

Performance Monitoring for Sensorimotor Confidence: A Visuomotor Tracking Study

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Abstract

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To best interact with the external world, humans are often required to consider the quality 2
of their actions. Sometimes the environment furnishes rewards or punishments to signal 3
action efficacy. However, when such feedback is absent or only partial, we must rely on 4
internally generated signals to evaluate our performance (i.e., metacognition). Yet, very 5
little is known about how humans form such judgements of sensorimotor confidence. Do 6
they monitor their actual performance or do they rely on cues to sensorimotor uncertainty? 7
We investigated sensorimotor metacognition in two visuomotor tracking experiments, where 8
participants followed an unpredictably moving dot cloud with a mouse cursor as it followed 9
a random horizontal trajectory. Their goal was to infer the underlying target generating the 10
dots, track it for several seconds, and then report their confidence in their tracking as bet- 11
ter or worse than their average. In Experiment 1, we manipulated task difficulty with two 12
methods: varying the size of the dot cloud and varying the stability of the target's velocity. 13
In Experiment 2, the stimulus statistics were fixed and duration of the stimulus presentation 14
was varied. We found similar levels of metacognitive sensitivity in all experiments, which 15
was evidence against the cue-based strategy. The temporal analysis of metacognitive sensi- 16
tivity revealed a recency effect, where error later in the trial had a greater influence on the 17
sensorimotor confidence, consistent with a performance-monitoring strategy. From these 18

results, we conclude that humans predominantly monitored their tracking performance, albeit inefficiently, to build a sense of sensorimotor confidence.

Keywords: *sensorimotor, confidence, metacognition, perception, action, tracking.*

Highlights

- Participants consciously reflected on their tracking performance with some accuracy
- Sensorimotor confidence was mostly influenced by recent error
- Expectations of task difficulty did not play a large role in sensorimotor confidence
- Metacognitive sensitivity of binary confidence judgements on continuous performance can be quantified with standard non-parametric techniques

1 Introduction

Sensorimotor decision-making is fundamental for humans and animals when interacting with their environment. It determines where we look, how we move our limbs through space, or what actions we select to intercept or avoid objects. In return, we may receive decision feedback from the environment, such as resources, knowledge, social standing, injury, or embarrassment. The outcomes of an action are often crucial for determining subsequent sensorimotor decision-making, particularly in dynamic scenarios where a series of actions are chained together to achieve a sensorimotor goal (e.g., dancing or tracking a target). But what happens if external feedback is absent, partial, or significantly delayed? How then do we judge if an action has been performed well? One possible solution is for the person to form their own subjective evaluation of sensorimotor performance using whatever sensory or motor signals are available. These metacognitive judgements reflect the person's confidence

that their action or series of actions were correct or well-suited to their sensorimotor goal. Yet, despite such judgements being a familiar and everyday occurrence, they have received relatively little direct scientific scrutiny.

Before surveying the scientific context for the current study, it is imperative we clearly define *sensorimotor confidence*. We consider three components necessary for the formation of sensorimotor confidence, illustrated in Figure 1. First, there must be sensory inputs relevant for action selection and a consideration of the perceptual uncertainty or error of these inputs when assigning confidence. That is, sensory signals weakened by external or internal noise (e.g., foggy day, low attentional resources) should negatively affect confidence. However, it is important to note that observers may hold false beliefs about their sensory observations, which should be reflected in their subjective evaluations. The second crucial element is the performed action, with a consideration of the specific action taken (i.e., motor awareness) and an estimate of uncertainty or error in the action execution. Decreased motor awareness or experience of large motor noise should decrease sensorimotor confidence, unless the actor holds false beliefs. Evaluations of motor performance can come from various sources of information, from motor commands, proprioception, or self-observation of the action with one of the senses (e.g., seeing one’s own hand during a reach). Finally, there must be a consideration of the sensorimotor goal, the objective for purposeful action, which defines the landscape of success and failure for the individual. First, the consequences of error may be asymmetric or lead to varying outcomes (e.g., stopping short of an intersection versus going too far; for an example of the effect of an asymmetric loss function, see Mamassian and Landy, 2010), so sensorimotor goals should be selected by appropriately factoring in the consequences of different potential outcomes (Trommershäuser et al., 2008). Alternatively, an entirely wrong goal can be selected, leading to errors even when actions are well-executed under ideal viewing conditions (e.g., mistakenly trying to unlock a car that is not yours but looks similar). From a more subjective perspective, individuals may differ in terms of what is considered success or failure, such as the goals of novice sports

players versus professionals, which colour their evaluations of performance. Thus, evaluating the sensorimotor goal itself should be considered part of sensorimotor confidence. We propose that subjective reports in the absence of any one of these three elements do not constitute sensorimotor confidence but rather different forms of confidence (e.g., perceptual confidence, motor-awareness confidence, etc.).

Elements of sensorimotor confidence have been touched upon in a variety of domains, highlighting many of brain's sophisticated monitoring and control processes that operate on internally-gathered information (see Figure 1 for a summary). For the highest level of processing, there is the study of cognitive control, which describes how the goals or plans translate into actual behaviour. It is thought that cognitive control is responsible for the appropriate deployment of attention, as well as voluntary selection, initiation, switching, or termination of tasks (Norman and Shallice, 1986; Botvinick et al., 2001; Alexander and Brown, 2010). At the lowest level of processing, there is the study of sensorimotor control. Usually, research questions focus on how the brain senses discrepancies between the intended outcome of motor commands, as specified by an internal model, and the actual action outcomes, that are processed as a feedback signal, to correct and update subsequent motor control signals (Wolpert et al., 1995; Todorov, 2004). While the understanding of sensorimotor processes is quite advanced, both at the behavioural and neural levels, very little is known about our ability to consciously monitor sensorimotor performance.

If the action is reduced to a simple report of what is perceived, the monitoring of sensorimotor performance reduces to the study of perceptual confidence (Pleskac and Busemeyer, 2010; Fleming and Dolan, 2012; Mamassian, 2016). Perceptual confidence is a metacognitive process that corresponds to the subjective sense of the correctness of our perceptual decisions (Galvin et al., 2003; Pouget et al., 2016). Human observers exhibit considerable sensitivity to the quality of the processing of sensory information and the resulting ability to predict the correctness of a perceptual choice (Barthelmé and Mamassian, 2010; Kiani et al., 2014; Adler and Ma, 2018). However this so-called Type-2 judgement often

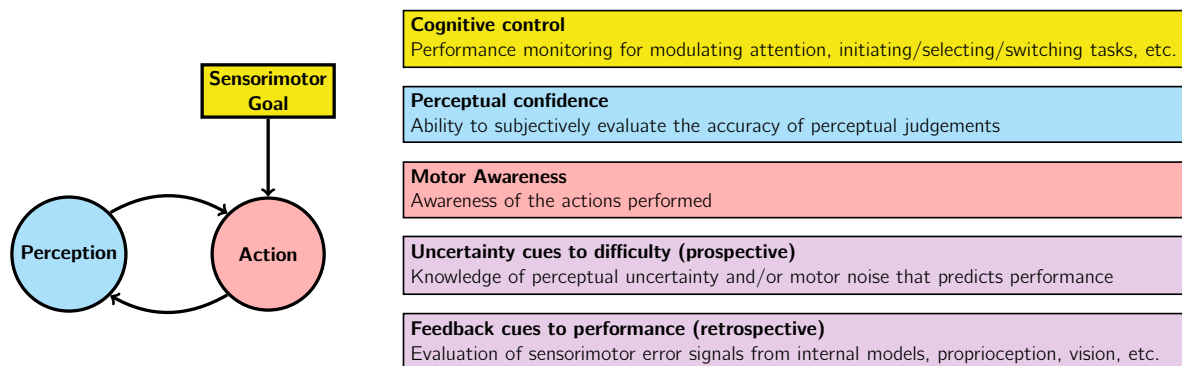


Figure 1: Components of sensorimotor control (left) and related topics in the literature (right). Sensorimotor confidence is a subjective evaluation of how well behaviour fulfilled the sensorimotor goal, considering both sensory and motor factors. The topic of sensorimotor confidence is complementary to the discussions of cognitive control, perceptual confidence, motor awareness, uncertainty, and self-generated feedback. It is likely that cues to difficulty and performance, that are responsible for the computation of sensorimotor confidence, originate both from sensory and motor sources. The former cues are prospective as they are related to how well the acting agent can potentially perform, whereas the latter are retrospective, they become available only after the action has occurred.

incurs additional noise, on top of the sensory noise that impairs perceptual performance (Type-1 decisions) (Maniscalco and Lau, 2016). More recently, researchers have considered the contribution of motor factors in perceptual confidence (Yeung and Summerfield, 2012; Kiani et al., 2014; Fleming and Daw, 2017). Such elements are crucial, for example, for the observer to respond “low confidence” on lapse trials where they are sure they mistakenly pressed the wrong key. In other examples, motor behaviour is used as an index of perceptual confidence by tracking hand kinematics while observers report their perceptual judgement (Resulaj et al., 2009; Patel et al., 2012; Dotan et al., 2018). However, these noted contributions are often restricted to simple motor behaviours, and do not take into account sources of response variability from action execution.

