Measures of Implicit and Explicit Adaptation Do Not Linearly Add

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Abstract

Moving effectively is essential for any animal. That's why many different kinds of brain processes likely contribute to learning and adapting movement. How these contributions are combined to shape behavior is unknown. Nevertheless, the field of motor adaptation has been working under the assumption that measures of explicit and implicit motor adaptation can simply be added in total adaptation – without testing this assumption. Here we put this additivity assumption to the test in various ways, but we find that measures of implicit and explicit adaptation are not additive. This means that future studies should measure both implicit and explicit adaptation directly. It also challenges us to disentangle how various motor adaptation processes combine when producing movements, and may have implications for our understanding of other kinds of learning as well.

(data and code: https://osf.io/kr5eh)

Introduction

Both implicit (unconscious, automatic) and explicit (conscious, intentional) processes contribute to various kinds of learning[1], including visuomotor adaptation[2–4]. Some research relies on the notion that implicit and explicit adaptation are related, assuming they linearly add to total adaptation[6,7]. Here, we test whether or not this additivity assumption holds.

The main idea is that there are only two kinds of processes contributing to in adaptation: those we are aware of, and those we are not aware of. The processes we are aware of, which are usually intentional, involve a strategy, can be verbalized, and are often effortful, are referred to as "explicit" adaptation. The processes we are not aware of are then not intentional but automatic, they can not be verbalized and since they are automatic they usually require less effort, and these kinds of processes are often called "implicit" adaptation. A further distinction is that explicit processes can be voluntarily disengaged, as opposed to implicit processes. Implicit and explicit adaptation could each be split up further, or overlap with other kinds of processes (e.g. reward-based learning could be both implicit and explicit). However, if we can split motor adaptation into implicit and explicit processes, it seems intuitive that we can also add them for an estimate of total adaptation, the "additivity assumption"[8]:

adaptation = implicit + explicit,

Often illustrated as in Figure 1A. This relationship, if true, could be rewritten as:

implicit = adaptation - explicit,

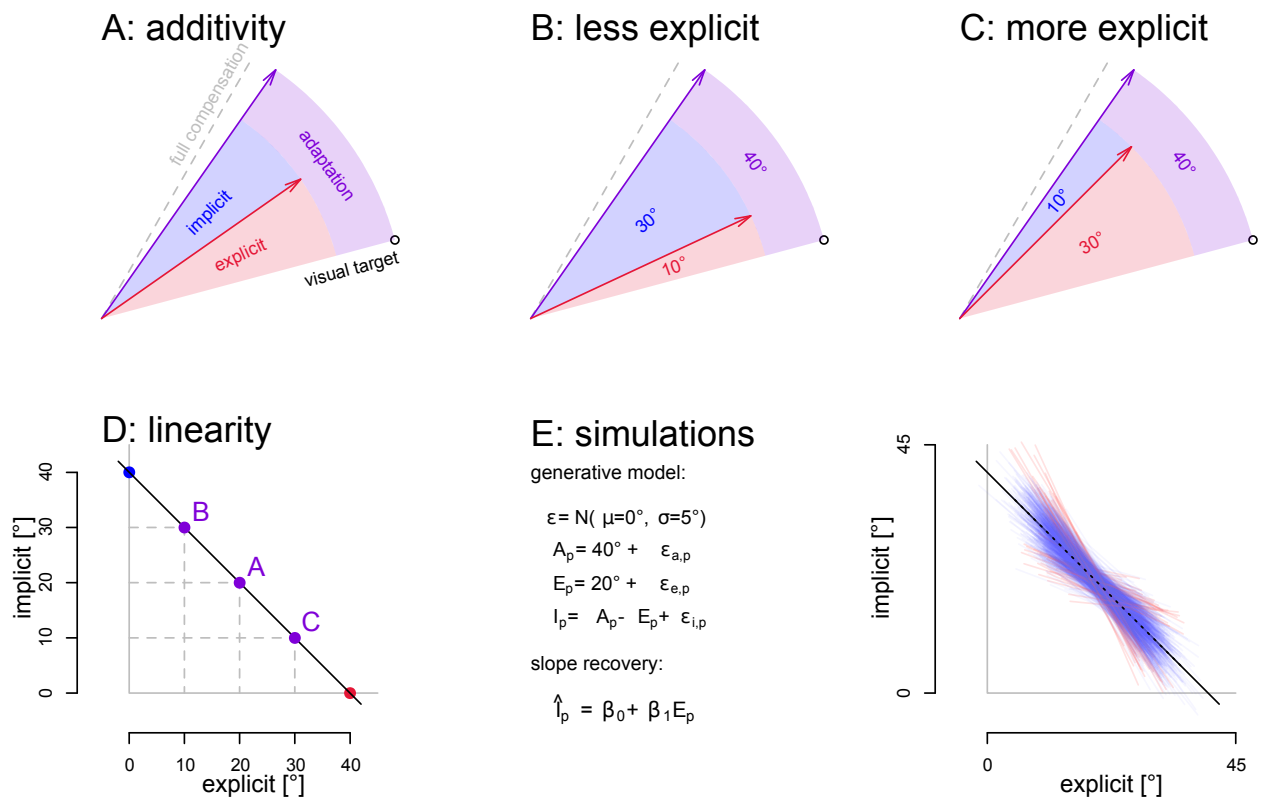


Fig 1: *The additivity assumption.* ***A:*** *Often, implicit adaptation (blue) is considered what is left after explicit adaptation (red) is subtracted from total adaptation (purple).* ***B,C:*** *Given less explicit adaptation, this would mean there is more implicit adaptation (B), and vice versa (C).* ***D:*** *This means that if explicit and implicit adaptation are additive, they should have a negative, linear relationship. The purple points depict the situations in panels A,B,C and also shown are situations where adaptation is fully implicit (blue) and fully explicit (red).* ***E:*** *We generated data with the mechanism prescribed by the additivity assumption (left side), and test if we can recover the predicted negative slope from linear models fitted to data (right). In ~95% of simulated data sets, the 95% confidence interval of the slope includes the predicted value of -1 (blue lines) and in ~5% it doesn't (red lines).*

In Figure 1A, implicit adaptation (blue wedge) is indeed depicted as what is left when explicit adaptation (red arrow) is subtracted from total adaptation (purple arrow). In practice, this is then regularly used to forego measuring implicit adaptation, but rather rely on the difference between total and explicit adaptation as if it were a valid measure of implicit adaptation. This indirect, "quasi measurement" of implicit adaptation is then also used to draw conclusions about implicit processes of adaptation[9–11]. Of course, if this is a valid approach, i.e., if the additivity assumption holds, there really is no need to measure implicit adaptation which would make visuomotor adaptation experiments easier or shorter. However, the underlying "additivity assumption" is not always replicated[12] and has been called the "least robust" assumption in motor adaptation[8]. That's why we test this common use of the additivity assumption here.

The general approach we follow, relies on the negative correlation between implicit and explicit adaptation that would be dictated by additivity. That is, when total adaptation is constant, and explicit adaptation decreases, implicit adaptation has to increase by the same amount (Fig 1B) and vice versa, when explicit adaptation increases, implicit adaptation decreases (Fig 1C). That relationship between implicit and explicit adaptation under additivity can be plotted as a linear function with an intercept equal to total adaptation and a slope of -1 (Fig 1D). To see if this would be reproducible in principle, we ran a simulation where we added noise to data generated with an additive model. All noise (ε) was drawn separately from a normal distribution with μ=0° and σ=5°. For each participant (p), total adaptation and explicit adaptation are given by:

$$A_p = 40° + \varepsilon_{a,p}$$
$$E_p = 20° + \varepsilon_{e,p}$$

And implicit adaptation is taken as the difference between total adaptation and explicit adaptation (plus noise):

$$I_p = A_p - E_p + \varepsilon_{i,p}$$

We can repeat this for a number of participants and then fit a linear model predicting the generated implicit adaptation from the corresponding explicit adaptation. We will see how well a linear model fitted to the generated data recovers the slope of -1. In particular we can test if the 95% confidence interval of the mean for the slope parameter includes -1. Using samples of 24 participants (equal to our experiment, see below) we've repeated this 1000 times (linear fits shown in Fig 1E), and in ~95% of simulations the 95% confidence interval of the slope includes -1 (blue lines in Fig 1E; red lines: 95% CI for the slope excludes -1). That is, in data that is generated according to additivity (plus noise), the linear relationship between implicit and explicit adaptation with a slope of around -1, can be recovered from noisy data, such that this can be used as a statistical test of additivity of implicit and explicit adaptation.

We will use this approach and variations on it in several tests of the additivity assumption, both in data from our own experiment and in an aggregate data set where data from several previous papers representing various labs, setups and paradigms.

Varying explicit adaptation in strict and loose additivity

If total adaptation is the sum of implicit and explicit adaptation, then, given (near) constant total adaptation, implicit and explicit adaptation should perfectly complement each other. That is: under the additivity assumption, a given change in explicit adaptation should result in a change in implicit adaptation that is of equal size, but in the opposite direction. And this should also be true across participants: a participant with higher explicit adaptation should have lower implicit adaptation and vice versa (see Fig 1). Thus, we did an experiment with three conditions that we expected to result in different levels of explicit adaptation, but highly similar total adaptation.

