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Research Article

Perceptual and attentional uncertainty impact global performance monitoring

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Abstract

We have a fair understanding of what contributes to our confidence when performing individual trials of a task. However, little is known regarding the factors driving more global metacognitive estimates when a task is repeated. The present study investigates the contribution of uncertainty to global performance monitoring. In two pre-registered experiments, participants performed four trials of an orientation matching task and reported their mean response and an estimated dispersion around this perceived mean as a proxy for global performance monitoring. We considered several sources of uncertainty: response-related uncertainty, related to the participants and observed in their response variability, and perceptual or attentional uncertainty related to the sensory stimulation. Our results suggest that adults can reliably estimate the mean and dispersion of their performance and use it together with stimulus-dependent uncertainty to inform their global performance monitoring. In particular, participants adequately report that their performance was worse when uncertainty was higher. However, this capacity decreases when different types of uncertainty increase jointly. We discuss these results in light of a model of confidence that reproduced our main findings. These behavioral and computational results clarify the role of uncertainty in perceptual metacognition and the relationship between local and global performance monitoring.

Keywords: performance monitoring; metacognition; sensorimotor uncertainty; oblique effect; attentional cueing

Introduction

Metacognition, the ability to monitor and critically assess our perception and actions (Koriat 2007, Dunlosky 2008, Fleming et al. 2012), is fundamental to shaping and adjusting behavior (Desender et al. 2018). Recent studies have increasingly focused on understanding the mechanisms and factors behind how we evaluate our performance on a task (Kepecs and Mainen 2012, Mamassian 2016). Key sources of information for self-monitoring include sensory data and prior knowledge (Kiani and Shadlen 2009, Constant et al. 2022), post-decisional evidence accumulation processes (Pleskac and Busemeyer 2010, Murphy et al. 2015, van den Berg et al. 2016, Balsdon et al. 2021, Pereira et al. 2022, Goueytes et al. 2025), action-related signals (Faivre et al. 2018, 2020, Gajdos et al. 2019, Filevich et al. 2020, Pereira et al. 2020), and stimulus variability (de Gardelle and Mamassian 2015, Bang and Fleming 2018, Spence et al. 2018).

Perceptual metacognition is conceptualized as a hierarchical structure, extending from evaluations of single-trial performance to broader self-beliefs (Seow et al. 2021), operating within a Bayesian framework where uncertainty plays a key role. However, critical questions remain regarding this hierarchy. It is unknown whether the same factors contribute across all levels and what underlying "currency" is shared to interconnect these levels. In this study, we targeted a mesoscopic level of performance monitoring, i.e. above local, trial-based metacognition but below the general task, or even skill level. To illustrate these different levels of monitoring, we can imagine a student taking an English exam: their local monitoring processes will be at play if they evaluate their response to a given question before moving on to the next one. Mesoscopic monitoring processes will allow them to evaluate their own performance on a certain section of the exam, and task- or skill-level monitoring processes will allow them to estimate how well they did on the test, or assess their overall English skills. In the present study, we first examine how different sources of uncertainty, known to impact single-trial performance evaluation (Denison et al. 2018; Geurts et al. 2022), also impact global performance monitoring. By doing so, we assess the extent to which the Bayesian framework, which accounts for local metacognition, can also explain more global levels of metacognition. Furthermore, leveraging the model proposed by Geurts et al. (2022), we identify the main sources of evidence on which mesoscopic performance monitoring seems to operate,

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namely the successive sensory percepts (single-trial performance) or local decisions (single-trial judgment of performance) formed across trials.

Most of this literature focuses on local confidence judgments following single events, usually a binary task where participants can be correct or incorrect. Recently, the need to develop new paradigms to approach metacognition and corresponding models of performance evaluation has been highlighted as a crucial goal for the future of the field (Rahnev et al. 2022). The current study introduces a new paradigm based on a stimulus-orientation matching task to examine performance monitoring over repeated trials of the same task. We investigated if this type of metacognitive evaluation about several repetitions of the same task relies on similar performance and stimulus-related cues as the metacognitive judgments about single trials.

In the present task, we asked participants to reproduce the orientation of briefly presented stimuli several times in a row. After four trials involving the same target orientation (plus or minus a jitter), participants provided two types of global performance monitoring: (i) the mean orientation of their responses across four trials, and (ii) a confidence area indicating how much they believed their responses varied around this mean. Since participants had to track their own cognitive process (response to an orientation task) over several trials, we considered these two reports to reflect a form of mesoscopic performance monitoring. We considered such performance monitoring as accurate in case the reports closely matched the actual mean and dispersion of responses, respectively. Thus, here, the targeted metacognitive ability is not to judge their performance against an objective criterion (i.e. the target orientation) but to efficiently track the different responses they gave to the task. We considered three factors that should be taken into account to efficiently monitor one's performance: the participant's actual mean performance, the corresponding variability, as well as two sources of uncertainty of perceptual and attentional origins known to impact performance. We quantified how these factors influenced specific aspects of performance monitoring, namely (i) the evaluation of the end result of the successive trials (mean) compared to the presented target and (ii) the evaluation of the response precision (dispersion) regardless of the target orientation. Indeed, participants could accurately track their mean response while poorly evaluating how precise they were. Such a pattern of global performance monitoring could be explained by a correct estimation of perceptual uncertainty underlying the first report, but a failure to do so for the second report. Moreover, the participant's response variability could be disregarded when evaluating the mean response (first report) since only the participant's actual responses need to be tracked, regardless how spread they are, while it is crucial to evaluate the dispersion around the end results (second report).

In a first experiment, perceptual uncertainty was manipulated by presenting ordinal or cardinal orientations that differ in terms of stimulus-dependent sensory noise (i.e. *oblique effect*; Appelle 1972, Girshick et al. 2011). In a second experiment, we manipulated the allocation of attention by changing the proportion of valid versus invalid exogenous cues during task repetitions. Such exogenous manipulation is known to increase uncertainty (Carrasco 2011), impacting both perceptual decisions and confidence for isolated events (Denison et al. 2018). We predicted that this change in attentional focus would also impair global performance monitoring.

Materials and methods

Transparency and openness

The study design and analysis plan were registered before data acquisition on a public repository (https://osf.io/knufx). Data were collected in 2022. We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study, and we follow JARS (Appelbaum et al. 2018). All data, analysis code, and research materials are available at https://gitlab.com/nfaivre/meta_angle_public. All procedures were performed in accordance with ethical standards and were approved by our institutional research committee (CERGA-Avis-2022-16).

Participants

Participants were recruited via the Prolific marketplace (https://www.prolific.co/). Data was collected on a server from the Pavlovia platform (https://pavlovia.org/), and the experimental scripts were written using HTML/JavaScript/CSS, and the JsPsych library (https://www.jspsych.org/7.0/). We adopted an open-ended sequential Bayes factor design and stopped data collection when our statistical model reached strong evidence for either H0 (the variable of interest does not contribute to performance monitoring reports) or H1 (the variable of interest contributed to performance monitoring reports) for our main variable of interest (standard deviation of the participant's response within a set of trials), or any interaction including this variable. Thus, data were acquired until a Bayes factor equal or inferior to 0.2 or equal or superior to 5 was obtained. In experiment 1, 40 participants were recruited, and 36 participants were included (19 females, 21 males, mean age ± SD: 26.2 ± 7 yo, see exclusion criteria); in experiment 2, 40 participants were recruited, and 38 participants were included (18 females, 20 males, mean age ± SD: 26.2 ± 8 yo, see exclusion criteria).

Procedure

Experiment demo versions can be found here: https://mariechancel.com/exp/metaangle1/ (Exp 1), https://mariechancel.com/exp/metaangle2/ (Exp 2).

