bimodally (Fig 2A; unimodal vs. bimodal relative log-likelihood <.001) suggesting that aiming makes some fraction of participants aware of the rotation while others develop no strategy. Under the assumption that the fast process reflects explicit strategies in adaptation, these two sub-groups should have different model fits. Therefore, we split the aiming group in aware (N=9) and unaware aimers (N=15), and separately fit the state-space model to their averaged reaches (Fig 2B). In the aware aimers, the fast process is lower than aiming reports, and vice-versa in the unaware aimers (95% CIs of data exclude model processes). In both sub-groups the slow process is higher than exclusion

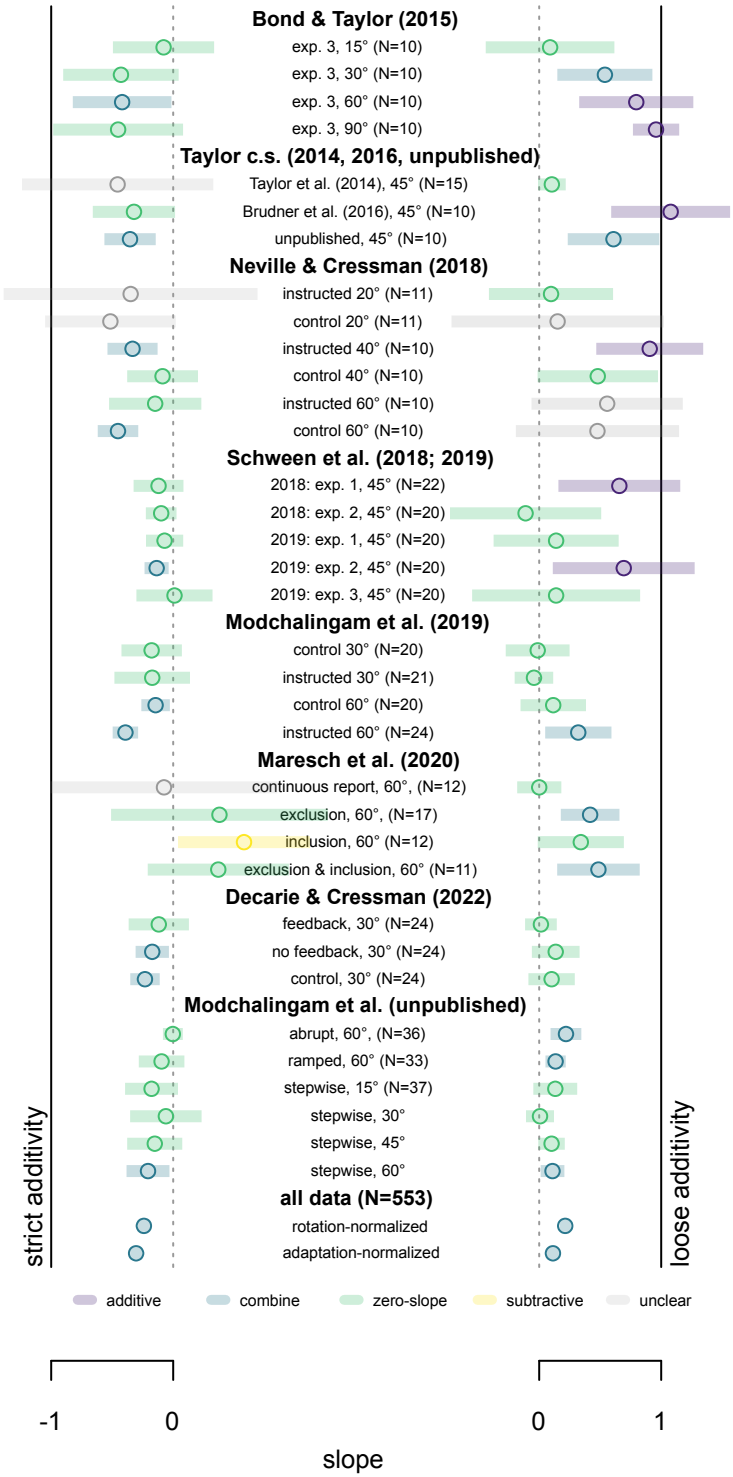

Fig 3. Additivity across a large cross-section of visuomotor adaptation experiments. *No groups demonstrate strict additivity, and only 6 of 35 subsets of the data show loose additivity.*

trials during all no-cursor blocks (95% CIs of data exclude model processes) confirming that the slow process does not capture implicit adaptation[17]. That is: the strictly additive processes of the state-space model do not align with direct measures of implicit and explicit adaptation in this data set.