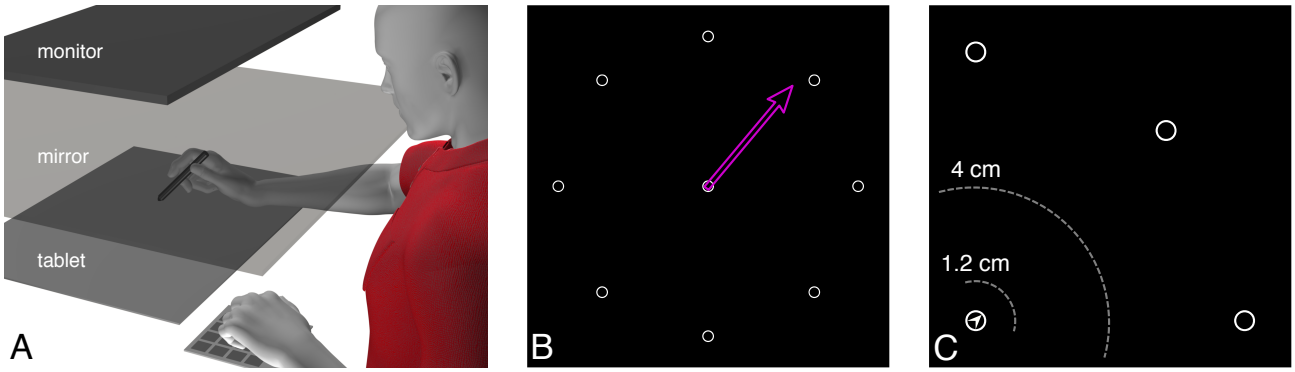


Fig 2: *Setup, aiming and no-cursor trials.* ***A:*** *Tablet setup with mirror. The stimuli appear in the same plane of depth as the tablet.* ***B:*** *Aiming: the upcoming target (1 of 8) is shown with an arrow used to indicate the intended reach direction, or "aim".* ***C:*** *The outward reach on no-cursor trials ends when the stylus stops moving for 250 ms and is at least 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, and participants move in the opposite direction. When the stylus is then back within 1.2 cm distance of the home position, a cursor appears that needs to be moved to the home position to start the next trial.*

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 1A). 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.

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[1,3] ("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[3,12–14]. 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."

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

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".

Procedure

All participants performed 264 reaching trials of various kinds (see Fig 2,3), 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 3 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 3: 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.

Strict 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] (cf. Fig 1):

$$A = I + E,$$

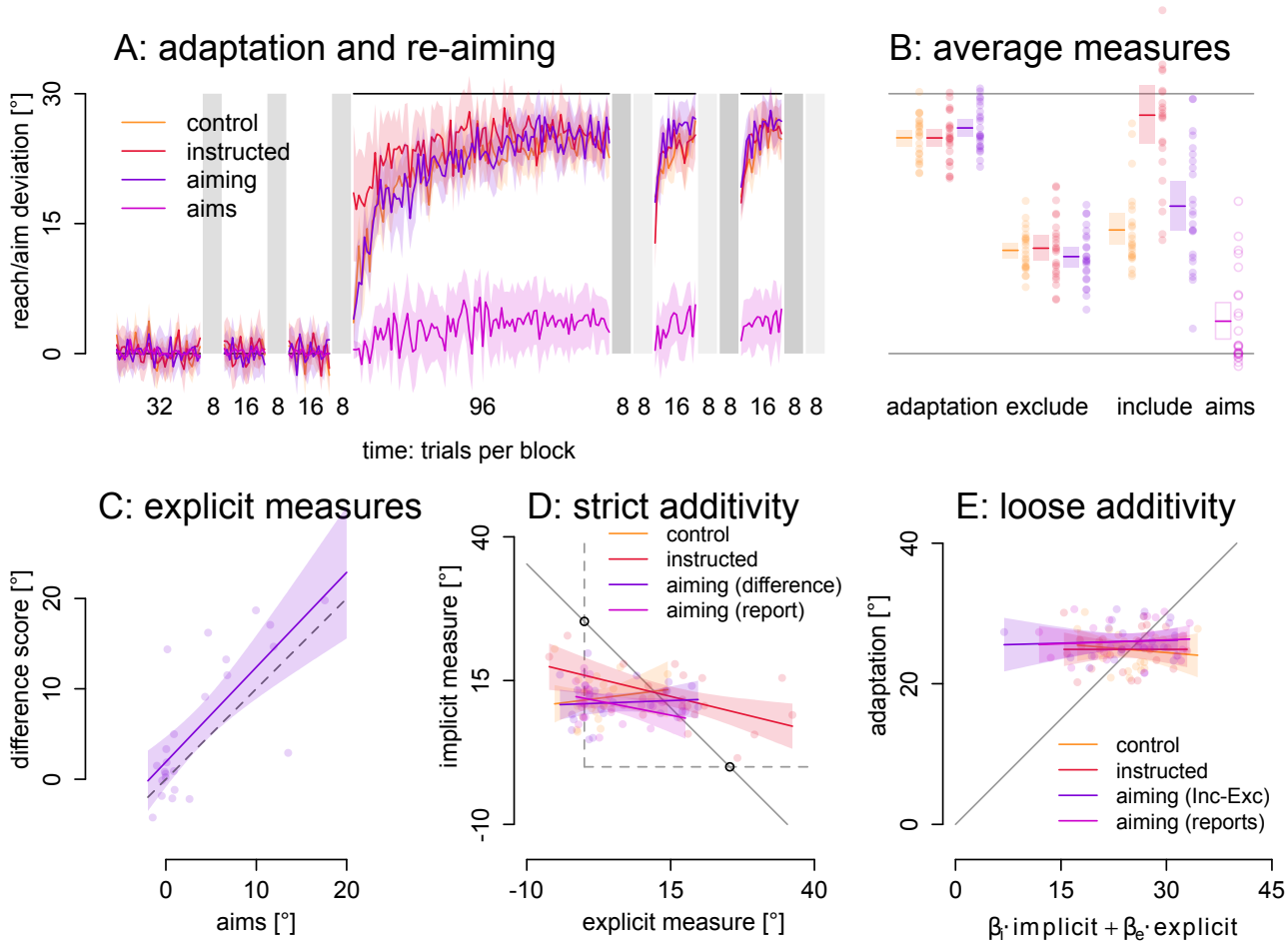
In particular, the way it is sometimes used to determine implicit adaptation:

$$I = A - E,$$

Which is equal to a linear model, expressing the relationship between implicit and explicit adaptation across participants (p):

$$\widehat{I}_p = \beta_0 A_p + \beta_1 E_p,$$

Where $\beta_0 A$ 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; Fig 1D,E). This linear model directly follows from the additivity assumption, and would apply both within and across participants. We could test if the intercept of the linear model is close to total adaptation, but since most of te data will be relatively far removed from the intercept point (were there is no explicit



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adaptation), we opt to test only the slope. A simulation to recover the slope of -1 from data generated according to this model plus noise, shows that the 95% confidence interval of the fitted slope includes -1 in ~95% of simulations (Fig 1E). That is, if we decide that actual data is in accordance with additivity when the 95% confidence interval of the slope of a linear model predicting implicit from explicit adaptation includes -1, this is equivalent to a NHST statistic with α=0.05. Hence, we will use this statistical approach.

Loose Linear Additivity

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:

$$\widehat{A}_p = \beta_0 I_p + \beta_1 E_p$$

If this model of loose additivity works, then there should be a linear relation between predicted and actual adaptation with an intercept of 0 and a slope of 1. And here we test this by fitting a linear model on real adaptation over predicted adaptation, and we consider the model confirmed if the 95% confidence interval for the slope includes 1.

Results

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 (Fig 3A,B; $F(2,69)=1.30$, $p=.28$, $\eta^2=.036$; $BF_{10}=0.316$) nor in exclusion as measure of implicit adaptation (Fig 3B; $F(2,69)=0.59$, $p=.555$, $\eta^2=.017$, $BF_{10}=0.185$). 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. That is, the group averages do not seem to show additivity.

But maybe additivity can be shown across individual participants instead. On average, we find a small re-aiming strategy in the aiming group (Fig 3B: 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 3C; $R^2=0.5192$, $p<.001$, intercept=1.9, slope=1.05), we will use both as estimates of explicit adaptation here (but see other work[13,15]). Strict additivity predicts that, across participants, measures of implicit and explicit adaptation would fall on a line with slope -1 (Fig 3D: 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, before being added to predict total adaptation. If this optimal weighted sum is an accurate model, then actual adaptation over predictions should lie on the identity line (Fig 3E: gray diagonal), but they don't (slopes 95% CIs exclude 1). In short, neither strict nor loose additivity predict adaptation across individual participants.

Do the fast and slow processes map onto measures of explicit and implicit adaptation?

Next, we test a particular application of the additivity assumption, in a common state-space model with two adaptive processes. In this model, the so-called "slow" and "fast" processes are strictly

additive[16], and are sometimes assumed to map onto implicit and explicit adaptation respectively[9]. In previous work[9], the similarity between aiming reports and the fast process is striking. However, given that the model also assumes additivity and that the measure of explicit adaptation matches the model's fast process fairly well, it has to be the case that the subtractive estimate of implicit adaptation matches the slow process equally well. That is, while the literature supports a link between the model's fast process and explicit adaptation, the link between the slow process and implicit adaptation is fully dependent on the largely untested assumption of strict linear additivity. We test this here in the data from the aiming group in the experiment described above.

Methods

Two-Rate Model

Using data from the experiment described above, we test a state-space model with a strong additivity assumption[16], and two learning processes that are sometimes assumed to map onto implicit and explicit adaptation[9]. 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 each determined by a learning rate (L) applied to the error on the previous trial, and a retention rate (R) applied to the state of each process on the previous trial:

$F_t = L^f \cdot E_{t-1} + R^f \cdot F_{t-1}$, 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 likely not for individual participants[17]. 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 + random noise drawn from a normal distribution with mean=0 and 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 (at the group level), 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 observed that the distribution of the differences between inclusion and exclusion reach deviations for participants in the aiming group is bimodal [relative log-likelihood based on AICs of unimodal distribution compared to bimodal: p>0.001]. The two peaks are close to the average inclusion-exclusion differences in the control and in the instruction group (Fig 4A). This could indicate that for 9/24 participants, the addition of aiming had the same effect as instructions, but no effect for the remaining participants.