Experiment 1

We aimed to assess the contributions of task performance and uncertainty to global performance monitoring. We distinguished stimulus-dependent and response-related sources of uncertainty based on the origin of the change in uncertainty: experimental (i.e. stimulus-dependent) or from the participants' response (i.e. response-related). We manipulated perceptual (stimulus-dependent) uncertainty by setting the stimulus orientation to be either cardinal or oblique (i.e. *oblique effect*; Appelle 1972, Girshick et al. 2011). We approximated the response-related uncertainty using participants' behavioral variability.

The first part of the experiment ensured a similar difficulty level across participants using a staircase procedure (Levitt 1971). After a fixation cross (shown for 1 s), a visual stimulus (Gabor patch) made to occupy 80% of the screen's height (to run the experiment, full-screen display was forced), was displayed on a dark gray background (HEX color code #222222) for 500 ms, generated by overlaying a 2D Gaussian window on a sine-wave grating (spatial frequency = 2 cycles/°), with an initial Michelson contrast of 0.6, oriented at cardinal (0°, 90°) or oblique (45°, 135°) orientations. The visual stimulus was immediately followed by a mask made with concentric circles and Gaussian noise presented for 300 ms to avoid after-effects (Barbosa and Kouider 2018). Once the mask disappeared, a white response bar appeared at a random initial angle. Participants were instructed to click on the bar and drag it until its orientation matched the orientation of the previously seen Gabor patch. When participants were satisfied with the bar orientation, they validated and ended the trial by pressing the spacebar (Fig. 1a). If the absolute error between the actual target angle and the participants' response was above 10°, the contrast of the next Gabor patch increased by 0.005. If the absolute error between the actual target angle and the participants' response was under 10° twice in a row, the contrast of the next Gabor patch decreased by 0.005. This staircase-like procedure stopped after 80 trials (all four orientations were presented 20 times in a pseudorandom order), and the final contrast level was kept for the rest of the experiment. This procedure allowed us to match the task difficulty between participants. Participants could also click on a button to skip a trial when the response bar appeared if they missed the corresponding Gabor patch (e.g. if they looked away when the visual stimulus was presented). They were instructed to use this button only if they did not see the visual stimulus, not if they did not remember or were unsure about its orientation (see exclusion criteria section for the processing of these "missed" trials). This initial part of the experiment lasted around 5 min. Participants' performance on the calibration step are displayed in Fig. S1 and S7 (for experiment 1 and 2, respectively).

The main part of the experiment started after this initial calibration phase. Once again, participants were asked to move the response bar to match the orientation after seeing the same sequence as in the calibration phase (Gabor patch—mask—response bar). However, this time, this sequence was presented four times in a row, with the same angular orientation and a predetermined jitter of either −5, −2.5, 2.5, or 5° with a randomized order. After performing these four trials, participants were asked to assess their overall performance (Fig. 1a). To do so, a disk of the same size as the Gabor patch was presented to the participants, with a bar to mark the diameter (at a random orientation) that could be rotated around the disk's center and an interactive red "confidence" area around this bar. They were requested (i) to rotate the central bar to match the mean of the orientation of their responses across the four previous trials and then (ii) to adjust the size of the confidence area (click and drag the edge) following the instruction: "how precise were you in matching this orientation across the past four trials?." Thus, participants had to monitor two aspects of their global performance: their overall response (i) and precision (ii). We associated these reports to global metacognitive variables since participants had to track their own cognitive process (response to an orientation task) over several trials separated in time (Son and Schwartz 2002). Each step was validated by pressing the spacebar. Each orientation level ([0°, 45°, 90°, or 135°]) was repeated 24 times in a pseudorandomized order, and the experiment was divided into 4 blocks. Between each block, the participants were encouraged to take a short break. This part of the experiment lasted approximately 40 min for a total of 384 trials (96 sets).

Experiment 2

Experiment 2 attempted to replicate our main findings from Experiment 1 while introducing another manipulation of uncertainty by influencing the participants' level of attention through exogenous cueing (Posner 1980). This method is known to induce an additional uncertainty that observers incorporate into their perceptual decisions and local confidence estimates (Denison et al. 2018). We hypothesized that this type of attentional uncertainty would also affect participants' performance monitoring over each set of four trials.

To test this hypothesis, we used the same experimental procedure described above with the following modifications. Not just one but two Gabor patches with different orientations (cardinal orientations only, ± jitter) were presented, one on the right side of the screen, the other on the left side of the screen (Fig. 1b). Participants were instructed to remember both orientations. Both Gabor patches were then masked, and a response bar appeared on the side of the screen corresponding to the Gabor whose orientation had to be reported. On each stimulus presentation, before the appearance of the two Gabor patches, an arrow appeared for 300 ms pointing either toward the stimulus to be reported (valid cue) or toward the opposite side (invalid cue). Like in Experiment 1, participants were asked to match the target stimulus' orientation and to assess their performance (mean response and confidence area) after four trials. Within a set of four trials, the number of valid cues was parametrically varied. A set could contain four (*full* set), three (*valid* set), two (*neutral* set), or one valid cues (invalid set)—but there were no sets with no valid cues—, resulting in four different conditions of cueing at the level of a set. Each cardinal orientation ([0°, 90°]) was repeated 72 times in a pseudorandomized order, divided into 4 blocks. This part of the experiment lasted approximately 60 min for a total of 576 trials (144 sets, including 47 full, 47 valid, 25 neural, and 25 invalid sets). This imbalance in favor of valid cueing was chosen to implement our attentional manipulation, as participants had a strategic advantage if they took the cue into account instead of simply ignoring it.

Data analysis

Single-trial performance

We first evaluated whether the stimulus orientation impacted performance on single trials. The error on a single trial was computed as the difference between the target angle (Gabor patch orientation + jitter) and the participants' response (response bar orientation) on each trial. Thus, the error on a single trial was negative for an overshoot and positive for an undershoot response. We analyzed the magnitude of this single-trial error, i.e. the absolute value as a function of stimulus orientation using Bayesian mixed-effects linear regressions (the regression models' labels in this paper are always labeled starting with an M).

$$\mathbf{M\_orientation} :|\ \text{Single} - \text{trial error}\ | \sim \text{Orientation} + (\text{Orientation}|\ \text{participant})$$

Global performance monitoring

We expected three main factors to contribute to the participants' global performance monitoring (i.e. monitoring of the performance over four consecutive trials): their actual mean performance, their response-related uncertainty, and the stimulus-related (perceptual) uncertainty. The actual mean error was computed as the average of the single-trial errors, i.e. the signed difference between the target angle and the participants' response for each set of four trials (Fig. 2). We aimed to extract the actual mean response in terms of orientation, not magnitude. Using a signed error at the level of a single trial allows us to distinguish a −2° error from a +2° error (the mean orientation for these two theoretical trials would be 0° while the mean magnitude would be 2°). Importantly, considering the signed value is necessary to avoid a trivial correlation between the magnitude and the standard deviation on a set. Indeed, the response-related uncertainty was measured as the response