While it stands to reason that adaptation is larger when both implicit and explicit adaptation processes contribute[2,18,19], few studies indicate some form of additivity[6,7]. Other studies don't show additivity[3,11,20,21] or they show partial additivity, or additivity only in some participants[19,22] or it is unclear to us whether or not the data support additivity[13,14].

In short, the literature is divided on the additivity assumption of implicit and explicit adaptation[12]. That's why we re-analyzed data from 8 studies[7,11,19,20,23–26] with 32 groups of participants (total N=553) and independent measures of implicit and explicit adaptation. For every participant we took an average across multiple trials at the end of training to estimate explicit, implicit and total adaptation (the "stepwise" participants are assessed 4 times, for 35 'groups' total). We divide each participants' estimates by their total adaptation, and for each subgroup accept strict additivity or loose additivity if the 95% CI for the slope of the model includes -1 or 1 respectively (as above; Fig 1D). None of the groups support strict additivity (see Fig 3), and only 6 of 35 subgroups support loose additivity. Consequently, in all participants combined (Fig 3 bottom) there is no support for additivity either.

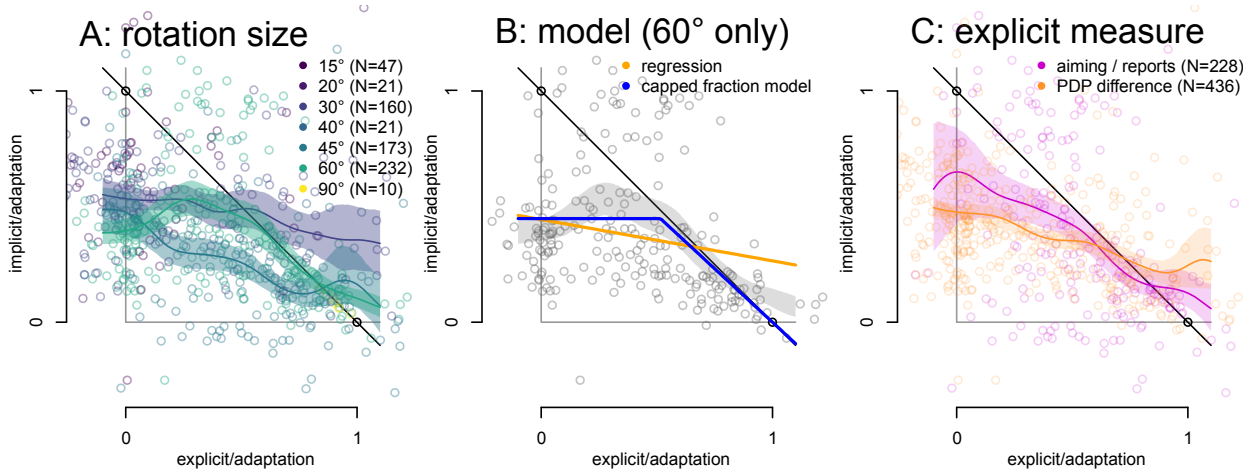

Fig 4. Relationship between implicit and explicit adaptation. A: *All data and trends for rotations with 100+ participants.* **B:** *Capped fraction model for 60° participants.* **C:** *Trends for different methods of measuring explicit adaptation.*

The aggregate data does show a combined effect: slopes are different from 0. To explore this (Fig 4), we first look at a smoothed estimate of implicit over explicit measures for rotations with more than 100 participants (30°, 45° and 60°; see methods for details). We see that in the range around 0 explicit adaptation, the proportion of adaptation that can be explained as implicit, decreases with increasing rotation: a signature of capped implicit adaptation[5]. We can also see that for 30° and 45° conditions the data seems to follow a roughly linear trend. For the 60° conditions there might be a cap on implicit adaptation when explicit adaptation is low,