We split the aiming group into aware aimers and unaware aimers, as these subgroups

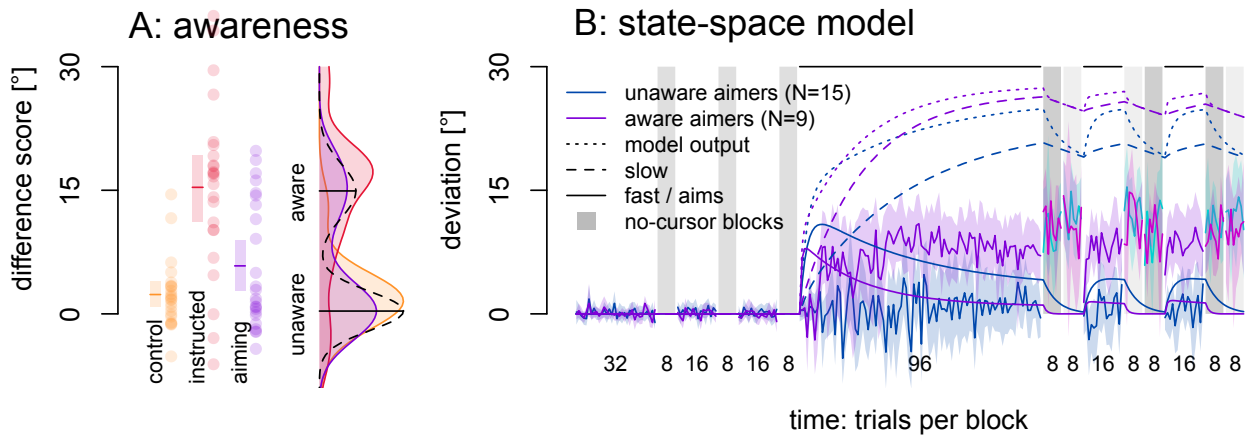

Fig 4: *Additive state-space model.* ***A:*** *Distributions of differences between include- and exclude strategy reach deviations. In the aiming condition, the distribution is bi-modal (p<.001) suggesting aware and unaware subgroups. If the fast process really maps onto explicit adaptation, then these two subgroups should have a different two-rate model fit, so we split the participants.* ***B:*** *In the aware subgroup, the fast process (smooth continuous purple line) for the most part is outside the 95% confidence interval of the aiming responses (jagged continuous purple line with 95% confidence interval). In the unaware subgroup, the confidence interval of the aiming responses (jagged continuous dark blue line with 95% confidence interval) is near zero and excludes the fast process on most trials. Similarly, the slow process of each subgroup's model fit (the dashed lines) are above the 95% confidence interval for the exclude strategy reach deviations (jagged continuous lines in the no-cursor blocks: light blue for the unaware aiming group, light pink for the aware aiming group). In short: in neither subgroup does the fast process predict aiming responses, nor does the slow process predict strategy exclusion reach deviations.*

should have different levels of explicit adaptation. We fit a separate two-rate model to the averaged training reach deviations in the aware aimers as well as those in the unaware aimers. We then test whether or not the fast process falls in the 95% confidence interval of each subgroups' aiming responses, and whether or not the slow process falls in the 95% confidence interval of exclusion reach deviations in each subgroup. The comparison between the slow process and exclude-strategy reach deviations (implicit) can only be done in the no-cursor blocks, when the processes have presumably saturated. The comparison between aiming responses and the fast process is then also done when the processes have saturated: during the 8 trials just before the no-cursor blocks. If the model processes fall within the 95% confidence interval of the data, this would support additivity as implemented in the two-rate model.

Results

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 separately fit the state-space model to the averaged reach deviations in the aware and unaware aimers (Fig 4A). In the aware aimers (Fig4B,

purple), the fast process (purple smooth continuous line) is lower than aiming reports (purple jagged line with 95% confidence interval), and vice-versa in the unaware aimers (dark blue). In both subgroups the 95% confidence interval of the aiming data excludes the fitted fast process, except for a few trials at the start. In both subgroups the slow process (dashed lines) is higher than exclusion trials during all no-cursor blocks (95% CIs of data exclude model processes; pink=aware aimers, light blue=unaware aimers). confirming that the slow process does not capture implicit adaptation[18]. 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.