Motor awareness, the degree to which we are conscious of the actions we take (Blakemore et al., 2002; Blakemore and Frith, 2003), is also likely to contribute to sensorimotor confidence. Not all actions are consciously monitored, and it is a common experience to act without conscious control. For example, when we are walking, we are not always thinking

of exactly how to place one foot in front of the other. Yet, for other actions, we must
consciously attend to them, such as threading a sewing needle. A seminal study on motor
awareness by Fournieret and Jeannerod (1998) found poor introspective ability for the ac-
tion made when an unseen hand movement is perturbed by a horizontal displacement in
the visual feedback signal. Participants discount their compensatory actions and instead
indicated that their hand position followed a trajectory much like the perturbed cursor.
Follow-up studies have modified the response to be a binary motor-awareness decision (e.g.,
“Was feedback perturbed or not”) followed by a confidence rating (Sinanaj et al., 2015;
Bègue et al., 2018). Another motor-awareness study measured confidence ratings following
a judgement of whether a visual dot was flashed ahead or behind their finger position dur-
ing up-down movement (Charles et al., 2020). However, we shall argue that none of these
measurements of confidence correspond to sensorimotor confidence as we have defined it.
Motor-awareness confidence reflects the knowledge held about the executed actions, but
lacks the sensory and goal components of sensorimotor confidence. To our knowledge, the
only study to ask participants to explicitly reflect on their sensorimotor performance was
by Mole et al. (2018), who had participants perform a virtual driving task. Green lines
were placed on the road to indicate a good-performance zone, and after completing the
trial, they were asked to report the percentage of time they spent in the green zone (i.e., a
continuous measure of sensorimotor confidence). They found that correspondence between
objective performance and sensorimotor confidence roughly followed difficulty of the task
but was otherwise limited.

The study of sensorimotor confidence should also be contrasted with the mere knowl-
edge of sensorimotor uncertainty in the absence of any particular instance of sensorimotor
control (Augustyn and Rosenbaum, 2005). In theory, this can be studied by examining
how knowledge of variability from sensory, motor, and task sources, influences the action-
selection process in motor decision-making (Wolpert and Landy, 2012). The majority of
studies support the hypothesis that humans plan actions consistent with accurate knowledge

of their sensorimotor uncertainty (e.g., Augustyn and Rosenbaum, 2005; Trommershäuser et al., 2008; Stevenson et al., 2009; Bonnen et al., 2015), with some exceptions (e.g., Mamassian, 2008; Zhang et al., 2013). However, the degree to which this knowledge is consciously available to the person is highly debatable (Augustyn and Rosenbaum, 2005). Furthermore, judgements of one’s uncertainty in a planned action only allow one to predict the probability of a successful outcome. In this sense, they can act as prospective confidence judgements before the action is taken, but do not constitute retrospective confidence judgements made by reflecting on sensorimotor behaviour from performance monitoring. For example, one would typically have more prospective confidence for riding a bicycle than a unicycle. This belief is not derived from performance monitoring but rather from experience-informed expectation. In other areas of metacognitive research, such use of uncertainty information or other predictions of task difficulty are considered heuristics that can even impair the relationship between objective performance and confidence (e.g., Spence et al., 2015; De Gardelle and Mamassian, 2015; Mole et al., 2018; Charles et al., 2020). Thus, it is desirable to identify the degree to which sensorimotor confidence is based on conscious monitoring of performance from feedback cues versus prospective judgements of performance based on uncertainty cues.

Here, we report on two experiments explicitly measuring sensorimotor confidence in a visuomotor tracking task using a computer display and mouse. In both experiments, participants manually tracked an invisible target that moved horizontally by inferring its location from a noisy sample of evidence in the form of a twinkling dot cloud. The trajectory of the target was unpredictable, as its velocity profile was generated by a random-walk algorithm. A dynamic task was selected to mirror the sensorimotor goals typically encountered in the real world.

After tracking, participants reported their sensorimotor confidence by subjectively evaluating their tracking performance with a relative judgement of “better” or “worse” than their average. This confidence measure differs from that typically used in perceptual confidence

(Mamassian, 2020). For a perceptual judgement in a typical psychophysical experiment, there are only two choice outcomes, correct or incorrect, and the confidence report solicited by the experimenter reflects the belief in the correctness (Pouget et al., 2016). If given a full-scale confidence measure ranging from 0% to 100% (Weber and Brewer, 2003), participants can use the low end of the scale to report they are sure to be incorrect. In contrast, when given a half-scale ranging from 50% to 100%, the low end of the scale collapses both the ?correct-unsure? and ?incorrect-sure? responses. Sensorimotor decisions, however, do not produce binary outcomes (correct/incorrect). Rather, they produce continuous outcomes (e.g., 1 degree of error, 2 degrees, etc.) and will almost always have some amount of error. Knowing that interpreting calibration judgements is not very straightforward (Fleming and Lau, 2014), we did not ask participants to report perceived error on a continuous scale. Instead, we opted for the simpler request that participants perform a median split of better/worse performance, turning the confidence judgement into a binary judgement. How does this map onto low-error/high-error (like correct and incorrect for perceptual decisions) and sure/unsure? If they are sure of lower-than-average error or higher-than-average error they would just report ?worse? or ?better?. In the case they were unsure, they should essentially flip a coin, because they do not know. Thus our measure is more akin to a full-scale judgement with only two choice categories, and not the half scale you would get for a high/low confidence judgement. Our measure allowed us to assess the correspondence between true performance and subjective performance.

In Experiment 1, trials differed in terms of the uncertainty in target location. We used two manipulations to achieve this: varying the size of the dot cloud (i.e., dot-sample noise), and varying the stability of the target's velocity (i.e., random-walk noise). In Experiment 2, we manipulated only the stimulus-presentation duration to introduce uncertainty about when the confidence response would be required. We had several goals in this study: 1) to test whether humans are able to make reasonable sensorimotor confidence judgements from monitoring performance-error signals rather than relying only on uncertainty-based expect-

tations; 2) to quantify how well sensorimotor confidence reflected objective performance; 190
and 3) to examine how error information at different moments in time contributes to the 191
final sensorimotor confidence judgement. 192

2 Experiment 1 193

Experiment 1 sought to measure sensorimotor confidence in a visuomotor tracking task 194
and establish a metric of metacognitive sensitivity that quantified how well the confidence 195
judgements corresponded to objective tracking performance. Difficulty in the task was 196
manipulated in the *cloud-size* session by varying the external noise of the sensory evidence 197
indicating the target location. In the *velocity-stability* session, we varied the degree of noise 198
in the target's horizontal trajectory. To investigate the error evidence contributing to the 199
sensorimotor confidence, we investigated the temporal pattern of metacognitive sensitivity, 200
applying our metric to 1 s time bins within the trial. 201

2.1 Methods 202

Participants: Thirteen naive participants (23 – 35 years old, two left-handed, four female) 203
took part in the study. All had normal or corrected-to-normal vision and self-reported 204
normal motor functioning. They received details of the experimental procedures and gave 205
informed consent prior to the experiment. Participants were tested in accordance with the 206
ethics requirements of the École Normale Supérieure and the Declaration of Helsinki. 207

Apparatus: Stimuli were displayed on a V3D245 LCD monitor (Viewsonic, Brea, CA; 208
52 x 29.5 cm, 1920 x 1080 pixels, 60 Hz). Participants sat 46.5 cm from the monitor with 209
their head stabilised by a chin rest. Manual tracking was performed using a Logitech M325 210
wireless optical mouse (60 Hz sampling rate, standard acceleration profile for Mac OS X), 211
operated by the participant's right hand. Subjective assessments of performance were re- 212
ported on a standard computer keyboard with the left hand. The experiment was conducted 213

using custom-written code in MATLAB version R2014a (The MathWorks, Natick, MA),
using Psychtoolbox version 3.0.12 (Brainard, 1997; Pelli, 1997; Kleiner et al., 2007).

Dot-cloud stimulus: On every frame, the horizontal and vertical coordinates of two
white dots were drawn from a 2D circularly symmetric Gaussian generating distribution
with standard deviation σ_{cloud} . The mean of the distribution was the tracking target, which
was invisible to observers and must be inferred from the dot cloud. Each dot had a one-
frame lifetime and two new dots were drawn every frame. Due to the persistence of vision,
participants had the impression of seeing up to 10 dots at any one time (Figure 2A). Dots
had a diameter of 0.25 deg and were presented on a mid-grey background. Dots were gen-
erated using Psychtoolbox functions that rendered them with sub-pixel dot placement and
high quality anti-aliasing. The horizontal position of the target changed every frame accord-
ing to a random walk in velocity space (Figure 2B): $v_{t+1} = v_t + \epsilon$ and $\epsilon \sim \mathcal{N}(0, \sigma_{\text{walk}})$ deg/s.
This gave the target momentum, making it more akin to a real-world moving target (Fig-
ure 2C). Both the target and the black cursor dot (diam.: 0.19 deg) were always centred
vertically on the screen. The cursor could not deviate vertically during tracking (i.e., any
vertical movements of the mouse were ignored in the rendering of the cursor icon) and
participants were informed of this during training. Trajectories that caused the target to
move closer than $2 \times \max(\sigma_{\text{cloud}})$ from the screen edge were discarded and resampled prior
to presentation.

Task: The trial sequence (Figure 2D) began with a red dot at the centre of the screen.
Participants initiated the tracking portion of the trial by moving the black cursor dot to this
red dot, causing the red dot to disappear. The dot-cloud stimulus appeared immediately,
with the target centred horizontally. The target followed its horizontal random walk for
10 s. Then, the participant made a subjective assessment of tracking performance while
viewing a blank grey screen, reporting by keypress whether they believed their tracking
performance was better or worse than their session average.