but with higher explicit adaptation, implicit and explicit adaptation may follow linear additivity. We fit two models; a linear regression mimicking the relationship in smaller rotations (orange line in Fig 4B) and a model setting implicit adaptation as the minimum of an intercept term ("capped implicit") and a proportion of 1-explicit ("additive"; blue line in Fig 4B). The second model fits the 60° data best (relative log-likelihood based on MSE-derived AIC: $p<.001$), but the assumptions underlying it do not seem to apply to smaller rotations. Finally, since our experiment showed that requiring participants to report their aiming strategy increased explicit adaptation in some participants (9/24, Fig 2A), we split the aggregate data by method of explicit measure, grouping various forms of reporting aiming strategy (in pink, Fig 4C) as well as methods that use difference scores between include strategy and exclude strategy no-cursor trials (in orange, Fig 4C). We can see that overall the data falls on a rough line, but the (absolute) slope and intercept are higher in the data from experiments with aiming reports. The difference could be explained both by aiming reports measuring explicit adaptation differently and by aiming reports changing the underlying learning processes.

While both implicit and explicit processes contribute to adaptation, ultimately a model needs to both leave room for other processes, and combine processes non-additively. The competition model[27] essentially implements this as implicit adaptation (I) taking up some proportion p (0...1) of the rotation (r) that explicit adaptation (E) is not learning: $I = p(r – E)$. This leads to slopes (values of $p * -1$) in the range of -0.6 to -0.8 which seems to match the aggregate data (Fig 4A,C) albeit not the 60° subset. Within the framework of the competition model the large spread in data between individual data would indicate fluctuations in the learning parameter p. A few models, PReMO[28] is a recent example, use mechanisms akin to maximum likelihood estimates, but may focus less on how explicit adaptation combines with implicit. While we think the competition model and others are interesting steps, any model that aims to fully explain how various adaptation processes combine would also need to handle 1) possible saturation points of various adaptation processes[5]; 2) interactions between processes[27,28]; 3) the method by and time at which processes are measured[13]; 4) task contexts such as number of targets[7], the presence of landmarks, setups, and importantly instructions and feedback to participants[11,21,26], and ideally, although these are harder: 5) differences between individual participants in motivation or higher level goals.

In our experiment, as well as in a cross-section of other data, there was unexpectedly little evidence of an additive relationship between independent measures of explicit and implicit adaptation. This means that implicit adaptation cannot be estimated by subtracting explicit adaptation from total adaptation, or vice versa. Previous work on visuomotor adaptation might need to be re-evaluated if their findings on implicit adaptation rely on a strict additivity assumption, while to our knowledge people do not seem to use implicit adaptation to estimate explicit adaptation. These findings might have consequences for our understanding of other types of learning as well. Our first conclusion is simple: in order to investigate implicit and explicit processes, we should use independent measures of both. Our re-analysis of other data shows there might be a kind of relationship between measures of implicit and explicit adaptation, but 1) this relationship is not strictly additive, 2) this ignores other adaptation processes, 3) the data appears to be highly variable and 4) the nature of the relationship may

strongly depend on other factors such as setup or instructions. These notions lead to our second conclusion; the field should try to understand the (neural) mechanism by which various adaptation processes are combined to shape behavior.

Acknowledgements

We are grateful to Dr. Jana Maresch and MSc. Amelia Decarie for making their data publicly available, and to Dr. Erin Cressman, Dr. Jordan Taylor, and Dr. Raphael Schween for sharing some of their data with us. We are also thankful for discussions with Dr. Opher Donchin, and Dr. Scott Albert that shaped the content of this paper.

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Methods

Participants

For this study 72 right-handed participants (55 female; mean age 19.8, sd 3.7; demographics not stored for 1 participant) were recruited from an undergraduate participant pool, 24 for each of 3 groups (aiming, instructed, control). All participants reported having normal, or corrected-to-normal vision and gave prior, written, informed consent. All procedures were approved by York

University's Human Participant Review Committee.

Setup

The participants made reaching movements with a stylus on a digitizing tablet, controlling a cursor that was displayed on a downward facing monitor (60 Hz, 20", 1680x1050, Dell E2009Wt) seen through an upward facing mirror in between the tablet and monitor (see Fig 4A). This puts the perceived stimuli in the same plane of depth as the hand, and the displacement of the cursor was scaled to match the displacement of the stylus.