Testing additivity across the field

While it stands to reason that adaptation is larger when both implicit and explicit adaptation processes contribute[2,19,20], few studies indicate some form of additivity[6,7]. Other studies don't show additivity[3,12,14,21] or they show partial additivity, or additivity only in some participants[20,22] or it is

Study	Data source	Adaptation	Implicit	Explicit
Bond & Taylor (2015); Taylor et al. (2014); Brudner et al. (2016); unpublished data set	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 across targets straddling the peak of the averaged normalization 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. (preprint)	https://osf.io/a7k6s/	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.*

unclear to us whether or not the data support additivity[13,15]. So far, we rejected 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 implications for the field. Hence, we test strict and loose linear additivity in a number of other data sets, with independent if not simultaneous measures of explicit, implicit and total adaptation. We collected data sets from previous work, both from other labs and our own, to test strict and loose additivity beyond the single experiment described above with data representing various approaches in the field.

Methods

We either asked the original authors[7,20,23,24] or downloaded data from public repositories[11,12,24,27], and used one unpublished data set sent to us by Dr. Jordan Taylor. This is not an exhaustive literature search, but should represent several types of equipment, approaches and research groups, and it should increase power. See Table 1 for more information.

Normalization

As before, we 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. The rotations varied between 15° and 90°, so we need to normalize the measures to be able to compare data across groups. Since the additivity assumption predicts adaptation (not rotation), we normalize relative to each participants' estimate of total adaptation. If additivity holds, the normalized measures of implicit and explicit adaptation should then sum to 1. We do test normalization by rotation on all data combined as well, and this yields highly similar results (Fig 5, last two rows). However, to stay more in line with the tested additivity assumption, we use only the adaptation-normalized scores for the further exploration of aggregate data.

Results

The literature is divided on the additivity assumption of implicit and explicit adaptation[8]. That's why we re-analyzed data from 8 studies[7,12,20,21,23–25,27,28] 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 when each of these measures should have saturated (the "stepwise" participants[27] are assessed 4 times, for 35 'groups' total). We divide each participants' estimates by their total adaptation, and for each subgroup accept strict additivity (Fig 5: left) or loose additivity (Fig 5: right) if the 95% CI for the slope of the model includes -1 or 1 respectively (as above; Fig 1D&E, Fig 3D&E). None of the groups support strict additivity (see Fig 5), and only 6 of 35 subgroups support loose additivity. Consequently, in all participants combined (Fig 5, bottom two rows) there is no support for additivity either.