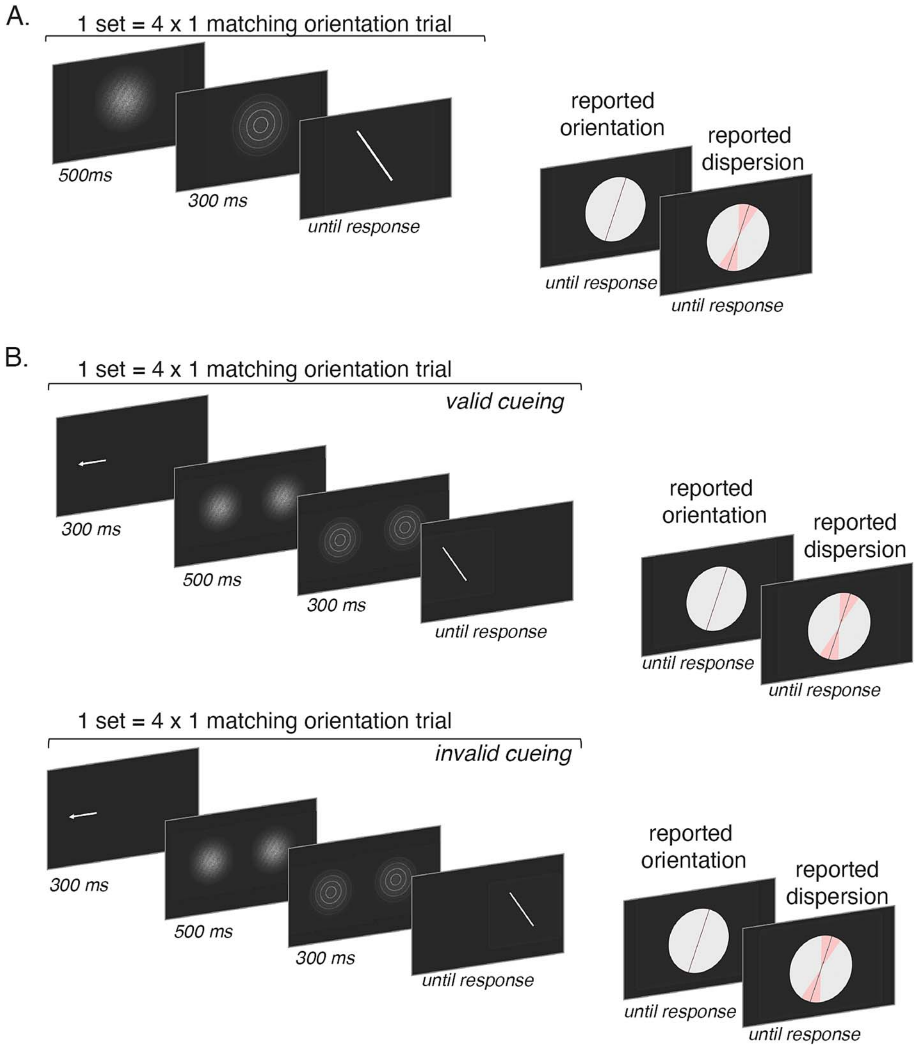

Figure 1. Summary experiments' procedure. (a) Bar orientation task: a Gabor patch was displayed at an angle of 0°, 45°, 90°, or 135° (± jitter [−5°, −2.5°, 2.5°, 5°]) from the horizontal, followed by a mask made of concentric circles. Then, the response bar appeared, and participants were asked to rotate it until its orientation matched the orientation of the Gabor patch they saw. This sequence of stimuli was used both in the initial calibration and the main phase of the experiment. In the main phase of the experiment, each target angle (± jitter) was presented four times in a row. Then, the participants were asked to report (i) their mean response orientation, (ii) their "area of confidence," i.e. how precisely they thought they had reported the correct orientation across the four previous trials. (b) Schematic representation of experiment 2 including exogenous attentional cueing. Two Gabor patches were presented to the participants, followed by the response bar appearing on the side of the screen corresponding to the stimulus that should be reported. The exogenous cue shown before displaying the Gabor patches could be valid (same side as the Gabor patch to be reported at the end of the trial, upper panel) or invalid (opposite side to the Gabor patch to be reported at the end of the trial, lower panel). The number of valid/invalid trials varied, creating four different conditions of exogenous cueing.

standard deviation for each set of four trials. We then evaluated their contribution to two metacognitive variables: (i) the reported mean response; To evaluate the accuracy of this report, we considered the absolute difference between this reported mean response and the displayed target across the four trials, and (ii) the angle of the confidence area. These two global performance monitoring variables decrease when participants evaluate that their performance improves (reduced mean error and dispersion). Thus, if participants are able to efficiently monitor their global performance, the error between the mean response they report and the target as well as the angle of their confidence area should decrease when (i) participants are more accurate on average, (ii) participants are more precise (i.e. low response-related uncertainty), and (iii) when stimulus-dependent sensory uncertainty is low (i.e. for cardinal orientations compared to oblique orientations). A summary of all used variables can be found in table S1.

To test these predictions, we used Bayesian mixed-effects linear regressions with the following formulae to examine each variable:

$$\mathbf{M1}: \mathrm{Reported\_Error} \sim \mathrm{poly}(\mathrm{Actual\_Error}, 2) * \mathrm{Actual\_Dispersion} * \mathrm{Orientation} + (\mathrm{poly}(\mathrm{Actual\_Error}, 2) + \mathrm{Actual\_Dispersion} + \mathrm{Orientation} | \mathrm{participant})$$

$$\mathbf{M2}: \mathrm{Reported\_Dispersion} \sim \mathrm{poly}(\mathrm{Actual\_Error}, 2) * \mathrm{Actual\_Dispersion} * \mathrm{Orientation} + (\mathrm{poly}(\mathrm{Actual\_Error}, 2) + \mathrm{Actual\_Dispersion} + \mathrm{Orientation} | \mathrm{participant})$$

Worse performance on a set corresponded to a larger mean error, involving either an overshoot (negative value) or undershoot (positive value). In both these cases of worse actual performance,

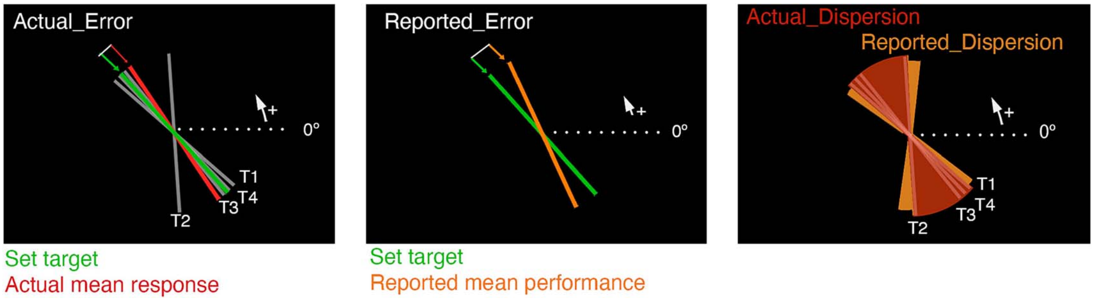

Figure 2. Computing actual performance and global performance monitoring variables. The actual mean error (*Actual_Error*) was computed as the signed difference between the average of raw individual trials' response (T1 to 4) and the target angle. The response-related uncertainty was measured as the response standard deviation (*Actual_Dispersion*) for each set of four trials. We collected two global performance monitoring variables: (i) the reported mean performance. To evaluate the accuracy of this report, we considered the absolute value of the difference between this reported mean performance and the displayed target across the four trials (*Reported_Error*). (ii) The angle of the confidence area (*Reported_Dispersion*). In the depicted example, the participant reported a dispersion around their mean response larger than the actual dispersion of their individual responses. This figure is for illustrative purposes only and does not correspond to what was displayed to the participants.

we expected the participant to be less accurate when reporting their mean response (mean report further away from target orientation) and to report a less precise confidence area (larger dispersion angle). Thus, we added a quadratic expansion to the factor corresponding to the actual mean performance using poly(*Actual_Error*,2) to account for the expected U-shape relationship it had with our dependent variables. In the results section and figures, effects involving the linear component will be noted as *Actual_Error*, while the quadratic component will be written as *Actual_Error^2*.