Stimuli: The background of the screen was kept black. An open gray circle (radius: 0.25 cm) served as a home position and was located at the center of the screen (see Fig 1B). Eight reach targets were located at 8 cm from the start position at 0°, 45°, 90°, 135°, 180°, 225°, 270° and 305° and were also displayed as open gray circles (radius: 0.25 cm). A filled circle was used as a cursor (white disc, radius: 0.25 cm) on training trials. In the aiming group only (see below), an open pink arrow originating at the home position and extending 7 cm was used on aiming trials (it initially deviated ±10° or ±5° from the target, randomly chosen on each trial). On no-cursor trials a small gray arrow head was presented within the home position, pointing to where the unseen cursor would be, in intervals of 45°, to guide participants back to the home position. More details below.

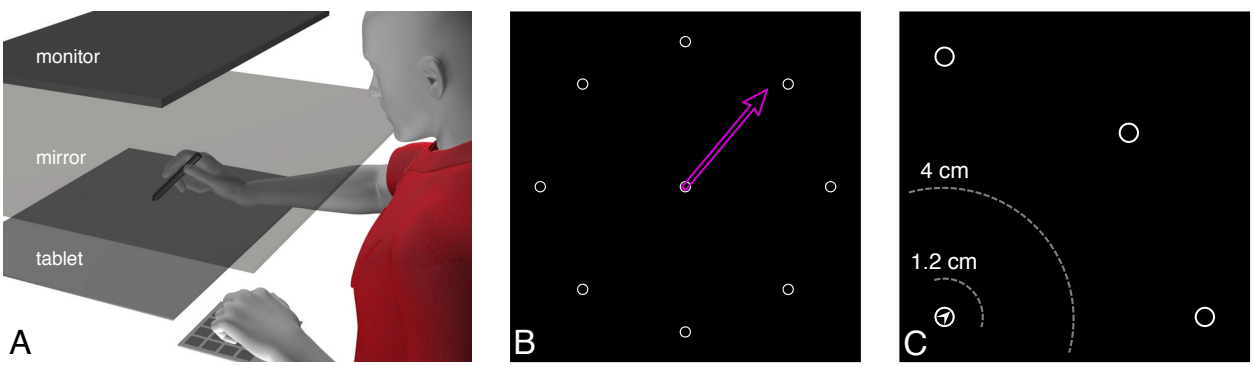

Fig 5: Setup, aiming and no-cursor trials. A: *Tablet setup with mirror. The stimuli appear in the same plane of depth as the tablet.* **B:** *Aiming: the upcoming target (1 of 8) is shown with an arrow used to indicate the intended reach direction, or "aim".* **C:** *The outward reach on no-cursor trials end when the stylus stops moving for 250 ms and is 4 cm away from the home position (outer gray ring). For the return home, a small arrow-head in the home position indicates at 45° intervals where the cursor is, participants move the opposite direction. When the stylus is then back within 1.2 cm distance of the home position (inner gray ring), a cursor appears that needs to be moved to the home position to start the next trial.*

Tasks

In each trial, participants used the stylus to move from a central home position to one of the 8 targets. Before each reach, participants have to keep the cursor at the home position for 2.0 s (trials without aiming) or 0.5 s (trials with aiming). After the hold period the target would appear and the home position would disappear, signaling to participants they should move to the target.

Training trials: In training trials, a cursor had to be moved from the home position to the target and back. When the cursor's center was within the radius of the target, the reach was considered ended. At that point the target disappeared and the home position reappeared, signaling that the participant should move back to the home position. Once the cursor's center was within the radius of the home position, the trial ended. During the aligned phase, the cursor was aligned with the tip of the stylus. In the rotated phase, it was rotated 30° around the home position.

No-cursor trials: In no-cursor trials, the cursor disappears as soon as it's center no longer overlaps with the home position. The reach is considered ended if the stylus has moved beyond 50% of the home-target distance (4 cm) and there is no movement for 250 ms (or the total movement during the last 250 ms is less than 1% of the home-target distance). At this point, the target disappears, the home position reappears, and an arrow at the home position indicates where the (rotated) cursor would be relative to the home position (in increments of 45 degrees). Participants use this to move back toward the home position, and when the cursor position is within 15% of the home-target distance (1.2 cm), the cursor is shown again, to get back on to the home position.