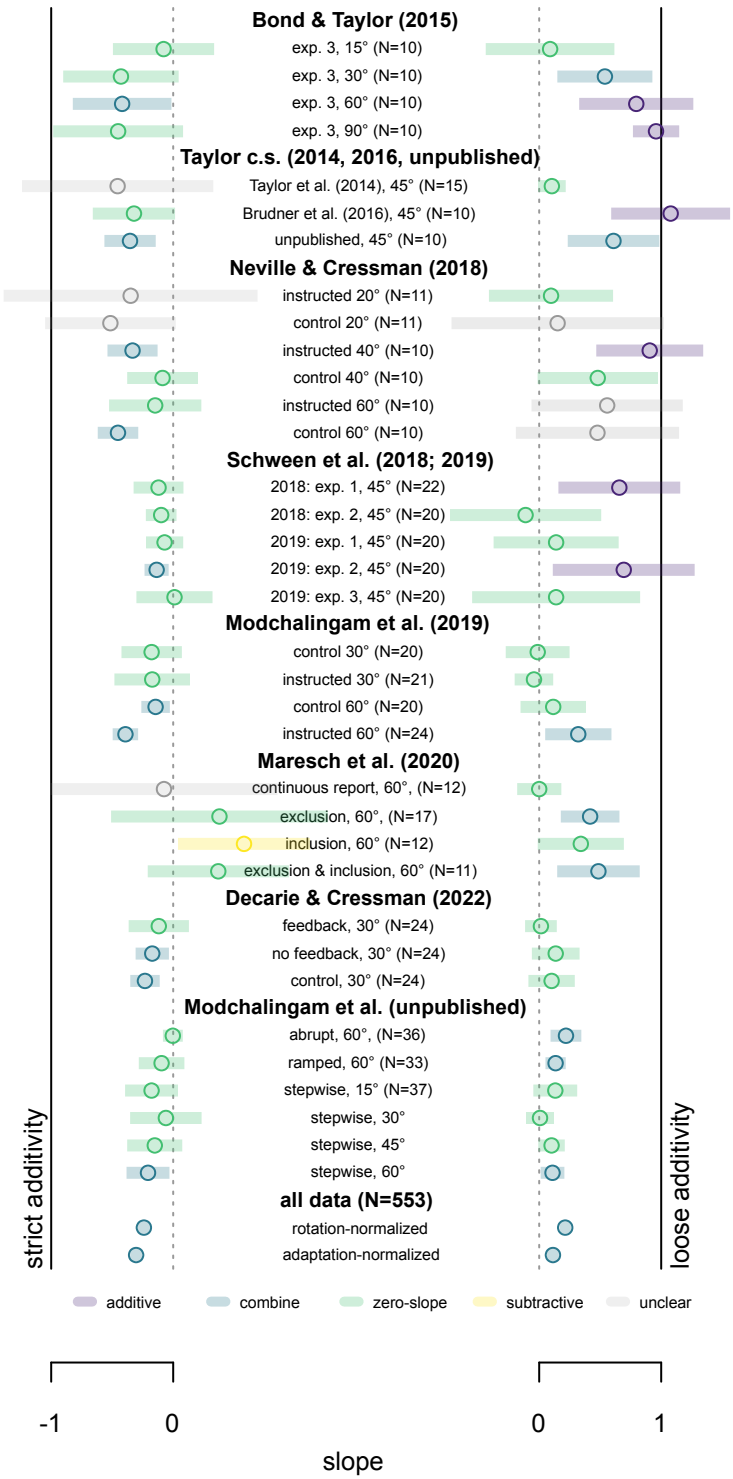

Fig 5: *Additivity across a large cross-section of visuomotor adaptation experiments. No groups demonstrate strict additivity, and only 6 of 35 subsets show loose additivity. In the combined data (bottom two rows), there does seem to be support for some form of combining explicit and implicit adaptation.*

Alternative relationships between implicit and explicit adaptation

The aggregate data does show a combined effect: slopes *are* different from 0. We use the collection of data sets to further explore possible relationships.

Methods

Kernel smoothing

For visualizing trends in implicit adaptation across various levels of explicit adaptation (in Fig 6A,B) 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 linear 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[26]) but subject this to a maximum amount of implicit adaptation (akin to "capped" implicit work[28]). This model predicts implicit adaptation (i) using explicit adaptation (e) as:

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

Where p is fraction of adaptation (a) that is not explicit, and c is a constant, or capped level of implicit adaptation, and both p and c are free parameters.

Maximum Likelihood Estimates

To test if implicit and explicit adaptation are combined based on their relative reliability, with a greater contribution for the more reliable process, we applied a maximum likelihood estimate. Here each of the processes is weighted by the relative inverse of their variance within each participant:

$$w_{i,p} = \frac{1/\sigma_{i,p}}{(1/\sigma_{i,p}) + (1/\sigma_{e,p})}, \text{ and}$$

$$w_{e,p} = \frac{1/\sigma_{e,p}}{(1/\sigma_{i,p}) + (1/\sigma_{e,p})}.$$

Where $w_{i,p}$ and $w_{e,p}$ are the weights for implicit and explicit adaptation respectively for participant p, and $\sigma_{i,p}$ and $\sigma_{e,p}$ are the variance of implicit and explicit measures for participant p. These are based on the data, but require a direct measure of each. This is only possible for independent

measures of implicit adaptation (such as exclusion trials) as well as for explicit adaptation (such as re-aiming) with a fair number of individual trials available. This restricts us to data from 4 papers[7,8,23,24] plus one unpublished group for 127 participants adapting to rotations of 15°, 30°, 45°, 60° and 90°. The estimates of total adaptation for each participant p are then:

$\widehat{A_p} = w_{i,p} E_p + w_{e,p} I_p$, in the maximum likelihood estimate, and simply

$\widehat{A_p} = E_p + I_p$, for the comparable additive model.

To be clear, in each case $\widehat{A_p}$ is the predicted adaptation for participant p, based on: E_p and I_p, the average measure of explicit and implicit adaptation for the same participant.

The linearly additive model has the same form as the maximum likelihood model, but with two weights of 1, summing to 2. In our implementation of maximum likelihood estimates here, the weights sum to 1, as as is more typical for MLE models. Other variations of MLE models are possible, for example adding a constant, or scaling the predicted adaptation, or fitting additional constant weights for each component. These all produce comparable results, so we opted for presenting the simplest model.

Since adaptation as well as its implicit and explicit components scale with rotation size, combining non-normalized data across very different rotation sizes will artificially increase the goodness of fit. To counter this, both predicted and measured adaptation are divided by rotation before testing goodness of fit.

Results

We first look at a smoothed estimate of implicit over explicit measures for rotations with more than 100 participants (30°, 45° and 60°; Fig 6). 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 more or less linear additivity. We fit two models; a linear regression mimicking the relationship in smaller rotations (orange line in Fig 6B) and a model that applies the notion that implicit adaptation is capped at some level when explicit adaptation is low, and that implicit and explicit are loosely additive for higher explicit adaptation (blue line in Fig 6B). This is implemented by setting implicit adaptation as the minimum of a constant ("capped") and a proportion of 1-explicit ("fraction"). 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.