The experiment was conducted in two 1-hour sessions on separate days. In the “cloud

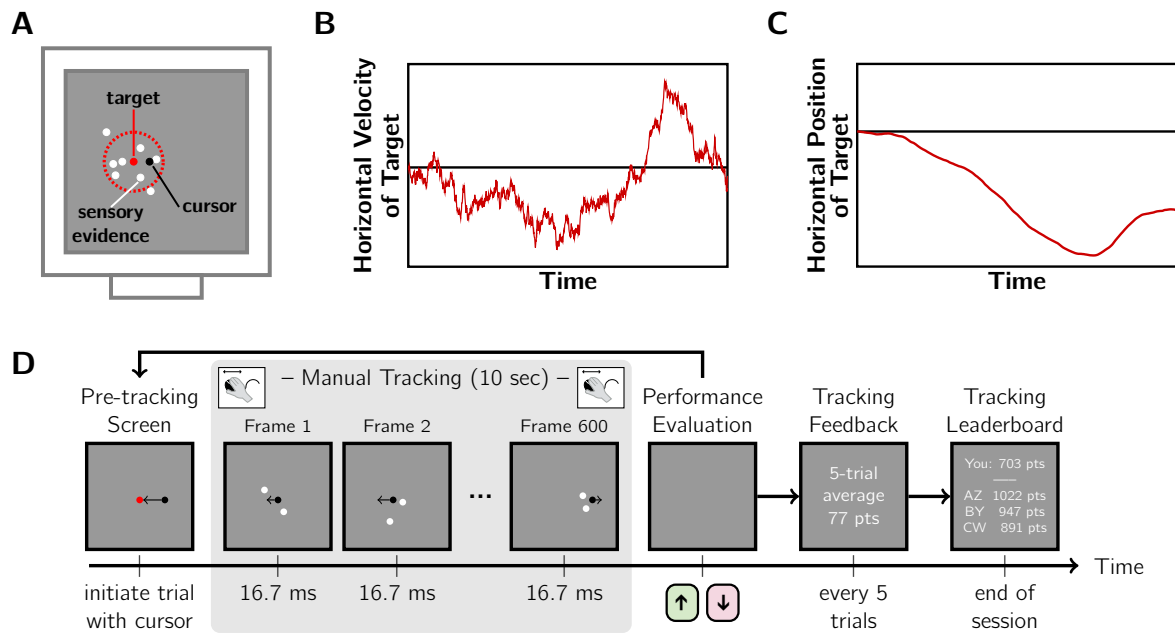


Figure 2: Visuomotor tracking task. A: The “twinkling” dot cloud stimulus (white), generated by drawing two dots per frame from a 2D Gaussian generating distribution. Red: mean and 1 SD circle, which were not displayed. Black: mouse cursor. The dots provided sensory evidence of target location (generating distribution mean). As illustrated, more than two dots were perceived at any moment due to temporal averaging in the visual system. B: Example target random-walk trajectory in velocity space. C: The corresponding horizontal trajectory of the target. D: Trial sequence. Trials were initiated by the observer, followed by 10 s of manual tracking of the inferred target with a computer mouse. Then, participants reported their sensorimotor confidence by indicating whether their performance on that trial was better or worse than their average. Objective performance feedback was provided intermittently including average points awarded and a final leaderboard. Difficulty manipulations: cloud size (σ_{cloud}) and velocity stability (σ_{walk}) were varied in separate sessions.

size” session, the standard deviation of the dot cloud, σ_{cloud} , was varied from trial to trial (5 levels: 1, 1.5, 2, 2.5, and 3 deg) and the standard deviation of the random walk, σ_{walk} , was fixed at 0.15 deg/s. In the “velocity stability” session, σ_{walk} was varied (5 levels: 0.05, 0.10, 0.15, 0.20, and 0.25 deg/s) and σ_{cloud} was fixed at 2 deg. Examples of the stimuli for both sessions are provided as Supplementary media files. The order of sessions was counterbalanced across participants to the best extent possible. Each session began with a training block (20 trials, 4 per stimulus level in random order), where only tracking responses were required. The training trials allowed participants to become familiar with the stimulus and set-up, and to form an estimate of their average performance. The main testing session followed (250 trials, 50 per stimulus level in random order). For the second session, participants were instructed to form a new estimate of average performance, and not to rely on their previous estimate.

Grading objective performance: For our analyses, we used root-mean-squared-error (RMSE) in deg as our measure of tracking error, calculated from the horizontal distance between the target (i.e., the current distribution mean) and the cursor. For the purposes of feedback, the tracking performance on each trial was converted to a score according to the formula $points = 100 - 30 * RMSE$. Typical scores ranged from 60 to 80 points. Every 5 trials, the average score for the previous 5-trials was reported. This feedback was provided for both training and test trials. Presenting the average score served several purposes. The primary purpose of the feedback was to focus the efforts of participants on their tracking, thus discouraging them choosing ahead of time whether the trial was to be “better” or “worse” and executing tracking to match their metacognitive rating. Feedback also could have encouraged consistent performance across the session and helped participants to maintain a calibrated internal estimate of average performance. At the end of a session, participants were shown their cumulative score for that session and ranking on a performance leaderboard.

Metacognitive sensitivity metric: To examine sensorimotor confidence, we sought

a metacognitive sensitivity metric that reflected how well the confidence reports discriminated good from bad tracking performance (i.e., low versus high RMSE). This concept is similar to the one used in perceptual confidence, where metacognitive sensitivity refers to a person's ability to distinguish correct from incorrect decisions (Fleming and Lau, 2014). As the outcome of tracking was not binary (e.g., correct vs. incorrect), we considered the objective tracking performance within a trial relative to all trials within the session performed by that participant. We constructed two objective-performance probability distributions conditioned on the sensorimotor confidence: one distribution for trials followed by a "better than average" response and one for "worse than average" responses (Figure 3A-B). A high overlap in these conditional distributions would reflect low metacognitive sensitivity as this means objective performance is a poor predictor of the participant's evaluation of their performance. Conversely, low overlap indicates high metacognitive sensitivity. We used an empirical Receiver Operating Characteristic (ROC) curve, also known as a quantile-quantile plot (Figure 3C), for a non-parametric measure of metacognitive sensitivity that reflected the separation of these distributions, independent of any specific criterion for average performance. As shown in Figure 3D, completely overlapping distributions would fall along the equality line in an ROC plot, resulting in an Area Under the ROC curve (AUROC) of 0.5. In contrast, complete separation would yield an AUROC of 1. An advantage of this technique over methods that rely on averaging (e.g., classification images) is that this method is suitable for continuous performance distributions of any shape (e.g., skewed). There are two things worth noting about the interpretation of this metric. First, this is not the ROC method other researchers typically use to measure perceptual confidence (Barrett et al., 2013; Fleming and Lau, 2014). AUROC has, however, been used previously to explore the relationship between choice correctness and continuous confidence ratings as well as reaction times (Faivre et al., 2018). Second, our AUROC measure has the following interpretation: if the experimenter was given the RMSE of two trials and was told one was rated "worse" and the other "better", the AUROC would reflect the probability of correctly inferring that

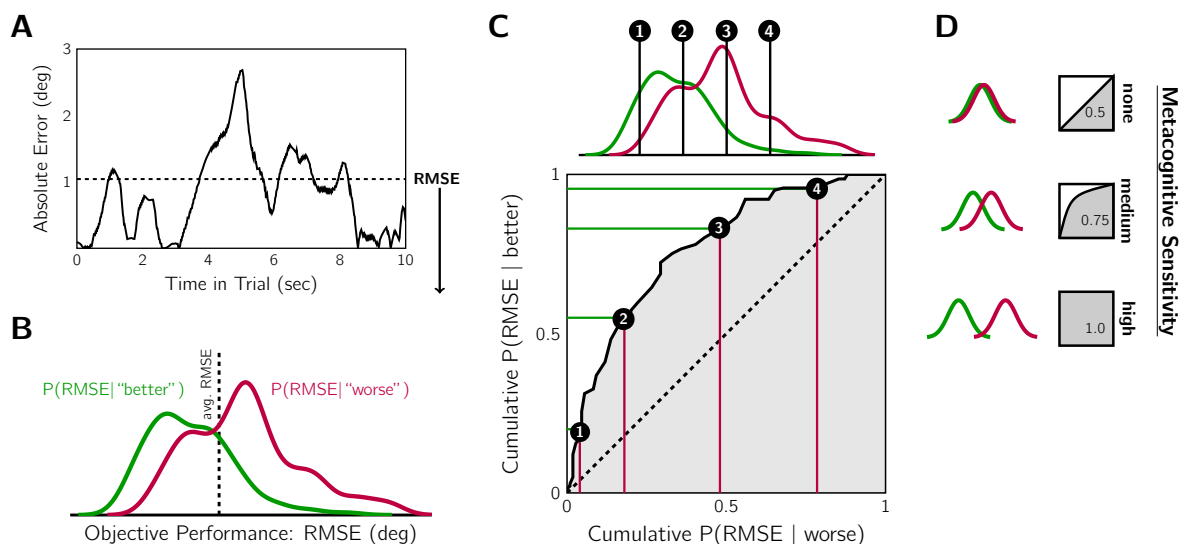


Figure 3: A metacognitive sensitivity metric. A: Example of tracking error within a trial. Root-mean-squared-error (RMSE, dashed line) was the objective performance measure. B: Example participant’s objective-error distributions, conditioned on sensorimotor confidence, for all trials in the variable cloud-size session. True average performance (dashed line) indicates the ideal criterion. Smaller RMSE tended to elicit “better” reports, and larger RMSE “worse”. C: Metacognitive sensitivity was quantified by the separation of the conditional objective-error distributions with a non-parametric calculation of the Area Under the ROC (AUROC) using a quantile-quantile plot. At every point along the objective-performance axis, the cumulative probability of each conditional error distribution was contrasted. D: The area under the resulting curve is the AUROC statistic, with 0.5 indicating no meta-cognitive sensitivity and 1 indicating maximum sensitivity. The greater the separation of the conditional distributions, the more the objective tracking performance was predictive of sensorimotor confidence, and thus the higher the metacognitive sensitivity.

the objectively better trial of the two was rated as “better” by the participant.

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2.2 Results

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Confirming the difficulty manipulation: We first examined whether the difficulty ma-
manipulation affected objective tracking performance. Figure 4A shows the mean RMSE for
each stimulus level for the two difficulty manipulations. Qualitatively, the difficulty levels
appear matched for most participants: performance curves follow the equality line. To check
this result, we fit a linear mixed-effects model (LMM) to the RMSE values of each trial.

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The fixed effects in the model were difficulty manipulation (cloud-size or velocity-stability), stimulus difficulty (five levels), trial number, and an intercept term. The random effect was the participant affecting only the intercept term. Trial number was included to test whether learning occurred during the experiment. An analysis of deviance was performed using Type II Wald chi-square tests, revealing several significant effects. As expected, difficulty level had a significant effect on tracking performance ($\chi^2 = 3044.40$, $p < 0.05$), with larger RMSE for more difficult trials. This confirms that the difficulty manipulations had the desired effect on tracking performance. We also found that the cloud-size difficulty manipulation had significantly higher tracking error than velocity-stability ($\chi^2 = 15.34$, $p < 0.05$), indicating that tracking in the velocity-stability session was easier than in the cloud-size session. There was no significant interaction between difficulty manipulation and stimulus level ($p > 0.05$). Trial number also had a significant effect on performance ($\chi^2 = 5.25$, $p < 0.05$), with later trials having larger error. This suggests training trials were likely sufficient for performance to stabilise prior to the main task, but fatigue likely affected performance later in the session.