We used the Bayesian factor (BF) to assess the strength of the evidence supporting an effect (inference criterion: $BF10 > 5$ or $BF01 < 0.02$). All models were fitted once using an uninformed, neutral prior (Gaussian distribution with mean = 0 and SD = 2) and a second time with a prior informed by the result of a pilot study ($N = 19$ participants) using the same experimental procedure as in Experiment 1. Those informed priors had the same means as the pilot posterior means, and SDs equal to 1.5 times the pilot posterior SDs. Considering the results with both types of priors is relevant since using an informed prior leads to more precise but more biased estimates (Morris et al. 2013, Zampieri et al. 2021). Uninformed and informed priors provided qualitatively similar results. The full result tables and results obtained with informed priors can be found in the Supplementary Materials (Table S4 and Fig. S4). We also evaluated the contribution of the evolution of the participants' performance over 4 trials to the corresponding global performance monitoring. This analysis is reported in the Supplementary Materials (Fig. S2 and Fig. S8).

Transformations

We investigated the effect of performance and uncertainty on global performance monitoring. To focus on relative values and minimize the influence of response bias (e.g. large or small errors, over- or under-evaluation of dispersion), we z-scored all ratings separately for each participant before fitting the models.

One exception however: we did not z-score the actual mean response. Because participants were not expected to equally overshoot and undershoot the target orientation, the actual mean error would not be centered on 0. In cases where a participant consistently overshot the target (resulting in only negative values), a z-transformation would misrepresent the data. The largest actual mean error values (most positive z-values) would correspond to the smallest mean error in the raw data. Given our model's syntax, this would incorrectly imply that global performance monitoring variables increase as actual mean error approach 0, whereas we predict such an increase with larger deviations from the target orientation.

Data exclusion

As pre-registered, participants were excluded in case they did not use the confidence area properly (i.e. no significant difference in the area of confidence between trials) or made an orienting error superior to 45° in more than half trials (four participants in Experiment 1, two participants in Experiment 2). Finally, response time distributions were inspected to ensure the good quality of the data; however, no participants were excluded based on this criterion.

When a trial was flagged as missed (see *Procedure* section), the whole set of four trials was removed from further analysis to avoid having "random guess" trials included in the metacognitive assessment of their performance. Moreover, trials were excluded if participants took an unusually long time to respond (trial duration above 10 s). After applying these criteria, a total of 130 sets of four trials (out of 13 328, all participants included) were excluded from Experiment 1 and 435 (out of 20 532, all participants included) from Experiment 2.

Exploratory analyses

We also explored the relationship between the two global performance monitoring reports by adding the error between the reported mean and the target orientation as a factor to the model M2:

$$\begin{aligned}\textbf{M2\_Extended}&: \text{Reported\_Dispersion} \sim \text{Reported\_Error}\\ &* \text{poly}(\text{Actual\_Error}, 2) * \text{Actual\_Dispersion} * \text{Orientation}\\ &+ (\text{Reported\_Error} + \text{poly}(\text{Actual\_Error}, 2) + \text{Actual\_Dispersion}\\ &+ \text{Orientation} \mid \text{participant})\end{aligned}$$

Results

Experiment 1

Concerning single trial performance, on average the absolute error (± SD) on a single matching orientation was 7.54° (± 3.4) and the oblique effect was in the expected direction, i.e. smaller errors for cardinal than oblique orientations, but with anecdotal evidence as the 95% credible interval of posterior estimates did

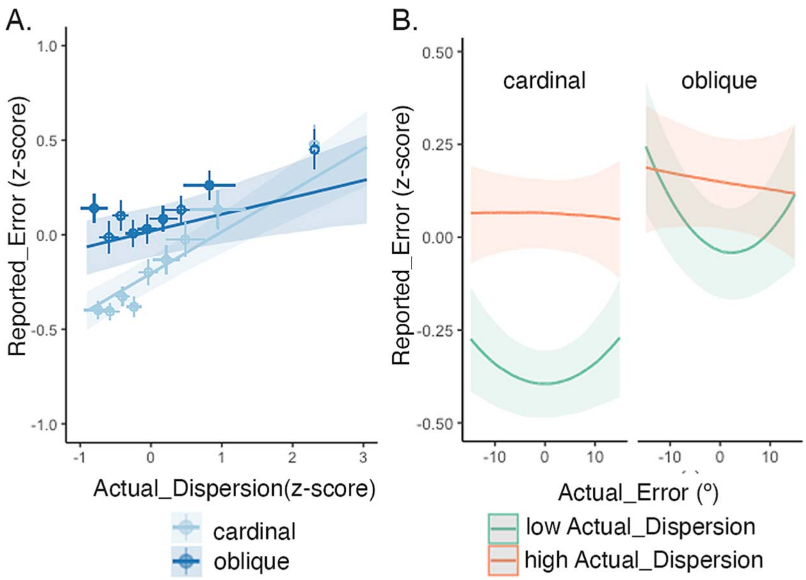

Figure 3. Variation of the distance between the reported mean response and the set's target (*Reported_Error*), depending on the actual mean response, the response-related uncertainty, and the stimulus-dependent uncertainty. (a) The magnitude of *Reported_Error* changed with the participant's variability (*Actual_Dispersion*) more steeply for cardinal (low stimulus-dependent uncertainty in light blue) than for oblique stimuli (high stimulus-dependent uncertainty in dark blue). Although the model took continuous variables as input, for illustrative purposes, we plotted dots and error bars that represent the mean ± 95% confidence interval over participants after grouping *Actual_Dispersion* in deciles. (b) Model predictions reflecting the triple interaction *Actual_Error*^2 × *Actual_Dispersion* × *orientation*. Lines and shaded areas correspond to the regression model predictions and 95% confidence interval. For illustrative purposes, we divided (median-split) the sets into two levels of *Actual_Dispersion* (green/orange: low/high response-related uncertainty). *Reported_Error* is lower for more accurate performance sets (low *Actual_Error*^2) and low exogenous uncertainty (cardinal stimuli, left panel), especially for low response-related uncertainty sets (low *Actual_Dispersion*). *Reported_Error* is lower for less accurate performance sets (high *Actual_Error*^2) and/or high stimulus-dependent uncertainty (oblique stimuli, right panel) with a reduced difference between low and high response-related uncertainty sets. The posterior plot can be found in Supplementary Fig. S3.

not overlap with zero, but BF did not exceed 3 (effect of orientation: M_Orientation = 0.22, 95% CI = [0.05, 0.38], BF10 = 1.14).

We now turn to analyses of the reported mean response. Supplementary Table S2 gathers the full outcome table for the Bayesian mixed-effects regression M1 that considers the absolute value of the difference between the reported mean response and the target orientation on a set of four trials to evaluate the accuracy of global performance monitoring. This regression revealed a main effect of response-related uncertainty: participants reported a mean response further from the target orientation (increased error between the reported mean response and the target orientation) when their responses were more variable (increased response dispersion on the set), (posterior distribution of the model estimate mean: M = 0.22, 95% CI = [0.16, 0.28], BF10 > 1 000). This shows that participants judged their overall performance on a set of four individual trials based on a measure of their responses' variability. However, this effect was reduced when the stimulus-dependent sensory uncertainty also increased: the distance between the reported mean and the target increased less with the participants' variability for oblique than for cardinal stimuli (M = −0.15, 95% CI = [−0.22, −0.08], BF10 > 1 000, Fig. 3a). This difficulty to correctly account for response-related and stimulus-dependent sensory uncertainty when both increased also limited the participants' ability to correctly track their actual mean performance on a set, i.e. the distance between their actual mean response and the target. This is revealed by the triple interaction between the actual mean error, the actual response dispersion on the set, and the target orientation (M = −2.33, 95% CI = [−4.62, −0.06], BF10 = 3.73, Fig. 3b and c).