In the rotated phase, these were used in a Process Dissociation Procedure ("PDP") in all three groups. In this Process Dissociation Procedure, people reach for a target without cursor, while either including or excluding their strategy (see below). The 'exclude' strategy blocks are a measure of implicit adaptation, while the include strategy blocks should measure both implicit and explicit adaptation[3,11,13,21]. If implicit and explicit adaptation are additive, then subtracting reach deviations measured in include strategy blocks from reach deviations measured in exclude strategy blocks should be a measure of explicit adaptation. Whether or not this is true, if the responses are different in the two blocks, then participants can dissociate their strategic responses from unconscious adaptation, which shows that some degree of explicit adaptation is occurring. Note that if there is no difference in the responses, this is highly suggestive that no explicit adaptation is occurring, but not definitive proof.

Aiming: Before training trials, participants in the aiming group would see the upcoming target and they could orient an arrow using the arrow keys on an extra key pad, to indicate the direction in which they would move their hand in order to get the cursor to the target. In the aiming group, the training blocks are called "Aim and reach" blocks, and the instructions they were given includes: "Point the arrow as accurately as you can to indicate the movement you want your hand to make, so that you can get the cursor on the target."

Instructions

Strategy: Participants in the instructed group received detailed instructions in between the aligned and rotated phase, while participants in the other groups had a break of about the same duration. The instruction included an animation of the perturbation, and explanation of a strategy to counter the perturbation (move in direction rotated 1 hour on a clock face). They were tested on understanding the strategy by drawing reaches on a clock face toward targets in all quadrants.

All groups were informed that the way the cursor moves changes in the next part of the experiment, and they were told that they have to figure out how to deal with this, and that they

should remember what their strategy is, since they will be asked to reach while using this strategy and while not using this strategy, with this instruction:

> "This is part 2 of the experiment. For these coming tasks, the filled cursor will move a bit differently, and you will need to compensate for this. However you compensate, keep that strategy in mind since you will be asked to use this strategy several times, when reaching without a cursor. Sometimes you will be asked to NOT use this strategy when reaching without a cursor."

Process Dissociation Procedure: At the end of the rotated session, participants do no-cursor reaches in two kinds of blocks: either while including or excluding their strategy, with these instructions:

> Include: "For THESE trials, make full use of any strategies you learned just now".
> Exclude: "For THESE trials, do not make use of any strategies you learned earlier and treat this as you did the original *'reach for target'* task in part 1".

These instructions were read to participants before the rotated part of the task.

Procedure

All participants performed 264 reaching trials of various kinds (see Fig 2), organized into blocks of 8 trials. In each block, all 8 targets were used in a randomized order. The task started with an aligned phase with first 32 training trials, and 3 blocks of no-cursor trials (Fig 2 gray rectangles), with two blocks of training trials before the second and third no-cursor block. In the rotated phase, a rotation of 30° is applied to the cursors (Fig 2 black lines indicate perfect reaches). These included 96 training trials, followed by 3 sets of 2 no-cursor trial blocks. Adaptation is “topped up” before the second and third of these sets of no-cursor trials with 16 rotated training trials. The no-cursor trials in the rotated part are divided into 2 blocks: one where participants are instructed to include their strategy, and one where they do not include their strategy. In one group, the "aiming" group, every training trial is preceded by aiming: participants are shown the upcoming target and are asked to indicate where they will move their hand in order to get the cursor to the target. In the other groups, participants wait 1.5 s instead of aiming, to keep the total time roughly equal.

Participants were intermittently monitored during the experiment and encouraged to make straight, smooth reaches, to faithfully do no-cursor reaches according to instructions and to really consider where the aiming arrow should be pointed, if experimenters suspected the participant not to perform optimally.

Analyses

For all reaches (both training and no-cursor trials) we calculated the angular reach deviation at ⅓ the home-target distance (~2.67 cm) and similarly used the aiming arrows angular deviation for comparison. We remove training reaches and re-aiming responses deviating more than 60° from the target (controls: 0, instructed: 1, aiming: 3, re-aiming responses: 0), and subsequently all angular deviations outside the average +/- 3 standard deviation for each trial across participants within the group (controls: 15, instructed: 10, aiming: 12, re-aiming responses: 30). The maximum number of data points removed for any participant was 6 (control: 3, instructed:

4, aiming: 6, re-aiming responses 6), and many participants had no trials removed (control: 16, instructed: 19, aiming: 16, re-aiming responses: 12). No participants were removed, and no trials were removed from no-cursor data.