Overall metacognitive accuracy: Next, we examine metacognitive accuracy, which is the percentage of trials correctly judged as better or worse than average. Performance in both sessions was significantly better than chance (cloud-size session: $64.4 \pm 1.2\%$ correct; velocity-stability session: $64.7 \pm 2.3\%$). The accuracy results for each session are contrasted in Figure 4B. Four participants had significantly higher accuracy in the cloud-size session, according to the 95% binomial error confidence intervals, and four participants were significantly more accurate in the velocity-stability session. Overall, evaluation of tracking performance was similar in the two conditions. However, this accuracy metric may be subject to response bias. Therefore, we examined meta-cognitive sensitivity.

Overall metacognitive sensitivity: The pattern of results for metacognitive sensitivity (AUROC, see Methods) was similar to the one found for metacognitive accuracy. Metacognitive sensitivity is contrasted between the sessions in Figure 4C and the individual

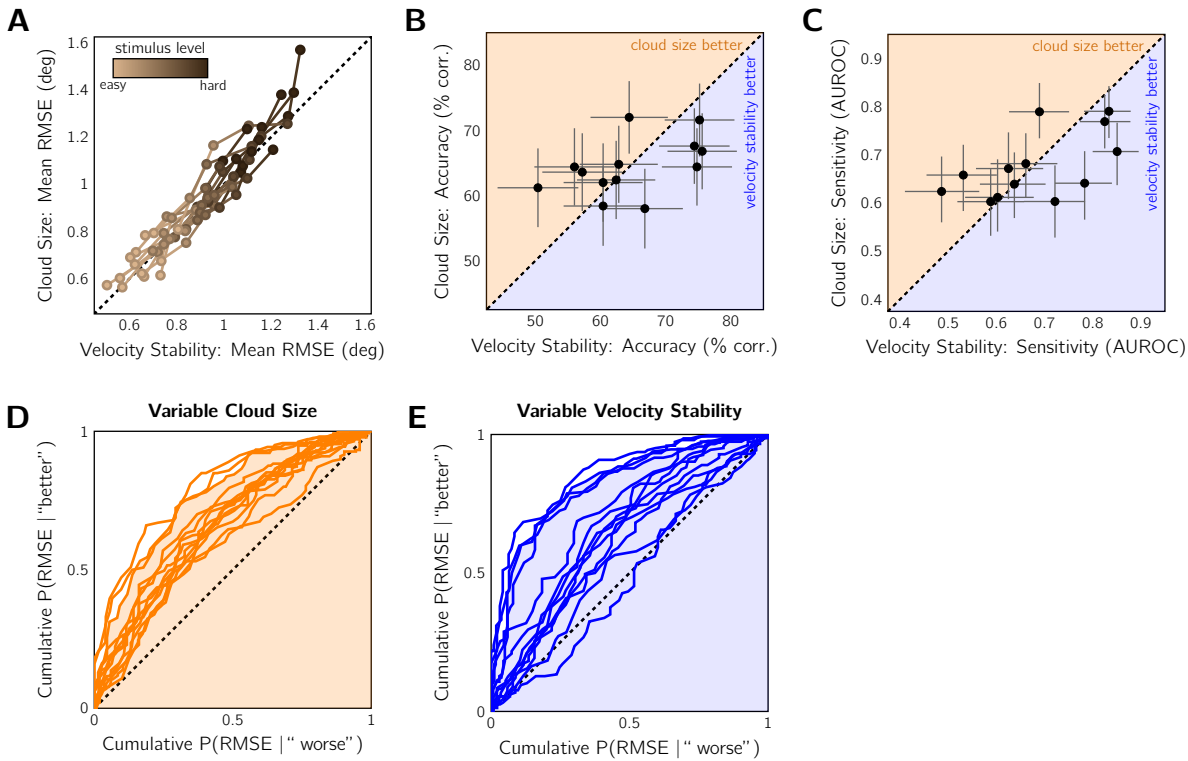


Figure 4: Comparable above-chance metacognitive sensitivity for cloud-size and velocity-stability difficulty manipulations in Experiment 1 ($n = 13$). A: Effect of difficulty manipulation on tracking error. Mean RMSE contrasted for equivalent difficulty levels in the variable cloud-size session and the variable velocity-stability session. Colour: difficulty level. Curves: individual participants. Dashed line: equivalent difficulty. B: Comparison of metacognitive accuracy for the two difficulty-manipulation techniques, pooled across difficulty levels. Data points: individual subjects. Dashed line: equivalent accuracy. Error bars: 95% binomial SE. Shaded regions indicate whether metacognitive accuracy was better for the cloud-size or velocity-stability session. C: Same as in (B) but comparing the sensitivity of the sensorimotor confidence judgement. Dashed line: equivalent sensitivity. Error bars: 95% confidence intervals by non-parametric bootstrap. D: ROC-style curves for individual participants in the cloud-size session, pooled across difficulty levels. Shading: AUROC of example observer. Dashed line: the no-sensitivity lower bound. E: Same as (D) for the velocity-stability session. Shading corresponds to the same example observer.

ROC-style curves for the cloud-size and velocity-stability sessions are shown in Figures 4D and 4E, respectively. Almost all participants displayed some degree of metacognitive sensitivity in both sessions (i.e., have ROC-style curves above the equality line). On average, the AUROC in the cloud-size session was 0.68 ± 0.02 (mean $\pm$ SEM) and was 0.68 ± 0.03 for the velocity-stability session. At the group level, a Wilcoxon's Matched-Pairs Signed-Ranks Test revealed no significant difference between AUROCs from the two sessions ($n = 13$, $T = 45$, $p > 0.05$). To examine the sensitivity at the individual subject level, we performed a bootstrap procedure in which the AUROC was computed for each participant 1000 times, sampling from their trial set with replacement, allowing us to calculate 95% confidence intervals for our estimates (Figure 4C). Four participants were significantly more sensitive in the velocity-stability session, three were significantly more sensitive in the cloud-size session, and the remaining six showed no significant difference between the two conditions. It is unlikely that these results are due to a learning effect across sessions: four of the seven significant results come from greater meta-cognitive accuracy in the first session completed. Another consideration is the amount of variability in performance for each individual and session. A highly variable participant may have a higher metacognitive sensitivity score because distinguishing better from worse performance is easier if a better trial differs more, on average, from a worse trial (Rahnev and Fleming, 2019). Also, variance could have differed between the two difficulty manipulations, affecting within-participant comparisons of metacognitive sensitivity. To examine this we fit a GLMM of the AUROC with participant as the random effect (intercept term only), and fixed effects of RMSE variance (pooled across difficulty levels), difficulty manipulation, and an intercept term. We found no significant effect of any of our predictors. To check the strength of the non-significant relationship between variance and metacognitive sensitivity, we calculated the Bayesian Information Criterion (BIC) for this linear model and compared it to the same model without trial variance as a predictor. This simplified model had a lower BIC score ($\Delta\text{BIC} = 5.35$), supporting the claim that performance variance has little influence on metacognitive sensitivity.

Temporal profile of metacognitive sensitivity: We conducted an analysis of metacognitive sensitivity for each 1 s time bin within the 10 s trial to examine the degree to which each second of tracking contributed to the final sensorimotor confidence judgement. An AUROC of 0.5 indicates that error in that 1 s time bin has no predictive power for the metacognitive judgement; an AUROC of 1 indicates perfect predictive power. Figure 5A shows the results of this analysis. In both the cloud-size and the velocity-stability sessions there was a noticeable recency effect: error late in the trial was more predictive of sensorimotor confidence than error early in the trial. There was no discernible difference between the two difficulty manipulations, except for the first few seconds where early error was more predictive for the velocity-stability session.

For comparison, we also computed the temporal AUROCs, replacing the participant's responses with simulated sensorimotor confidence judgements under two strategy extremes. Figure 5B shows the AUROC time course for an ideal observer that had perfect knowledge of performance (RMSE) and based the confidence judgement on whether the RMSE was truly better or worse than average (i.e., weighted all time points equally). After the first two seconds of tracking, the temporal AUROC is relatively level. Note that no time bin was perfectly predictive of the confidence judgement, because the error within one second is not equivalent to the total error across the entire trial. Figure 5C shows the AUROC time course for an observer that perfectly uses uncertainty cues (i.e., cloud-size, velocity-stability) to judge the difficulty level of the trial, and computes prospective confidence rather than basing the confidence judgement on performance monitoring. Again, no single time bin should be particularly informative if one is assessing a cue that does not disproportionately occur at or affect performance for one particular portion of the trial, such is the case with our difficulty manipulations. Note that for the heuristic-evaluation simulation, confidence was coded as “worse” for the two hardest difficulty levels, “better” for the two easiest, and flipping a 50-50 coin for the middle difficulty level. Again, both temporal profiles are flat after the first 2 s. Neither perfect monitoring nor prospective confidence based on