The same Bayesian mixed-effects regression applied to the confidence area revealed the same pattern of results as we found for the reported mean (Supplementary Table S2). Participants reported a larger dispersion of their responses on a set in more uncertain conditions, whether the uncertainty corresponded to high response-related uncertainty (*Actual_Dispersion*: M = 0.28, 95% CI = [0.20, 0.36], BF10 > 1 000) or stimulus-dependent uncertainty (cardinal versus oblique: M = 0.21, 95% CI = [0.08, 0.35], BF10 = 3.15), suggesting, in turn, that participants did not use heuristics or proxies to report their dispersion, but that, instead, they were able to correctly monitor the uncertainty corrupting their responses. However, once again this effect was reduced when both sources of uncertainty increased together: the increase of the confidence area with the participant's actual variability was weaker for oblique than for cardinal stimuli (M = −0.14, 95% CI = [−0.21, −0.06], BF10 = 20.16, Supplementary Fig. 4a).

Moreover, the increase of the confidence area reported by the participants with increasing response-related uncertainty was amplified when the magnitude of the participant's mean error also increased (*Actual_Error*^2 × *Actual_Dispersion*: M = 2.21, 95% CI = [0.68, 3.78], BF10 = 15.81). In other words, when asked to report the dispersion of their answer, participants accounted for the joint degradation of the actual accuracy and precision (Fig. 4b and c).

Finally, we examined the relation between the confidence area and mean response reported by the participants (M2_extended, Supplementary Table S3). This model indicates that participants reported a larger dispersion of their responses when their reported mean was further away from the target mean orientation (M = 0.22, 95% CI = [0.15, 0.29], BF > 1 000). This correlation between the two performance monitoring reports tended to be reduced under high stimulus-dependent uncertainty (*Reported_Error* × *Orientation:* M = −0.11, 95% CI = [−0.19, −0.04], BF10 = 1.43, Fig. 5a) and during worst sets, i.e. when the magnitude of the actual mean error increased (M = −2.10, 95% CI = [−3.86, −0.44], BF10 > 5, Fig. 5b

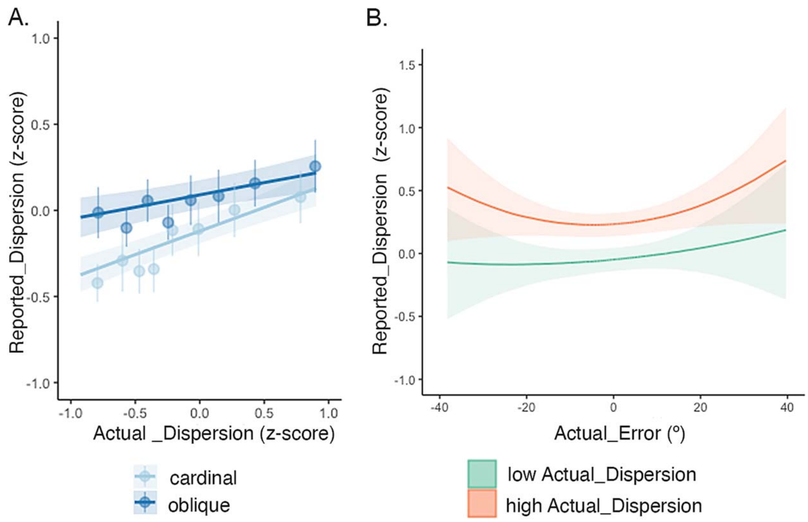

Figure 4. Variation of confidence area reported by the participants (*Reported_Dispersion)* depending on the actual mean response, the response-related uncertainty, and the stimulus-related uncertainty. (a) *Reported_Dispersion* increased with the variability of the participants' responses (*Actual_Dispersion*), more steeply for cardinal (low stimulus-dependent uncertainty in light blue) than for oblique stimuli (high stimulus-dependent uncertainty in dark blue). Although the model took continuous variables as input, for illustrative purposes, we plotted dots and error bars that represent the mean ± 95% confidence interval over participants after grouping *Actual_Dispersion* in deciles. (b) Model predictions corresponding to the interaction *Actual_Error*^2 × *Actual_Dispersion*. Continuous lines and shaded areas correspond to the regression model predictions and 95% confidence interval. Participants reported smaller *Reported_Dispersion* when *Actual_Error*^2 and *Actual_Dispersion* were both smaller (lower panel). The posterior plot can be found in Supplementary Fig. S3.

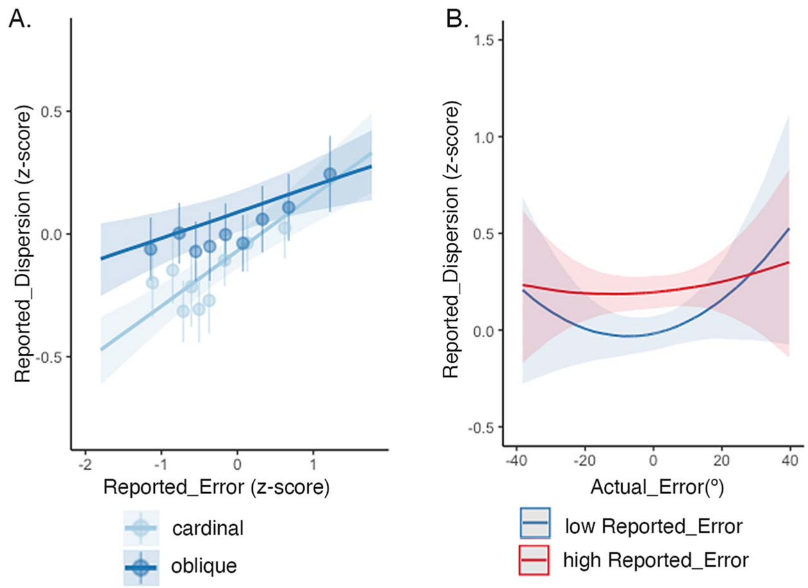

Figure 5. Variation of confidence area (*Reported_Dispersion*) depending on the error between the target orientation and the reported mean response, the actual mean response, the response-related uncertainty, and the stimulus-related uncertainty. (a) *Reported_Dispersion* increased with higher *Reported_Error*, more steeply for cardinal (low stimulus-dependent uncertainty in light blue) than for oblique stimuli (high stimulus-dependent uncertainty in dark blue). (b) Model (M2_extended) predictions corresponding to the interaction *Actual_Error*^2 × *Reported_Error*, this interaction revealed that participants reported a more precise global performance (smaller *Reported_Dispersion*) when they also reported a more accurate global performance (smaller *Reported_Error*), especially when they were more accurate (smaller *Actual_Error*). Posterior plot can be found in Fig. S3. Continuous lines and shaded areas correspond to the regression model predictions and 95% confidence interval. Although the model took continuous variables as input, for illustrative purposes, we plotted dots and error bars that represent the mean ± 95% confidence interval over participants after grouping the values of the independent variables in deciles in panel (a).

and c). Thus, stimulus-related uncertainty and the participant's performance accuracy altered the relationship between the two reported aspects of global performance monitoring.