Some models of adaptation use Bayesian mechanisms to weigh different contributions[29,30], so here we test if explicit and implicit adaptation are combined using a maximum likelihood estimate[31] (MLE). The weight applied to the average of each contribution is twice the relative inverse of its' respective variance for every participant which means that a separate estimate of variance of both implicit and explicit adaptation is required (details in methods; sum of weights equal to those in the strict additive case). This is only possible in 127 participants, and we test how well an additive and an MLE mechanism predict the measured adaptation. As can be seen (Fig

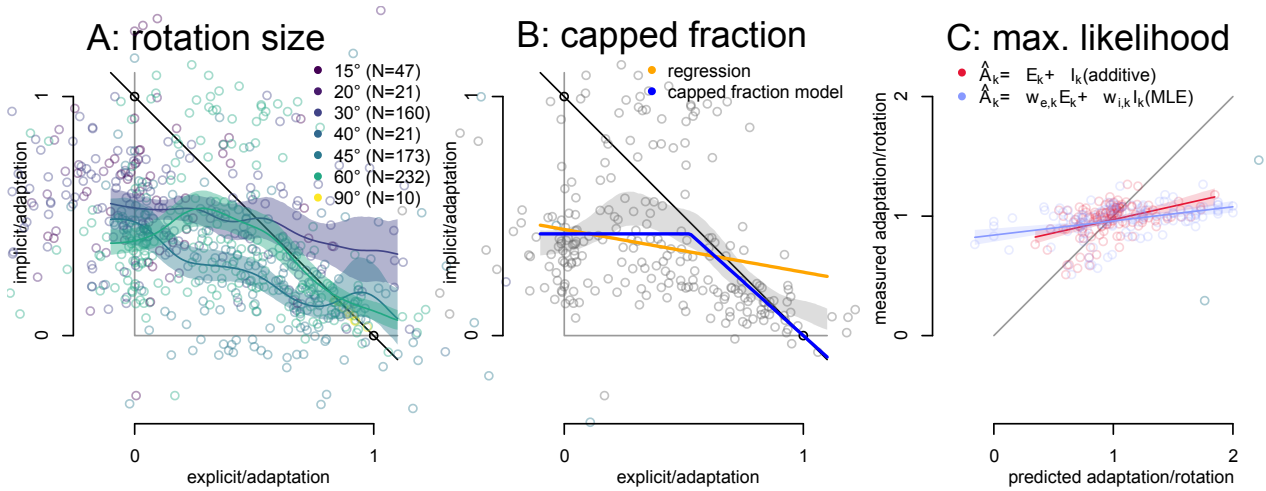

Fig 6: *Relationship between implicit and explicit adaptation.* ***A:*** *All data and trends for rotations with 100+ participants.* ***B:*** *Capped fraction model for 60° participants.* ***C:*** *Maximum likelihood (and strictly additive) predictions of adaptation for 127 participants.*

6C), neither predicts adaptation very well, and the maximum likelihood approach does slightly worse than the additive approach, so that maximum likelihood estimates are an unlikely mechanism as well.

Discussion

In this study we tested whether measures of implicit and explicit adaptation linearly add in total adaptation, in particular the way it is used in the field: to derive an indirect, "quasi" measurement of implicit adaptation by subtracting a measure of explicit adaptation from a measure of total adaptation. It seems that the two measures - and their underlying processes - are combined somehow, but we find no evidence supporting linear addition. Below, we discuss what this means for our understanding of explicit and implicit adaptation, implications for future practice, as well as the interpretation of some previous findings.

While both implicit and explicit processes contribute to adaptation, and a plethora of work has been done testing what either process is sensitive to, there are two main sources of problems with how we understand the contribution of each. First, the methods we use to measure both implicit and explicit adaptation all have their issues[13]. The second source is the focus here; we do not know the neural mechanism by which different learning mechanisms are combined in behavior. Simple, linear addition seems unlikely to be implemented in the brain. Some models explore new directions however, suggesting that separate adaptation processes can be sub-additive[26] or use Bayesian mechanisms[29,30], such as maximum likelihood estimates, that are well-known in the literature on multi-modal perception[31]. However, neither of these can explain the data we considered here (Fig 6B,C).

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 can not 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, e.g. when subtracting a measure of explicit adaptation from total adaptation as a measure of implicit adaptation. Conversely, explicit adaptation is sometimes gauged by subtracting reach deviations in exclusion trials from those in inclusion trials (this is done in this study as well). In the absence of a mechanism for combining implicit and explicit adaptation this can be justified in some cases, but it should not be relied on indiscriminately and a better alternative is needed.

The re-analysis of aggregate data from across the field shows there might be a relationship between measures of implicit and explicit adaptation, even when we didn't see this in our own data set. But, given the lack of clear patterns, 1) either the measures[13] or the underlying implicit and explicit adaptation processes are highly variable and may saturate[5] 2) the nature of the relationship between the two processes is unknown, but not strictly additive, and 3) this relationship is likely influenced by other factors such as interactions between processes[26,29], task contexts[7,12,14,25] or goals or motivations of participants. Beyond motor adaptation, these notions may apply to other types of learning as well.

What we learn from this study can be summed up in two broad points. First, in order to investigate implicit and explicit processes, we should use independent measures of both. Currently, this could be re-aiming responses for explicit, and strategy exclusion trials for implicit adaptation, while we should keep in mind that it is also unknown how neural adaptation processes map onto their behavioral measures. Second, the field should try to understand the (neural) mechanism by which various adaptation processes are combined to shape behavior.

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