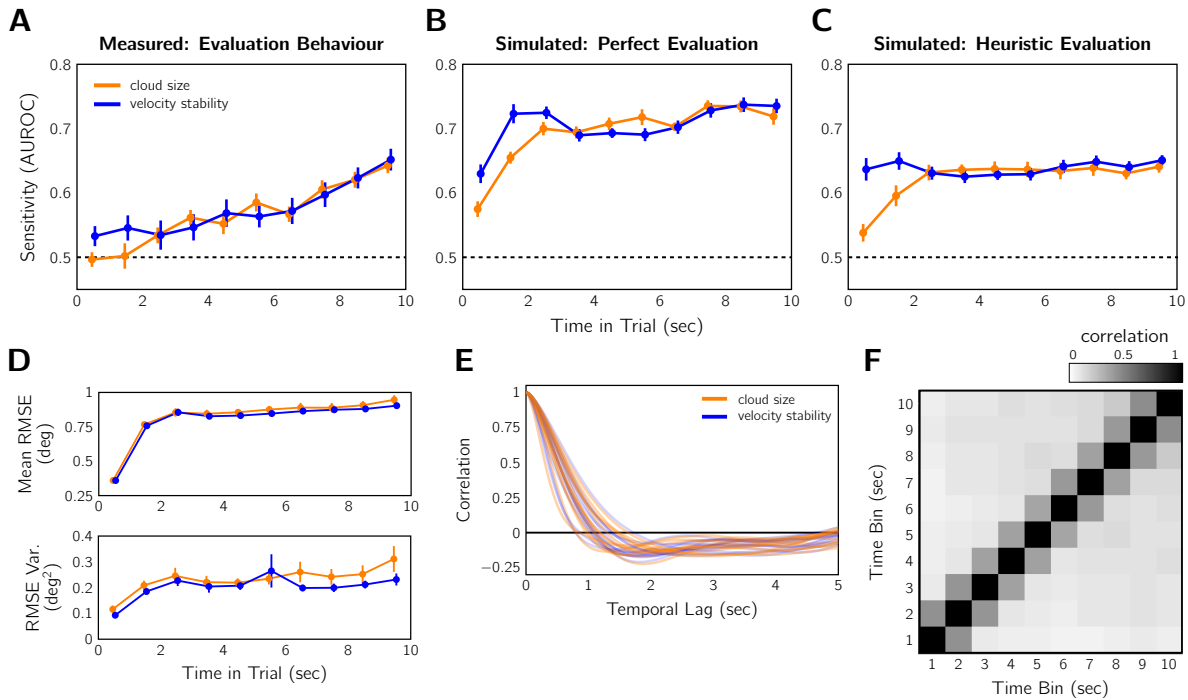


Figure 5: Performance weighting over time for sensorimotor confidence in Experiment 1 ($n = 13$). A: AUROC analysis performed based on each 1-s time bin in the tracking period. Error bars: SEM across participants. Error later in the trial is more predictive of sensorimotor confidence as indicated by the higher AUROC. B: The same analysis as in (A) for an ideal observer that has perfect knowledge of the error and compares the RMSE to the average RMSE. C: Temporal analysis performed with simulated responses based on expected performance according to the heuristic of difficulty level for each difficulty manipulation (see text). D: Mean and variance of the RMSE between target and cursor. Mean RMSE plateaus between 1-2 s and remains stable for the remainder of the trial. Variance is also quite stable after 2 s. Error bars: SEM across participants. E: Auto-correlation of the tracking error signal for each subject and each session. F: Autocorrelation matrix of the 1 s binned RMSE. Data pooled over trials, conditions, and participants. The correlation between time-bins is relatively low after 1 s.

uncertainty cues produced the recency effect in measured metacognitive behaviour. This
result, however, is not trivial due to the complex correlation structure of the error signal,
which we investigated next.

Weighing all time points equally is only an optimal strategy if all time bins are equally
predictive of trial-averaged performance. Error variability is one factor that can affect that:
periods of low error volatility have less impact on the predictive validity of a time bin for
overall RMSE. Thus, a recency effect might be an optimal strategy if there is higher error
volatility late in the trial. We found that error is overall lower and less variable before 2 s
(Figure 5D). This is because participants begin the trial by placing their cursor at the centre
of the screen, where the target is located. After this initial 2 s, however, tracking error vari-
ability is relatively constant, indicating that all these time points are similarly informative
about the final RMSE. Thus, error variance may explain why metacognitive sensitivity was
reduced for the initial 2 s for the measured and simulated sensorimotor confidence, but it
cannot explain the observed recency effect. Figure 5E shows the auto-correlation of the
signed error signal for each participant averaged across difficulty levels. This graph reveals
that error is correlated up to ± 1 s, and is slightly anti-correlated thereafter. Errors are
necessarily related from moment to moment, due to the continuous nature of tracking. To
resolve a tracking error, one needs to make a corrective action to compensate. The anti-
correlation is likely a result of such corrective actions. Figure 5F shows that this salient
auto-correlation up to ± 1 s is also present between the RMSE of neighbouring 1 s time
bins. These results indicate that some of the predictive power of error in one time bin
may be attributed to weighting of error in a neighbouring bin. Thus, if we ask for what
additional variance is accounted for, starting with last bin, the recency effect would appear
even stronger.

Other performance metrics: Our modelling thus far has been based on the error
between the location of the target and the cursor placement. However, this is not a realistic
model of how the participant perceives their error as they imperfectly infer target location

from the dot cloud, which is predominately affected by the external noise σ_{cloud} . To model
this perceptual process (Figure 6A), we opted for a simple exponential filtering of the cen-
troid signal (i.e., the mid-point of the two dots presented on each frame). The true centroid
position is a reasonable input, given that humans perform well at static centroid estimation
(McGowan et al., 1998; Juni et al., 2010). The smoothing aims to capture both the tem-
poral averaging in the visual system, which causes a cloud of 10 or so dots to be perceived,
as well as the averaging across time for strategic decision-making (Kleinman, 1969; Bonnen
et al., 2015). The current estimate of target position, $\hat{x}_t$, is obtained by computing the
weighted average at time t of the horizontal component of the current centroid, c_t , with the
previous estimate, $\hat{x}_{t-1}$:

$$\hat{x}_t = \alpha c_t + (1 - \alpha) \hat{x}_{t-1}. \quad (1)$$

The smoothing parameter, α , controls the steepness of the exponential. Larger α mean
that current sensory evidence is weighted more than previous target estimates, and vice
versa. The weighting is a trade-off that has to be balanced: averaging improves the amount
of information contributing to the estimate, but too much averaging into the past leads to
biased estimates.

We selected the value of α that minimised the sum of squared errors between true target
location and the model's estimate as a stand in for the observer's estimate of the current
location of the target. This was calculated separately for each stimulus level and condition
(Figure 6B). As expected, there is less smoothing (larger α) for the easy, small dot clouds
than the more difficult, large dot clouds (smaller α). This is because accepting some history
bias only makes sense when dealing with the noisier large dot clouds. The opposite pattern
is true for the velocity-stability condition. If velocity stability is high (easy), it is safer
to average further into the past to improve the estimate than if velocity stability is low
(difficult). It is not simple to use the tracking time series to estimate the true perceptual
smoothing performed by the observer as tracking actions are not smooth and continuous

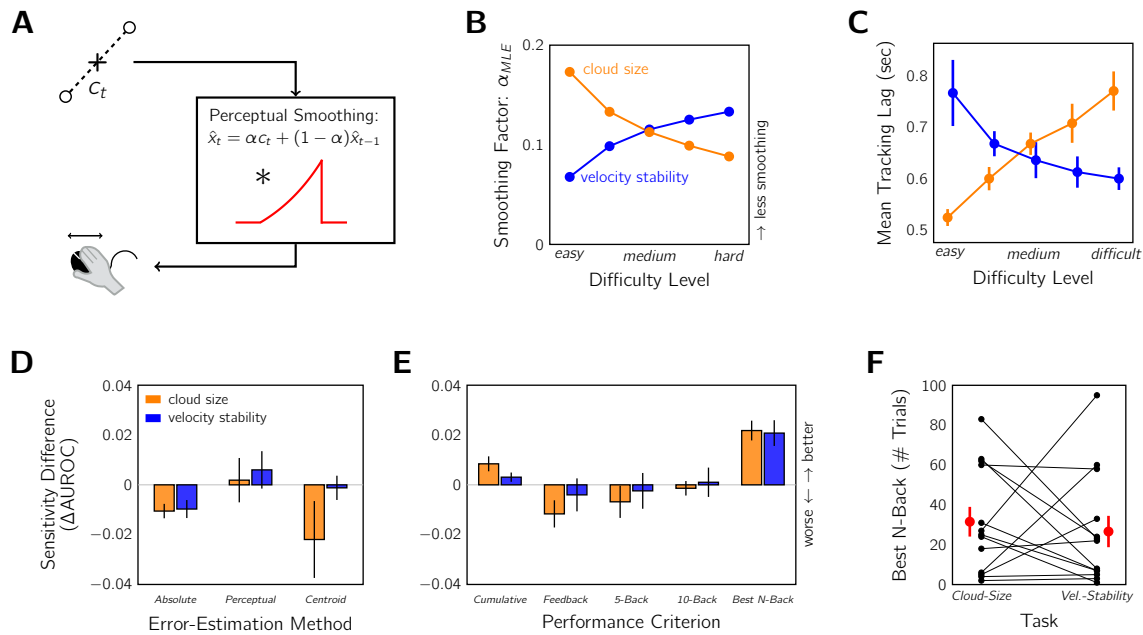


Figure 6: Comparing metacognitive sensitivity with different error-estimation methods and performance criteria. A: Diagram of the exponentially-smoothed perceptual model. Input: horizontal position of the dot-cloud centroid, c_t (i.e., dot midpoint on a single frame). The perceptual system smooths the signal by convolving with an exponential to produce the target estimate $\hat{x}$. This is equivalent to the weighted sum of current input and previous estimate, $\hat{x}_{t-1}$, according to the smoothing parameter, α . Output: perceived error determines the motor response. B: Setting of α that minimises the difference between true and perceived target location for each difficulty level and condition. C: Tracking lag as a measure of perceptual smoothing. As per the expected effects of difficulty level on perceptual smoothing (B), we found the corresponding X pattern in average tracking lags measured by a cross-correlation analysis (see text for details). Note that a larger α means greater weight on the current estimate and therefore less tracking lag. D: Metacognitive sensitivity AUROC as measured under several error-estimation methods compared to the standard RMSE method reported throughout. Absolute: mean absolute error between target and cursor. Perceptual: error according to the perceptual model in (A) with α values from (B). Centroid: RMSE calculated using dot-cloud centroid rather than true target location. Positive values indicate that this method yields higher sensitivity than the standard method. E: Same as in (D) but testing different performance criteria, comparing to the true-average criterion reported throughout. Cumulative: average error on a per-trial basis ignoring future performance. Feedback: last 5-trial performance feedback as criterion. N-back: windowed average of last N trials. Optimal calculated as N between 1 and 100 that maximises the AUROC. F: Computed optimal N for each condition. Black: individual participants. Red: group mean $\pm$ SEM.