Experiment 2

Experiment 1 revealed that observers considered their accuracy and both response-related and stimulus-dependent sources of uncertainty when monitoring their own performance in a repeated orientation reproduction task. In Experiment 2, we sought to replicate these results and examine another source of uncertainty modulation via exogenous attentional cueing. To manipulate participants' attentional focus, we presented two instead of one Gabor patches on each trial and preceded them with a valid or an invalid exogenous cue. Within a set of four

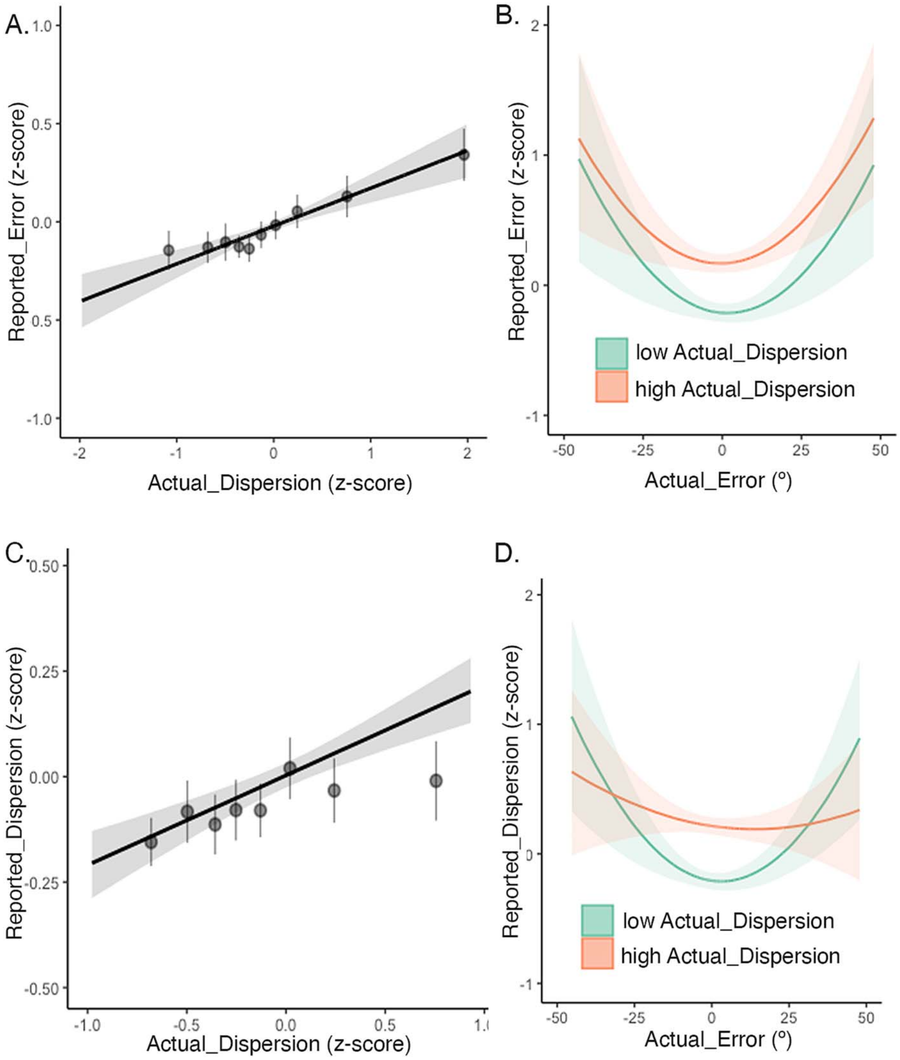

Figure 6. Variations of the error between the actual mean target orientation and the mean target orientation (*Reported_Error*, A, B, C) and the confidence area (*Reported_Dispersion*, D, E, F) depending on the actual mean performance and the response-related uncertainty. (a) Reported_Error increased with response-related uncertainty (*Actual_Dispersion*). (b) Model predictions corresponding to the interaction between *Actual_Error^2* and *Actual_Dispersion* revealing that participants reported smaller *Reported_Error* when they were more accurate (smaller *Actual_Error^2*) and more precise (smaller *Actual_Dispersion*, in green) in the orientation reproduction task. (c) Similarly, *Reported_Dispersion* increased with response-related uncertainty (*Actual_Dispersion*). (d) Model predictions corresponding to the interaction between *Actual_Error^2* and *Actual_Dispersion* revealing that participants felt that their global performance was more precise (smaller *Reported_Dispersion*) when their actual responses were more accurate and precise (smaller *Actual_Error* and *Actual_Dispersion*, respectively). Posterior plot can be found in Supplementary Fig. S9. Continuous lines and shaded areas correspond to the regression model predictions and 95% confidence interval. Although the model took continuous variables as input, for illustrative purposes, we plotted dots and error bars that represent the mean ± 95% confidence interval over participants after grouping the independent variables in deciles in panels (a) and (d).

trials, all cues (*full* set), three cues (*valid* set), two cues (*neutral* set), or only one cue could be valid (*invalid* set), resulting in four different conditions of cueing at the level of a set.

Mean (± SD) first-order performance pooled across all sets was very similar to experiment 1 (7.43° ± 4.14). Participants made larger errors on single trials that were invalidly cued, as compared to validly cued trials (M = −0.22, 95% CI = [−0.29, −0.14], BF10 > 1 000). This confirms that our attentional manipulation was effective.

Regarding global performance monitoring, we replicated the effect of the actual performance on a set (actual mean error and dispersion) on both the reported mean response and dispersion (Fig. 6; Supplementary Table S6). The reported mean response was further away from the target orientation when participants' responses were more variable (M = 0.18, 95% CI = [0.09, 0.27], BF10 > 5) and this effect was amplified by the magnitude of actual mean error on these sets (*Actual_Error^2* × *Actual_Dispersion*: M = 2.42, 95% CI = [0.64, 4.28], BF10 > 5). Similarly, reported confidence area at the end of a set increased when the participants' responses were more variable (M = 0.23, 95% CI = [0.15, 0.32], BF10 > 5) and this effect was also modulated by the magnitude of the actual mean error (*Actual_Error^2* × *Actual_Dispersion*: M = −4.28, 95% CI = [−6.19, −2.44], BF10 > 5). Once again, these results suggest that participants correctly accounted for changes in the performance accuracy and response-related uncertainty when monitoring different aspects of their performance over a series of trials.

The cueing condition modulated the effect of the participants' actual accuracy on the report of their mean response: the increase of the distance between the reported mean response and the