We use the average reach deviation in the last 8 trials before each of the no-cursor blocks, and subtracted the average in the aligned phase from the average in the rotated phase to assess final adaptation. In the aiming group we used the same blocks to assess final re-aiming. We use all the include/exclude strategy no-cursor trials to assess implicit and explicit adaptation using the Process Dissociation Procedure. We subtract reach deviations from the aligned part of the task from the same measures obtained in the rotated part of the task to correct for baseline biases. This way we obtain adaptation in the training trials, with- and without strategy no-cursor reach deviations and re-aiming in the aiming trials. All of these are based on an equal number of trials, and taken from parts of the experiment that are as similar as possible.

We compare the exclusion reach deviations as a measure of implicit adaptation, and the final, total adaptation between the three groups. To assess explicit adaptation, we then compare the difference between inclusion and exclusion reach deviations. Within the aiming group we also compare the difference between inclusion and exclusion reach deviations, with the final aiming responses, as measures of explicit adaptation. All these allow testing of additivity on estimates of common measures of implicit and explicit adaptation processes.

Linear Additivity

We test additivity in 2 approaches. First, we investigate the notion total adaptation is simply the sum of explicit and implicit adaptation[6]:

$$a = i + e,$$

In particular the way it is sometimes used to determine implicit adaptation:

$$i = a - e,$$

Which is equal to a linear model, expressing the relationship between implicit and explicit adaptation:

$$i = \beta_0 + \beta_1 e,$$

Where β_0 is the intercept, and β_1 is the slope. It simply means that, with no explicit adaptation, implicit adaptation is equal to total adaptation (the intercept), and with every increase in explicit adaptation, there is an equally sized decrease in implicit adaptation (slope of -1). This linear model is true, if, given some noise:

$\beta_0 = a$, and

$\beta_1 = -1$.

We test this by fitting a linear regression on implicit adaptation over explicit adaptation across all participants in a group, and getting the 95% confidence interval of the intercept and slope. Since for all groups, the slope should be -1 given strict additivity, while the intercept varies, we only

report tests on the slopes.

However, our measures of explicit, implicit and total adaptation necessarily come from different time points, and this might undermine strict additivity somewhat. Hence, in a second, less strict, model of additivity, we predict total adaptation by summing *weighted* versions of implicit and explicit adaptation across all participants in each group:

$$\hat{a}=\beta_0 i+\beta_1 e$$

If this model of loose additivity works, then the linear relation between predicted and actual adaptation should have an intercept of 0 and a slope of 1:

$\hat{a}=0+1a$ or $\hat{a}=a$.

And here we test this by fitting a linear model on real adaptation over predicted adaptation, and the model is confirmed if the 95% confidence interval for the slope includes 1.

Two-Rate Model

Next, we want to test a state-space model with a strong additivity assumption[15], and two learning processes that are sometimes assumed to map onto implicit and explicit adaptation[8]. The model posits that motor output on trial t (X_t) is the straightforward, unweighted sum of the states of a slow and fast learning process:

$$X_t=F_t+S_t$$

Where the states of both the fast and slow process are governed by a learning rate, and a retention rate:

$F_t=L^f \cdot E_{t-1}+R^f \cdot F_{t-1}$, and

$$S_t=L^s \cdot E_{t-1}+R^s \cdot S_{t-1}$$

This is further constrained by $L^s<L^f$, and $R^f<R^s$. The model typically is fit on data with a different perturbation schedule, but the 2 blocks of no-cursor reaches causing some decay in learning may suffice for a reasonable group-level fit, albeit not for individual participants[16]. To test this, we ran a parameter recovery simulation for the model using the training reach deviations in the control group (fit model 1000 times to data simulated as original model + normal noise with a standard deviation equal to the square root of the MSE of the original model fit). This shows that the parameters can be recovered quite well (not shown, bootstrapped data on OSF). For each parameter the originally fitted value falls in the 95% interval of the recovered values (L^s: 0.028 < 0.035 < 0.043; L^f: 0.087 < 0.105 < 0.129; R^s: 0.991 < 0.994 < 0.996; R^f: 0.832 < 0.885 < 0.912). This means that fitting the model to reach deviations in this perturbation schedule is robust, and we can use the model to test if its processes map onto the measures of explicit and implicit adaptation throughout learning in the aiming group. We observe that the distribution of the differences between inclusion and exclusion reach deviations for participants in the aiming group is bimodal (AICs for bimodal (5 free parameters) 156.3 and unimodal (2 free parameters) 532.1; relative log likelihood: $2.52*10^{-82}$). Since the two peaks are close to the average inclusion-exclusion differences in the control and in the instruction group, we split the aiming group into “aware” aimers and “unaware” aimers. We then subsequently fit a two-rate