(Miall et al., 1993). However, we did find evidence of such a pattern of perceptual smoothing 435
in the tracking lags by difficulty level (Figure 6C). Tracking lag was computed per observer 436
by finding the lag that maximised the cross-correlation between the velocity signal of the 437
target and cursor. The pattern is the reverse of that seen in Figure 6B: larger α means 438
greater weight on the current estimate and therefore shorter tracking lags, as the estimate 439
is less dependent on the history of the stimulus. 440

When the AUROC was calculated from the trial RMSE according to the perceptual 441
model, however, the results are only marginally improved by at most 0.01 in the AUROC 442
(Figure 6D). In fact, using the RMSE based on the raw centroid signal or absolute tracking 443
error also produced similar AUROC estimates, only slightly worse than the RMSE method. 444
The relatively unchanging AUROC across these performance metrics is likely due to the 445
high correlation between all of these error measures. As compared to the RMSE method, 446
the correlations for the cloud-size condition are $r = 0.98$, 0.94 , and 0.79 for absolute error, 447
perceptual error, and centroid error respectively. For the velocity-stability condition, these 448
are $r = 0.98$, 0.94 , and 0.95 . This is because all methods are measures of the mean 449
performance, which will change little with unbiased noise if given sufficient samples (i.e., 450
10 s of tracking). Thus, we conclude that our AUROC statistic was a robust measure and 451
that the overlap in the confidence-conditioned distributions is unlikely due to the selection 452
of RMSE as the objective-performance metric. 453

Another assumption we made in our analysis of metacognitive sensitivity was that the 454
average-performance criterion used by the participant was fixed. However, the participant 455
may have used a different strategy for judging sensorimotor confidence, such as keeping 456
a cumulative average, or relying on the most recent feedback, or considering only some 457
recent history of trials. To investigate this possibility, we tested whether the participant's 458
categorisation of "better" and "worse" trials was more consistent (i.e., less overlap of the 459
confidence-conditioned distributions) if the error in the trial was compared only to the 460
RMSE of previous trials and not simply the fixed sessional average of RMSE. Considering 461

only the RMSE of previous trials necessarily leads to a fluctuating average, in contrast
to considering both past and future performance, which leads to a fixed average RMSE.
To be clear, computing the relative RMSE of each trial according to a fluctuating average
would change the shape of the confidence-conditioned distributions (Figure 3B), but the
AUROC calculation would still be performed in the same manner (Figure 3C). If the partic-
ipant’s sensorimotor confidence response used a criterion that tracked the real fluctuations
in objective tracking performance, then the AUROC should be larger than our reported
main results (Figure 4C). We considered several potential strategies for computing rela-
tive performance: a trial’s RMSE could be compared to an average of all previous trials
(“Cumulative”), to the average RMSE used to calculate the score in the most recent 5-trial
performance feedback (“Feedback”), or to the RMSE average of only the most recent 5,
10 or best N trials (“5-Back”, “10-Back”, “Best N-Back”). The value of N for the Best
N-back model was computed separately for each participant and session by finding the size
of temporal-averaging window that maximised the AUROC. The metacognitive sensitivity
according to each strategy was then compared to the results reported as the main finding.
As shown in Figure 6E, only the Cumulative and Best N-back models improved the esti-
mated AUROCs for both sessions. On average, the number of trials in this latter model was
 31.5 ± 7.5 trials for the cloud-size session and 26.6 ± 7.9 trials for the velocity-stability session
(Figure 6F). Overall, the improvement in the AUROC was only marginal (a maximum of
2% for any model), indicating that accounting for performance fluctuations, as a proxy for
fluctuations in the average-performance criterion, did little to improve the understanding
of the sensorimotor confidence computation.

Summary: In Experiment 1, we measured sensorimotor confidence for visuomotor
tracking, under both cloud-size and velocity-stability manipulations of difficulty, to address
the three goals of this study. A robust AUROC statistic, that quantified the ability of the
confidence judgements to distinguish objectively good from bad tracking, indicated that
confidence judgements were made with comparable above-chance metacognitive sensitivity

for both difficulty manipulations. Furthermore, a temporal analysis revealed a recency
effect, where tracking error later in the trial was found to disproportionately influence
sensorimotor confidence. We propose that this is due to imperfect performance monitoring
and not prospective confidence based on heuristic cues to difficulty (i.e., cloud size, velocity
stability).

3 Experiment 2

The goal of Experiment 2 was to further investigate the recency effect. To this end, we re-
peated the task keeping the stimulus statistics fixed (σ_{cloud} and σ_{walk}) and instead varied the
duration of the stimulus presentation in an interleaved design. This made the time when the
sensorimotor-confidence judgement was required less predictable. Thus, participants would
be encouraged to sample error evidence for their confidence throughout the trial instead of
waiting until the final portion of the stimulus duration. If a response-expectation strategy
was the cause of the recency effect, we would expect to see flatter temporal AUROCs for this
mixed-duration design. Otherwise, if the recency effect is due to a processing limitation of
sensorimotor confidence, we would expect error in the last few seconds to largely determine
sensorimotor confidence regardless of the duration condition. Additionally, this experiment
allowed us to investigate sensorimotor confidence in the context of a fixed difficulty setting
that encourages participants to monitor their performance. This is because prospective
judgements of confidence, based on cues to sensorimotor uncertainty, are uninformative
when the stimulus statistics are unchanging.

3.1 Methods

Participants: There were seven new participants in Experiment 2 (21–31 years old, one
left-handed, four female). All participants had normal or corrected-to-normal vision and
no self-reported motor abnormalities. Participants were naive to the purpose of the studies

except one author. Prior to the experiment, the task was described to the participants
and consent forms were collected. Participants were tested in accordance with the ethics
requirements of the Institutional Review Board at New York University.

Apparatus: All experiments were conducted on a Mac LCD monitor (Apple, Cupertino, CA; late 2013 version, 60 x 34 cm, 1920 x 1080 pixels, 60 Hz), with participants seated 57 cm from the monitor. Participants operated a Kensington M01215 wired optical mouse (60 Hz sampling rate, standard acceleration profile for Mac OS X) with their right hand when manually tracking the stimulus. Subjective performance evaluations were collected on a standard computer keyboard. Experiments were conducted using custom-written code in MATLAB version R2014a (The MathWorks, Natick, MA), using Psychtoolbox version 3.0.12 (Brainard, 1997; Pelli, 1997; Kleiner et al., 2007).

Task: Stimulus presentation duration was manipulated with an interleaved design and three levels (6, 10, and 14 s) while the stimulus statistics remained fixed at $\sigma_{\text{cloud}} = 2$ deg and $\sigma_{\text{walk}} = 0.15$ deg/s. Data were collected over three 1-hour sessions, with each session composed of 15 training trials (5 per duration, randomised order) followed by 225 test trials (75 per duration, randomised order). Again, after each stimulus presentation, participants rated their subjective sense of their tracking performance as either “better” or “worse” than their session average. As shown in Experiment 1, tracking before 2 s in this task has a different error profile, due to the target and cursor both starting at the same location from stationary (Figure 4D). We opted to not count these initial 2 s of tracking in the final score so that trial duration could not serve as a difficulty manipulator in this experiment (e.g., a 6 s trial is more likely to have lower RMSE than a 14 s trial). In order to signal when the tracking contributed to the final score, the cursor was initially red (not contributing) and switched to green (contributing to the score) after 2 s. Furthermore, to ensure that all trials had the same stimulus statistics (e.g., position on screen, velocity), all trajectories were initially sampled as a 14 s stimulus and accepted or rejected before being temporally truncated to 6 or 10 s if the duration condition required. For example, this prevented an

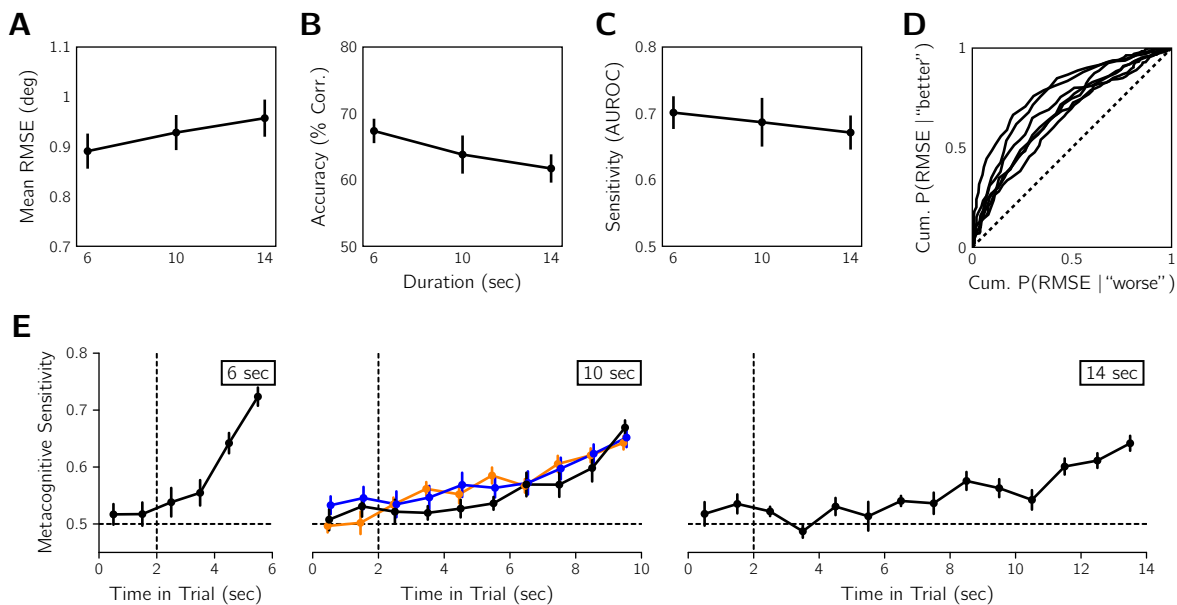


Figure 7: Effect of variable stimulus-presentation duration on tracking error and sensorimotor confidence in Experiment 2 ($n = 7$). A: Mean objective tracking performance for each duration condition averaged across observers. B: Sensorimotor-confidence accuracy for each duration condition. C: Metacognitive sensitivity for each duration condition. D: ROC-style curves for individual participants for AUROC pooled across durations. Dashed line: the no-sensitivity lower bound. Error before 2 s was excluded from the calculations in panels A-D. E: Temporal AUROCs calculated for 1 s time bins for each duration condition averaged across participants for Experiment 2 (black). For comparison, the results in Figure 4A are replotted (orange: cloud-size session; blue: velocity-stability session). The recency effect found in Experiment 1 is replicated here for Experiment 2. Vertical dashed line at 2 s indicates the timing of cursor colour-change cue to begin evaluating tracking. Horizontal dashed line the no-sensitivity line. Error bars in all graphs are SEM.