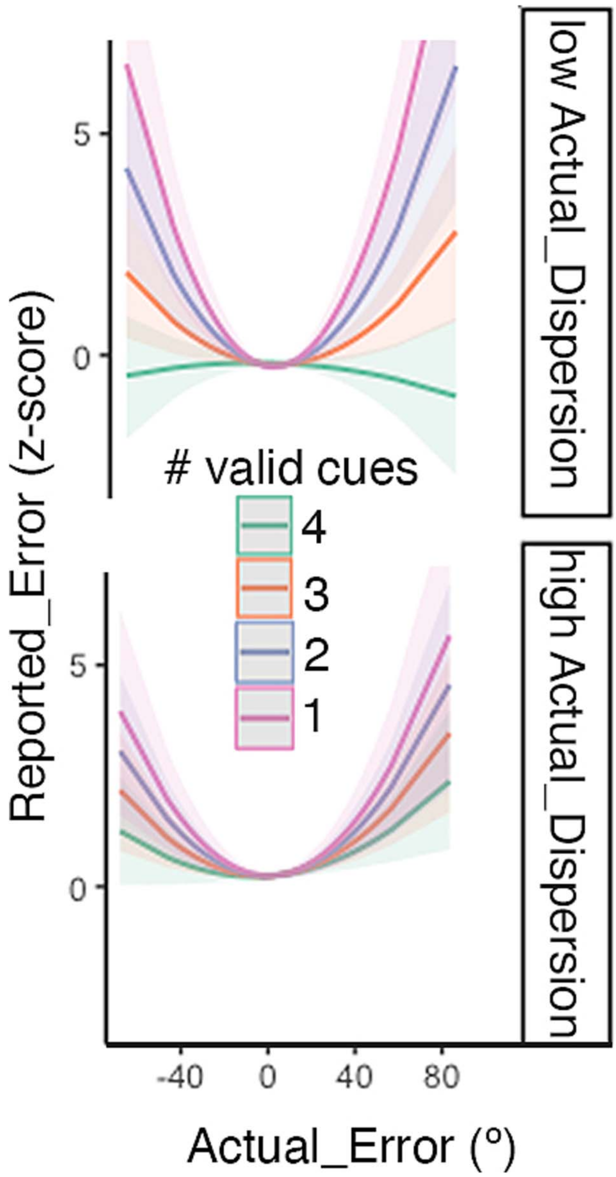

Figure 7. Variations in the reported mean response depending on the actual mean performance, the response-related uncertainty, and the cueing condition. For illustrative purposes, we divided the sets into two levels of absolute values of *Actual_Error* (gray: high mean error, yellow: low mean error on the set) and two levels of *Actual_Dispersion* (higher panel: low response-related uncertainty, lower panel: high response-related uncertainty, i.e. more variable responses with a set). The regression model predicted that *Reported_Error* increased when the actual performance on the set worsened (increasing *Actual_Error^2*) especially when participants were distracted by invalid cues. This effect of cueing was less pronounced in high response-related uncertainty sets (increasing *Actual_Dispersion*, low panel). The posterior plot can be found in Supplementary Fig. S9.

target orientation on a set with the actual mean error on this set changed with the proportion of invalid cues in a set (*Actual_Error^2* × *Cueing*: M = 4.70, 95% CI = [2.01, 7.45], BF10 > 5; *Actual_Error^2* × *Actual_Dispersion* × *Cueing*: M = −2.40, 95% CI = [−3.66, −1.13], BF10 > 5, Fig. 7). More specifically, the reported mean response diverged more from the target orientation with lower set accuracy, especially under low attentional focus; this effect of reduced attention toward the stimulus was less pronounced with increasing response-related uncertainty. Thus, uncertainty induced by attentional cueing appears to be taken into account in the participants' global reports. However, the capacity to monitor global performance decreases when different sources of uncertainty (response-related and attentional) are combined.

Finally, we examined the relation between the confidence area angle and the error between the reported mean orientation and the target orientation (M2_extended, Supplementary Table S7; Supplementary Fig. S9 and S10). The regression revealed one triple and one quadruple interaction (*Reported_Error* × *Actual_Error^2* × *Actual_Dispersion*; *Reported_Error* × *Actual_Error^2* × *Actual_Dispersion* × *Cueing*; Fig. 7), showing that the adjustment of the confidence area angle to the error between the reported mean orientation and the target orientation decreased when the first-order performance accuracy decreased (bigger actual mean error)and/or when the uncertainty increased (higher response variability or decreased attentional focus). Very simply put, this shows that participant's two metacognitive reports were less correlated with increasing mean error on a set, and with increasing attentional demands.

Discussion

We investigated how first-order accuracy and uncertainty contribute to mesoscopic performance monitoring, a global level of metacognition above local, trial-based metacognition but below the task level. Participants completed four trials of an orientation matching task and then reported their perceived mean response and the dispersion of their responses around this mean. This allowed us to assess the impact of first-order accuracy, response-related uncertainty (variability in responses), and perceptual and attentional uncertainty (stimulus-dependent sensory noise and attentional focus) on performance monitoring beyond single-trial assessment. Response-related uncertainty was estimated from the variability of first-order responses across the four repetitions of the orientation task. Perceptual uncertainty was manipulated by the amount of stimulus-dependent sensory noise affecting the stimuli in Experiment 1, while attentional uncertainty was manipulated through exogenous cueing in Experiment 2.

Our approach focuses on a global monitoring process anchored in a perceptual task (i.e. information-based metacognition, Koriat 2007). This type of metacognition is deliberate, reflective, and critical in conscious decision-making and problem-solving. It allows individuals to evaluate their cognitive processes with a focus on the content and quality of the information they have, rather than on their gut feelings or intuition, thus the present study's scope is positioned at a lower conceptual level than global self-performance beliefs. More specifically, the collected variables in the present study are about monitoring performance. Hence, the present task targets a metacognitive ability. Moreover, the reported dispersion area response was explicitly presented to the participant as a confidence area, i.e. a zone in which they felt confident their responses landed; thus, this task offers an opportunity to connect global performance monitoring and confidence. Only a handful of recent studies have explored the metacognitive evaluation of a series of events (Lee et al. 2021) and tasks (Rouault et al. 2019).

We found that participants used both the average and dispersion of their first-order performance to monitor their global performance. Lower response-related uncertainty (lower participant response variability) resulted in a steeper alteration of metacognitive judgments by first-order accuracy. Other sources of uncertainty also modulated the relationship between global metacognitive judgments and first-order performance. Higher stimulus-dependent uncertainty weakened the relationship between metacognitive reports and first-order response variability. Additionally, increased attention-related uncertainty from more invalid cues also affected global metacognitive judgments: participants correctly accounted for increased task difficulty with the proportion of invalid cueing when monitoring their global mean performance, but this effect was less pronounced when the participants' responses were more variable. These results highlight two key points: First, participants reliably estimated their mean performance and variability, and used it together with perceptual or attentional uncertainty to inform their global performance monitoring. Second, this capacity decreases when several sources of uncertainty increase concomitantly.

Our study builds on existing literature that emphasizes the role of uncertainty in local metacognitive judgments (Denison et al. 2018, Mole et al. 2018, Honig et al. 2020, Atiya et al. 2021, Rahnev 2021, Geurts et al. 2022). We extend these findings to global performance monitoring over multiple trials. Previous research shows that people can extract summary statistics from stimuli (de Gardelle and Summerfield 2011, Locke et al. 2020, Ji and Hayward 2021). Our study demonstrates that they can also use such statistics about their own performance, in addition to perceptual uncertainty, for global performance self-evaluation. Moreover, we also found that attention-related uncertainty influenced global performance self-evaluation, consistent with recent studies on local metacognitive judgments using similar spatial cueing methods (Denison et al. 2018, Recht et al. 2022). The mechanisms connecting attention to variation in overall uncertainty are still not fully defined (Carrasco 2011) and will deserve further investigation.

Interestingly, when uncertainty increased, such as with noisy (oblique orientation) or unattended stimuli (invalid cues), the increased variability in first-order responses led to a reduced calibration of global metacognitive judgments. This effect indicates a form of metacognitive inefficiency, i.e. a failure to accurately monitor behavior. Identifying and understanding the emergence of metacognitive inefficiency is a key research goal in metacognition (Shekhar and Rahnev 2021, Rahnev et al. 2022). Our study suggests that metacognitive inefficiency may arise when uncertainty becomes too high or when different sources of uncertainty are to be combined. Future work based on the present paradigm could benefit from its specificities: subjective dispersion/precision reports can be directly mapped onto objective performance. Thus, the participants' ability to correctly monitor different sources of uncertainty could be finely quantified (under- or overestimation). Approaches like ours are thus relevant to further investigate this open question of the source of suboptimality and inefficiency at the metacognitive level.