model to the training reach deviations in the aware aimers as well as the unaware aimers, to compare the fast process to aiming responses and the slow process to exclusion reach deviations in both sub-groups.

External data

Since we reject additivity based on one dataset only, it would be easy to dismiss these findings as a one-time occurrence. However, if additivity does not hold, this has far-reaching implications for the field. Hence, we test our models of strict and loose linear additivity in a number of other data sets (see Table 1), with independent if not simultaneous measures of explicit, implicit and total adaptation. We either asked the original authors[7,19,23,24] or downloaded data from public repositories[11,13,26], and used one unpublished data set sent to us by Dr. Jordan Taylor as well as a partially unpublished data set from our lab[27]. This is not an exhaustive literature search, but should represent several types of equipment, approaches and research groups.

Paper(s)	**Data source**	**Adaptation**	**Implicit**	**Explicit**
Bond & Taylor (2015); Taylor et al. (2014); Brudner et al. (2016); unpublished	private exchange	last 16 training trials	first 16 exclusion trials	last 16 aiming reports of training
Neville & Cressman (2018)	private exchange	last 9 training trials	9 exclusion trials in in last pre-pause PDP block	9 inclusion - 9 exclusion trials in last pre-pause PDP block
Schween et al. (2018 exp. 1 & 2 ; 2019 exp. 1, 2 & 3)	private exchange	average across 9 targets	average of 2 targets near the peak of the group's generalization curves	average across 9 targets
Modchalingam et al. (2019)	OSF repository linked in paper: https://osf.io/mx5u2/	last 18 trials of the first rotated training	4 x 9 exclusion trials	4 x 9 inclusion - 4 x 9 exclusion trials
Maresch et al. (2020)	OSF repository linked in paper: https://osf.io/6yj3u/	last 8 trials in "top-up" block	last 16 exclusion trials	last 16 inclusion - last 16 exclusion trials
Decarie & Cressman (2022)	supplementary file with paper: https://link.springer.com/article/10.1007/s00221-022-06352-4	last 15 trials of rotated reach training	last 6 exclusion trials	last 6 inclusion - last 6 exclusion trials
Modchalingam et al. (unpublished)	in-lab exchange	2 x 9 training trials before PDP blocks	2 x 9 exclusion trials	2 x 9 inclusion - 2 x 9 exclusion trials

Table 1: *Sources of external data. Number and time of trials are indicated, and these are mostly taken when adaptation has saturated.*

Normalization

We can test if the confidence intervals for the slopes of the strict and loose models of linear additivity include -1 and 1 respectively, both on all the individual data sets, and all the data combined. In the combined data sets, we normalize the measures both relative to the

rotation and relative to adaptation, before testing the models. This yields highly similar results (Fig 3, last two rows) so that we use only the adaptation-normalized scores for the exploration of aggregate data (Fig 4).

Kernel smoothing

For visualizing trends in Fig 4 we used a Nadaraya-Watson Gaussian kernel smoother with a width of 0.25 and ran it 1000 times on random samples of participants to also show a bootstrapped 95% confidence interval.

Capped Fraction Model

We fit both a regression to the normalized data for the participants doing a 60° rotation and a simple custom model. This 2-parameter model assumes that implicit adaptation is either a proportion of adaptation that is not covered by explicit adaptation (akin to the competition model) but subject this to a maximum amount of implicit adaptation (akin to "capped" implicit work). This model predicts implicit adaptation as:

$$i = min(c, p(a-e)),$$

Where p denotes implicit adaptation as a fraction of adaptation that is not explicit, but this is also capped at a constant level c, and both p and c are free parameters.