over-representation in shorter duration trials of the target approaching the screen boundaries 540
 quickly or rapidly accelerating after trial onset. Note that, as in Experiment 1, the criterion 541
 for rejecting trajectories was based on proximity of the target to the screen edge; any 542
 trajectory was resampled if at any point during the 14 s the target moved closer than 543
 $2 \times \sigma_{\text{cloud}}$ to the edge. Tracking performance was scored and feedback given in the same 544
 manner as the previous experiment. 545

3.2 Results

In Experiment 2, we manipulated the duration of stimulus presentation with three interleaved conditions of 6, 10, or 14 s. The consequence of duration on objective tracking performance was a small increase in RMSE for longer durations (Figure 7A). The sensorimotor confidence judgements also showed slightly lower metacognitive accuracy (Figure 7B) and sensitivity (Figure 7C) for longer durations. Overall, the average AUROC from pooling data across durations was 0.68 ± 0.04 SEM (Figure 7D) and all participants had above-chance metacognitive sensitivity according to bootstrapped confidence intervals calculated as per the same procedure as Experiment 1. When split by session, the AUROCs were 0.68 ± 0.04 , 0.68 ± 0.03 , and 0.71 ± 0.02 , suggesting that metacognitive performance was relatively unchanging across the sessions. Note that for these analyses we discarded the initial 2 s of tracking that the participants were instructed to ignore.

Figure 7E shows the temporal profile of metacognitive sensitivity for each duration as well as the results from Experiment 1. Participants were instructed to ignore tracking error occurring before 2 s, when the cursor changed colour, for estimating sensorimotor confidence, and we observed low metacognitive sensitivity for these time points. Due to RMSE being partially correlated between adjacent time bins (Figure 4F), slightly elevated sensitivity for the time bin at 2 s does not necessarily indicate non-compliance with task instructions. For the remainder of the trial, later time points tend to have higher metacognitive sensitivity, consistent with the recency effect observed in Experiment 1. The steepness of the temporal AUROC was also greater for shorter trial durations. This is to be expected as the contribution of a 1 s time bin to the final RMSE is greater when the trial is short. A recency effect is also consistent with the observed lower overall metacognitive performance for longer durations, because a smaller percentage of the total error signal contributes to sensorimotor confidence.

We attempted to compare the temporal AUROCs quantitatively with mixed success (see Supplementary Information). We found evidence for a stronger recency effect for

Experiment 2 than Experiment 1. Furthermore, in our supplementary analyses, accounting
for the recency effect and/or external noise via our perceptual model in Figure 5A gave little
benefit when attempting to predict sensorimotor confidence for either experiment (at most
 $\sim 2\%$ increase in predictive accuracy). However, we caution against strong conclusions from
these supplementary analyses as certain properties of the obtained data set were not ideal
for these quantitative model fits.

In sum, We replicated the recency effect of Experiment 1 for all stimulus durations.
Thus the final few seconds of tracking had the greatest influence on sensorimotor confi-
dence regardless of whether the participant knew when the stimulus would terminate. This
suggests that response expectation is unlikely to be the source of the recency effect.

4 Discussion

In two experiments, participants completed a visuomotor tracking task where trials were fol-
lowed by a sensorimotor confidence judgement of “better” or “worse” than average tracking
performance. We calculated the degree to which these judgements predicted objective track-
ing for manipulations of task difficulty (Experiment 1) and trial duration (Experiment 2),
with an AUROC metacognitive-sensitivity statistic that ranged from no sensitivity at 0.5
and perfect sensitivity at 1. In both experiments we found above-chance metacognitive
sensitivity and a temporal profile that suggested that error later in the trial contributed
more to sensorimotor confidence.

4.1 Performance monitoring

Our primary aim was to establish if humans would actively monitor their own performance
to judge sensorimotor confidence. An alternate strategy would have been to use cues to
uncertainty (e.g., cloud size) to predict task difficulty and thus the likelihood of perform-
ing well. From our experiments, we found several indicators of performance monitoring.

First, in Experiment 1, we manipulated task difficulty systematically with two methods, 597
varying either the cloud-size parameter (σ_{cloud}) or the velocity stability parameter (σ_{walk}) 598
of the procedure to generate our dynamic stimulus. The manipulation of σ_{cloud} was very 599
noticeable, with all participants reporting the stimulus manipulation in their debriefing in- 600
terviews, whereas varying σ_{walk} was more subtle and participants had difficulty identifying 601
the manipulation (supplementary media files are provided to illustrate the difficulty manip- 602
ulations). Thus, if the strategy was to rely exclusively on cues to uncertainty, and given that 603
the manipulations had sizeable and comparable effects on tracking performance, we would 604
expect higher metacognitive sensitivity for the cloud-size session than the velocity-stability 605
session. We did not find supporting evidence for this hypothesis as there was no significant 606
difference in sensitivity between the sessions. 607

Stronger supporting evidence for performance monitoring was found in Experiment 2, 608
where task difficulty was kept the same for all trials by fixing the stimulus statistics. In this 609
scenario, there are no explicit uncertainty cues for the participant to use. Yet, metacog- 610
nitive sensitivity was slightly better than that observed in Experiment 1 (AUROC of 0.68 611
in Experiment 2 versus 0.64 for cloud-size and 0.64 for velocity-stability in Experiment 1). 612
However, several factors complicate direct comparisons. Variability in tracking performance 613
is not the same for fixed- and variable-difficulty designs; RMSE differences are likely to be 614
lower for a fixed-difficulty design, complicating the comparison. Furthermore, the difficulty 615
manipulation in Experiment 1 may have permitted a mixed strategy, combining performance 616
monitoring and uncertainty heuristics. Thus, our results from Experiment 2 supporting the 617
performance-monitoring hypothesis are a better indicator of how well performance moni- 618
toring captures true tracking performance than the results of Experiment 1. 619

The best evidence for performance monitoring is the recency effect we observed in both 620
experiments. We found that sensorimotor confidence was most influenced by the error in last 621
few seconds of the trial. Such a result is unlikely from the prospective use of uncertainty cues 622
because it shows that the error occurring during the trial matters, with some moments being 623

treated differently from others. That is, for the cloud-size session, all time points equally
signal the uncertainty from cloud size, so there is no reason that the final seconds should
be privileged. Similarly, for the velocity-stability session, the behaviour of the target would
have to be observed for some period of time to assess velocity stability, but this could be done
at any point during the trial. One possibility is that participants were waiting until the end
of the trial to make these assessments, but the results of Experiment 2 argue against this, as
the recency effect was still found when stimulus-presentation duration was randomised. If
instead participants were using some other heuristic strategy (e.g., average velocity, amount
of leftward motion, etc.), this would also not produce a recency effect unless it predicted
performance later in the trial but not early performance. From an information-processing
standpoint, performance monitoring is likely to exhibit temporal sub-optimality due to
either leaky accumulation of the error signal during tracking (Busemeyer and Townsend,
1993; Smith and Ratcliff, 2004) or the temporal limitations of memory for retrospective
judgements (Atkinson and Shiffrin, 1968; Davelaar et al., 2005).

Before we examine the recency effect, we first comment on the possibility of a mixed
strategy of performance monitoring and uncertainty heuristics. Metacognitive judgements
based on a mixed strategy combining actual performance and cues to uncertainty have
been reported for sensorimotor confidence (Mole et al., 2018), motor-awareness confidence
(Charles et al., 2020), and perceptual confidence (De Gardelle and Mamassian, 2015; Spence
et al., 2015), with some exceptions (e.g., Barthelmé and Mamassian, 2010). Yet, it is
unclear if a mixed strategy was used in Experiment 1 of the present study. The anecdotal
differences in detecting the difficulty manipulations (cloud-size obvious, velocity-stability
subtle) coupled with comparable metacognitive performance in these sessions lends support
to a performance-monitoring strategy, but are weak evidence as difficulty detectability was
not rigorously tested. An ideal test for use of a mixed strategy would involve keeping
performance constant by fixing the difficulty while also varying likely uncertainty cues (e.g.,
titrating the mean and variability of the sensory signal; De Gardelle and Mamassian, 2015;

Spence et al., 2015). This is more difficult in sensorimotor tasks as motor variability will introduce noise into the error signal, hindering any attempt to match performance. One way around this problem would be to have participants judge sensorimotor confidence for replays of previously completed tracking and artificially adjust uncertainty cues. However, this would rely on metacognition acting similarly for active tracking and passive viewing, which has only been confirmed for motor-awareness confidence (Charles et al., 2020).