The current global performance monitoring results resonate with a recent study highlighting how stimulus-dependent and response-related uncertainty shaped local confidence according to Bayesian principles (Geurts et al. 2022). Future work using our task while collecting both local and global metacognitive judgments would be able to investigate the mechanisms governing the contribution of uncertainty to global metacognitive judgments. In particular, two main alternatives are possible: First-order performance and uncertainty may influence the global metacognitive estimates either directly or indirectly by influencing only local metacognitive estimates that are then combined to form global estimates. While this experiment was not designed to test these two possible models, we nevertheless conducted exploratory analyses by leveraging a model developed by Geurts et al. (2022). This Bayesian model suggested that participants adjust their confidence level to their performance in a single orientation matching trial. We adapted this model to the current paradigm to simulate a local confidence report for each of the four individual trials composing a set in our task.

We defined local confidence as a function of the expected magnitude of the error in the observer's response in the orientation task and the different types of noise (sensory, non-sensory, and response noise, see SI and Geurts et al. 2022). We then considered two approaches for a participant to generate a report of a confidence area for their global performance, i.e. the reported response dispersion (*Reported_Dispersion*, Supplementary Fig. S5). The first approach was to average the four local confidence estimates as defined above and to sample the reported response dispersion from a distribution centered on this average corrupted by a Gaussian metacognitive noise including response-related (*Actual_Dispersion*) and perceptual (stimulus-related) noise. This approach represents an indirect contribution of first-order performance on global metacognition via the use of local confidence. The second approach to define the reported response dispersion did not rely on local estimates but instead on the perceived magnitude of mean error in the observer's global performance (*Reported_Error*). This approach represents a direct contribution of first-order performance on global metacognition, irrespective of local confidence. We arbitrated between these two approaches according to the similarity between the simulated and observed values of the reported response dispersion. To do so, the same statistical model used on the observed *Reported_Dispersion* was applied to the simulated ones (M2_extended). This regression on the simulated *Reported_Dispersion* obtained with the first approach, i.e. from a combination of the local confidence following each isolated trial, did not reveal any influence of our variables of interest apart from the stimulus orientation. However, using simulated *Reported_Dispersion* obtained with the second approach revealed results similar to the one we obtained on collected data, namely that global confidence depended both on perceptual and response-related forms of uncertainty. The detailed simulation procedure and corresponding results can be found in the Supplementary Materials (Fig S5 and S6, Table S5). These simulations hint toward a heuristic behavior in our task: Instead of tracking their local performance and corresponding local confidence, observers used local performance estimates to directly compute their mean performance and used the latter to estimate global confidence levels. This hypothesis could be tested in a future experiment in which both local and global confidence estimates are collected. Another relevant future development could be to assess to what extent the choice to present only four target orientations might have impacted our results. Indeed, participants could have guessed that only cardinal and oblique orientation were presented and use a generic oblique or cardinal orientation to produce their responses. This is unlikely since the results showed that participants' performance (error and variability) impacted the "average" report they provided. Regardless, the fact that we used only four targets may have helped participants reduce the range of possible answers. This would be a general effect reducing the first-order error on a trial basis but should not impact our main results about the contributing factors to the global metacognitive reports. More target orientations could be used to explore this aspect of the results.

As mentioned before, continuous tasks, like ours, are ideally suited to quantifying local and global metacognitive judgments' formation as functions of uncertainty. To the best of our knowledge, only two studies have directly examined how global judgments derive from local confidence estimates in healthy adults (Rouault et al. 2019, Lee et al. 2021). Both studies used binary decisions as metacognitive reports, i.e. participants had to choose between two sets of trials of the same task (Lee et al. 2021) or two tasks (Rouault et al. 2019) the one for which they performed better. In both studies, global metacognitive judgments appeared to integrate information across multiple perceptual decisions and to be formed from local confidence reports. However, these studies disagree on whether each local estimate contributes equally to global metacognition (unlike Rouault et al., Lee et al. found a recency effect on global confidence) and on which components of first-order performance contribute to global metacognitive judgments (accuracy, response time, number of events to be considered).

Our study examined two global dependent variables, capturing distinct aspects of performance monitoring. Results revealed that these two variables were not independent. Participants' ability to track overall accuracy (*Reported_Error*) influenced their monitoring of overall precision (*Reported_Dispersion*). Plus, the correlation between these two metacognitive reports also depended on first-order performance accuracy and uncertainty levels. These latter results also suggested once again a weakening of the calibration mechanisms for global performance precision monitoring when both response-related and exogenous uncertainty increased. While it may seem that the reported dispersion reflects metacognitive uncertainty around the global performance mean, our findings indicate that performance dispersion monitoring is influenced by first-order performance. Therefore, it does not solely reflect metacognitive uncertainty (i.e. noise independent from first-order processes). Future work is needed to probe further the mechanisms linking different aspects of performance monitoring and global metacognitive judgments.

Another consideration is the part of perceptual averaging in the task the participant performed. Our paradigm involves an averaging task; however, it is not a case of averaging external stimuli (as found, for example, in de Gardelle and Summerfield 2011), but of one's own responses, which makes it a metacognitive, performance monitoring task. One result in support to this point is the meaningful influence of the actual dispersion of the participants responses on the participants' reports: if the participants were to average their individual responses, simply cumulating individual bar orientations visible on the screen, then only the arithmetical mean of these orientations would be relevant, not the dispersion of the responses. Moreover, the actual dispersion impacted the reported dispersion even once the contribution of the absolute value of the difference between the reported mean performance and the target orientation on a set of four trials is accounted for (M2_Extended model). This latter result suggests that participants were able to extract information about the precision of their responses regardless of the specific orientation that was to be reproduced. This capacity to assess the precision of one's behavior is a key aspect of metacognition (Constant et al. 2022). Thus, we argue that when participants report our DVs, they produce a metacognitive operation that goes beyond a simple perceptual averaging.

Finally, in regards to the connection between local and global metacognition, we emphasize once again a key feature of our approach: By asking participants to monitor their performance across four trials on a continuous orientation task, we focus on a metacognitive process that is more global than classical metacognitive judgments reported about an isolated event or task; yet these collected metacognitive estimates are still anchored in a perceptual task and are to be considered at a lower conceptual level than global beliefs about self-performance (i.e. information-based metacognition, Koriat 2007). This level of metacognition can be discussed in the framework proposed by Seow et al. (2021). Their theoretical model organizes metacognitive evaluation in a hierarchical manner from local to global metacognition. The level targeted by our task is above local, trial-based metacognition but below the task level. We thus consider our results pertain to global metacognition, but a more fine-grained qualifier could be mesoscopic metacognition.

Thus, our study presents a method to examine the relationship between local and global metacognitive judgments. Moreover, tasks such as the present one are also useful to finely quantify metacognition with greater ecological validity than those where confidence follows a single discrimination judgment, since we are more likely to evaluate our global performance after several repetitions of the same task in daily life rather than making a judgment on a visual scale following a single forced choice. We also asked participants not only for a point estimate of their performance but also for a range around it, stepping away from the classical reports of confidence. The need for such new paradigms aiming to expand both the scale and the scope of metacognitive reports has been highlighted as useful for future metacognitive neuroscience (Rahnev et al. 2022, Katyal and Fleming 2024).

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Author contributions

Marie Chancel (Conceptualization [equal], Data curation, Formal analysis, Methodology, Writing—original draft [lead]), Elisa Filevich (Conceptualization, Writing—review & editing [equal]), and Nathan Faivre (Conceptualization [equal], Funding acquisition, Supervision [lead], Writing—review & editing [equal])

Supplementary data

Supplementary data is available at *Neuroscience of Consciousness* online.

Conflict of interest

None declared.

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Data availability

Data and custom scripts are available on https://gitlab.com/nfaivre/meta_angle_public.

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