Finally, we acknowledge that the current study is limited in that it is unable to answer how participants are achieving performance monitoring. We cannot separate the contribution of visual information, knowledge of motor commands, and proprioception to the confidence judgements. This is because motor uncertainty could be directly assessed in our task by visually inspecting the movements of the cursor, making it possible that visual information was actually the primary cue used in our task. The contribution of visual information could be addressed to some extent if we replicated the experiments under poor viewing conditions, or by asking participants to track a stimulus in a different sensory modality, or after removing the cursor altogether. However, changing these experimental conditions would entail taking into account the potential increase in attentional resources required to perform well, the lower sensitivity to other sensory modalities, and the role of the sense of agency. While all these issues are important to understand how individual cues to sensorimotor performance influence confidence, they are beyond the scope of the present study.

4.2 The recency effect

In the sensorimotor feedback process, incoming error signals inform upcoming action plans and quickly become irrelevant (Todorov, 2004; Bonnen et al., 2015). In contrast, the goal of performance monitoring for sensorimotor confidence is to accumulate error signals across time, much like the accumulation of sensory evidence for perceptual decisions with a fixed viewing time. In fact, in the accumulation-of-evidence framework, considerable effort has

been made to incorporate a recency bias termed “leaky accumulation” (Busmeyer and
Townsend, 1993; Usher and McClelland, 2001; Brunton et al., 2013; Matsumori et al., 2018).
The main arguments for including a temporal-decay component is to account for memory
limitations of the observer (e.g., from neural limits of recurrent excitation) or intentional
forgetting for adaptation in volatile environments (Usher and McClelland, 2001; Nassar
et al., 2010; Norton et al., 2019). For our task, memory constraints are a more likely
explanation of the recency effect than intentional forgetting, because we have long trials of
6-14 s with no changes of stimulus statistics during a trial. One contributor to the error
signal we have no control over, however, is the participant’s motivation to do the task.
Even though tracking performance was constant when averaged across trials, fluctuations
in motivation during a trial could lead to fluctuations in sensorimotor performance that
do cause volatility in the error signal. Thus, alternating between bouts of good and poor
performance could bias the participant to be more forgetful.

Previous efforts to characterise the time course of a metacognitive judgement have been
limited to the perceptual domain. Using the reverse-correlation technique, Zylberberg et al.
(2012) measured the temporal weighting function for confidence in two perceptual tasks and
found a primacy effect: the initial hundreds of milliseconds of stimulus presentation had the
greatest influence on perceptual confidence. Their finding and associated modelling suggests
evidence accumulation for the metacognitive judgement stops once an internal bound for
decision commitment has been reached. Our results suggest that sensorimotor confidence
does not follow the same accumulation-to-bound structure, otherwise early error would have
been more predictive of confidence than late error. One reason we may not have found a
primacy effect is that the participant interacts with the stimulus to produce the errors that
determine performance, allowing them a sense of agency that they can change or modify
performance. As a result, there is no reason to settle on a confidence judgement based
on initial performance. A contradictory finding to Zylberberg et al. (2012) is that sensory
evidence late in the trial, during the period between the sensory decision and the metacog-

nitive decision, can influence perceptual confidence in what is termed post-accumulation of
evidence (Pleskac and Busemeyer, 2010), but this finding is hard to apply to our visuomotor
task. Evaluating tracking is different from a single perceptual decision, because tracking is
a series of motor-planning decisions (Wolpert and Landy, 2012). The error signal used to
plan the next tracking movement is also the feedback of the error from the last moment
of tracking. Additionally, subsequent estimates of target location could theoretically pro-
vide additional information about previous locations of the target. Identifying the source
of the error signal for sensorimotor confidence, either by computational modelling or brain
imaging, would help clarify the nature of the accumulation process.

So far we have considered an online computation of sensorimotor confidence that ac-
companies sensorimotor decision making. Another alternative is that the evaluation of
performance is computed retrospectively. Baranski and Petrusic (1998) showed that reac-
tion times for confidence responses differed for speeded and unspeeded perceptual decisions,
leading to the conclusion that perceptual confidence is computed online unless time pressure
forces it to be evaluated retrospectively. It is reasonable to assume that the continual de-
mand of cursor adjustment to track an unpredictable stimulus is taxing, leaving participants
no choice but to introspect on their performance upon termination of the trial. If this were
the case, we would likely see temporal biases consistent with memory retrieval. In the mem-
ory literature, there has been extensive evidence of both primacy and recency effects, which
are thought to be associated with long-term and short-term memory processes respectively
(Atkinson and Shiffrin, 1968; Innocenti et al., 2013). Thus, the observed recency effect
in our experiment could be interpreted as short-term memory limitations constraining the
time constant. Another reason observers may delay performance evaluation until after the
trial is because tracking is typically a goal-directed behaviour, which can be evaluated by
its success (e.g., catching the prey after a chase, hitting the target in a first-person shooter
game, or correctly intercepting a hand in a handshake). Still, one may want to introspect
about performance while tracking to decide whether the tracking was in vain. We did not

incentivise participants to adopt a particular strategy in the task, so they may have treated
error towards the end of the trial as their success in “catching” the target.

4.3 Metacognitive efficiency

We quantified metacognitive sensitivity for sensorimotor tracking with an AUROC metric
that reflected the separation of the objective-performance distributions conditioned on sen-
sorimotor confidence. This approach superficially shares some similarities with the metacog-
nitive metric meta- d' in perceptual confidence. For meta- d' , an ROC curve, relating the
probability of a confidence rating conditioned on whether the observer was correct vs. incor-
rect, is computed as part of the analysis to obtain a bias-free sensitivity metric that reflects
the observer’s ability to distinguish between correct and incorrect perceptual responses
(Fleming and Lau, 2014; Mamassian, 2016). However, the area under this ROC curve
(AUROC) has little meaning, as it is highly dependent on the sensitivity of the primary
perceptual judgement (Galvin et al., 2003). Instead, the appropriate comparison is between
the perceptual sensitivity, d' , and the metacognitive sensitivity, meta- d' . Typically, a ratio
of these sensitivities is computed, with a value of 1 being considered ideal metacognitive
efficiency (i.e., the best the observer can do given the identical sensory evidence available
for the metacognitive judgement as the perceptual judgement). Empirically, ratios less
than 1 are most often observed, indicating less efficient, more noisy decision-making at the
metacognitive level (Maniscalco and Lau, 2012, 2016).

The purpose of our AUROC metric is not to quantify how well the sensory information
is used for the sensorimotor control versus sensorimotor confidence, but as a non-parametric
way of quantifying how sensitive an observer is to their true performance. The metric ranges
from no sensitivity (i.e., chance performance) at 0.5 to perfect classification performance
at 1. As with perceptual confidence, we do expect that the AUROC will depend to some
degree on the variance in the performance of the primary task (e.g., tracking), even if it
wasn’t observed in our task. For example, if there is little variance, then it should be diffi-

cult to identify well executed from poorly executed trials, whereas a large variance means
performance could be more easily categorised. A second use of the AUROC metric was to
quantify the degree to which a model of metacognitive behaviour could predict sensorimo-
tor confidence (see Supplementary Information). By replacing the objective-performance
axis with an internal decision-variable axis according to a model, a model's explanatory
power can be measured on a scale from none at 0.5 to perfect at 1. While we were unsuc-
cessful at improving performance more than 2% in any of our experiments, which we did
by accounting for both the recency effect and the effect of external sensory noise instead
of simply computing RMSE using the true target location, the method of analysis nicely
complemented our goal of quantifying how well sensorimotor confidence reflected objective
performance.

We examined metacognitive efficiency by determining what error information contributed
to sensorimotor confidence. The recency effect we observed constitutes an inefficiency in
that not all information used for the primary sensorimotor decision-making was used for
the metacognitive judgement as was instructed. Based on the similarity in shape of the
recency effect for the duration conditions of Experiment 2, we can conclude that efficiency
is inversely proportional to the duration of tracking. However, given long, multi-action se-
quences, it is not that surprising to find that some part of the perceptual information about
error is lost. Some amount of forgetting is likely advantageous in real-world scenarios. For
future metacognitive studies of action, it would be informative to examine estimates of
sensorimotor confidence during action and how sensorimotor confidence interacts with goal
planning, explicit learning, and expertise. For example, it would be worthwhile to investi-
gate how sensorimotor confidence relates to cognitive control functions such as switching or
abandoning motor tasks (Alexander and Brown, 2010), or how athletes and novices judge
sensorimotor confidence (MacIntyre et al., 2014).

4.4 Conclusion

In sum, we found considerable evidence that humans are able to compute sensorimotor confidence, that is, they are able to monitor their motor performance in relationship to a goal. However, they do so inefficiently, in particular because of the recency effect that we revealed, disproportionately weighting the tracking error at the end of the trial to judge whether their performance was better than average. We replicated this effect with unpredictable stimulus-presentation durations to confirm that it was not the result of a response-preparation strategy. In our analyses, we have introduced the AUROC statistic, which we found useful for two purposes. First, it allowed us to quantify the relationship between sensorimotor confidence and objective tracking performance, and second, it provided a model-fit metric for elaborated decision models (see Supplementary information). Our results, obtained from a relatively simple goal of visuomotor tracking, raise many questions for future studies on sensorimotor confidence. For example, is the recency effect a key characteristic of sensorimotor confidence? And, does it result from leaky online evidence accumulation or biased retrospective memory retrieval? What factors determine the strength of the recency effect for sensorimotor confidence (i.e., attention, sensorimotor goals, etc.)? Further work will help provide a clearer link between models of sensorimotor behaviour and models of sensorimotor metacognition.

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Author note

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www.biorxiv.org/content/10.1101/861302v1. Data from this study can be found at 810
<https://osf.io/enxdt/>. Individual author contributions in the CRediT taxonomy style 811
 are as follows (black: major contribution, gray: minor contribution, see [https://www.](https://www.casrai.org/credit.html) 812
[casrai.org/credit.html](https://www.casrai.org/credit.html) for more details): 813

	SML	PM	MSL
Conceptualization			
Data curation			
Formal analysis			
Funding acquisition			
Investigation			
Methodology			
Project administration			
Resources			
Software			
Supervision			
Validation			
Visualization			
Writing - original draft			
Writing - review, editing			

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