Controllability reveals defining features of information seeking

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Summary

In uncertain environments, seeking information about alternative choice options is essential for adaptive learning and decision-making. However, information seeking is usually confounded with changes-of-mind about the reliability of the preferred option. Here, we exploited the fact that information seeking requires control over which option to sample to isolate its behavioral and neurophysiological signatures. We found that changes-of-mind occurring with control require more evidence against the current option, are associated with reduced confidence, but are nevertheless more likely to be confirmed on the next decision. Multimodal neurophysiological recordings showed that these changes-of-mind are preceded by stronger activation of the dorsal attention network in magnetoencephalography (MEG), and followed by increased pupil-linked arousal during the presentation of decision outcomes. Together, these findings indicate that information seeking increases the saliency of evidence perceived as the direct consequence of one's own actions.

Highlights

- Exploration-exploitation dilemmas confound information seeking with changes-of-mind.
- Unlike changes-of-mind, information seeking requires control over information sampling.
- Information seeking is associated with reduced confidence and active hypothesis testing.
- Stronger neurophysiological correlates of attention and arousal during information seeking.

Introduction

The ability to form and revise uncertain beliefs through information sampling is a hallmark of human cognition. This inference process has been extensively studied using two main classes of decision tasks (Bartolo and Averbeck, 2021; Wyart and Koechlin, 2016). In passive sampling tasks, participants are observers who sample information over which they have no instrumental control (Murphy et al., 2016; van den Berg et al., 2016; Zylberberg et al., 2018). This is the case in most perceptual decision tasks, in which the experimenter controls the sensory information provided to participants (for reviews, see (Gold and Shadlen, 2007; Hanks and Summerfield, 2017)). Outside the laboratory, for example, one might see an ad for a new movie at a bus stop. By contrast, active sampling tasks let participants choose which source of information to sample from (Charpentier et al., 2018; Gureckis and Markant, 2012; Markant and Gureckis, 2014). In these situations, the information provided to participants corresponds to the outcome of their own choices. Using the same example, one can alternatively browse the web for information about new movies. Critically, unlike passive sampling, active sampling provides participants with control over which source of information to sample from, even if the information itself (about the new movie) can be exactly the same in both cases.

In both passive and active sampling tasks, recent work has assigned a key role for confidence in the formation and revision of uncertain beliefs (Meyniel et al., 2015; Nassar et al., 2010; Rouault et al., 2019; Sarafyazd and Jazayeri, 2019). Low confidence in current beliefs has been shown to predict changes-of-mind (Balsdon et al., 2020; Folke et al., 2016), and allows for the flexible adaptation of behavioral strategies even when external feedback is unavailable (Desender et al., 2018; 2019; Fleming et al., 2018; Rollwage et al., 2020). But besides this pervasive role of confidence in belief updating, the control conferred by active sampling allows to seek information about alternative strategies, a cognitive process that is by definition not possible in the absence of control over information sampling. Information seeking has been mostly studied using 'exploration-exploitation' dilemmas (Costa et al., 2019; Daw et al., 2006), where it is confounded with changes-of-mind about the reliability of the current behavioral strategy.

Here, to isolate the specific signatures of information seeking, we contrasted changes-of-mind occurring with and without control over information sampling. We employed an adaptive decision-making task that allows comparing the formation and revision of uncertain beliefs between controllable and uncontrollable conditions (Fig. 1). We found that participants need more evidence against their current beliefs to change their behavior in the controllable condition, and that they do so with decreased confidence. Nevertheless, participants are more likely to probe again their new behavioral strategy on the next decision, even in the absence of objective evidence supporting this new strategy – a form of active 'hypothesis testing' (Markant and Gureckis, 2014). Using computational modelling (Glaze et al., 2015; Weiss et al., 2021), we show

that controllability increases the stability of participants' beliefs, a mechanism that explains the observed behavioral correlates of information seeking. At the physiological level, changes-of-mind occurring in the controllable condition are preceded by stronger suppression of neuromagnetic alpha-band activity in the dorsal attention network, and followed by increased pupil-linked arousal during the presentation of decision outcomes. Taken together, these features suggest that information seeking increases the saliency of information that is perceived as the direct consequence of one's own actions.

Results

Experimental paradigm

To examine the cognitive signatures of information seeking in controllable environments, we asked human participants to perform an adaptive decision-making task consisting of two tightly matched conditions which only vary in the degree of control over information sampling bestowed to participants (Weiss et al., 2021). Participants were presented with visual sequences of oriented stimuli drawn from either of two categories (blue or orange) associated with distinct but overlapping probability distributions over orientation (Fig. 1A; see Methods). At the end of each sequence, participants were asked to provide a response regarding the current hidden state of the task, together with a binary confidence estimate in their response (high or low confidence) using four response keys (Fig. 1B).

In the uncontrollable (cue-based, Cb) condition, participants were asked to monitor the category from which stimuli were drawn, and to report this category at the end of each sequence. By contrast, in the controllable (outcome-based, Ob) condition, the same participants were asked to draw stimuli from either of the two categories. In this Ob condition, the two response keys from one hand were associated with a draw of stimuli from the target category, whereas the other two response keys were associated with a draw from the other (non-target) category (Fig. 1B). In the cue-based condition, the drawn category reversed unpredictably, requiring participants to adapt their responses to these changes (Fig. 1D). By contrast, in the outcome-based condition, it is the association between response keys and categories which reversed unpredictably, also requiring participants to adapt their responses to these changes. By design, the only difference between conditions is the degree of instrumental control bestowed to participants over the sampling of stimuli. Participants were observers monitoring the external source of stimuli in the Cb (uncontrollable) condition, whereas participants were agents sampling stimuli through their actions in the Ob (controllable) condition (Fig. 1C).

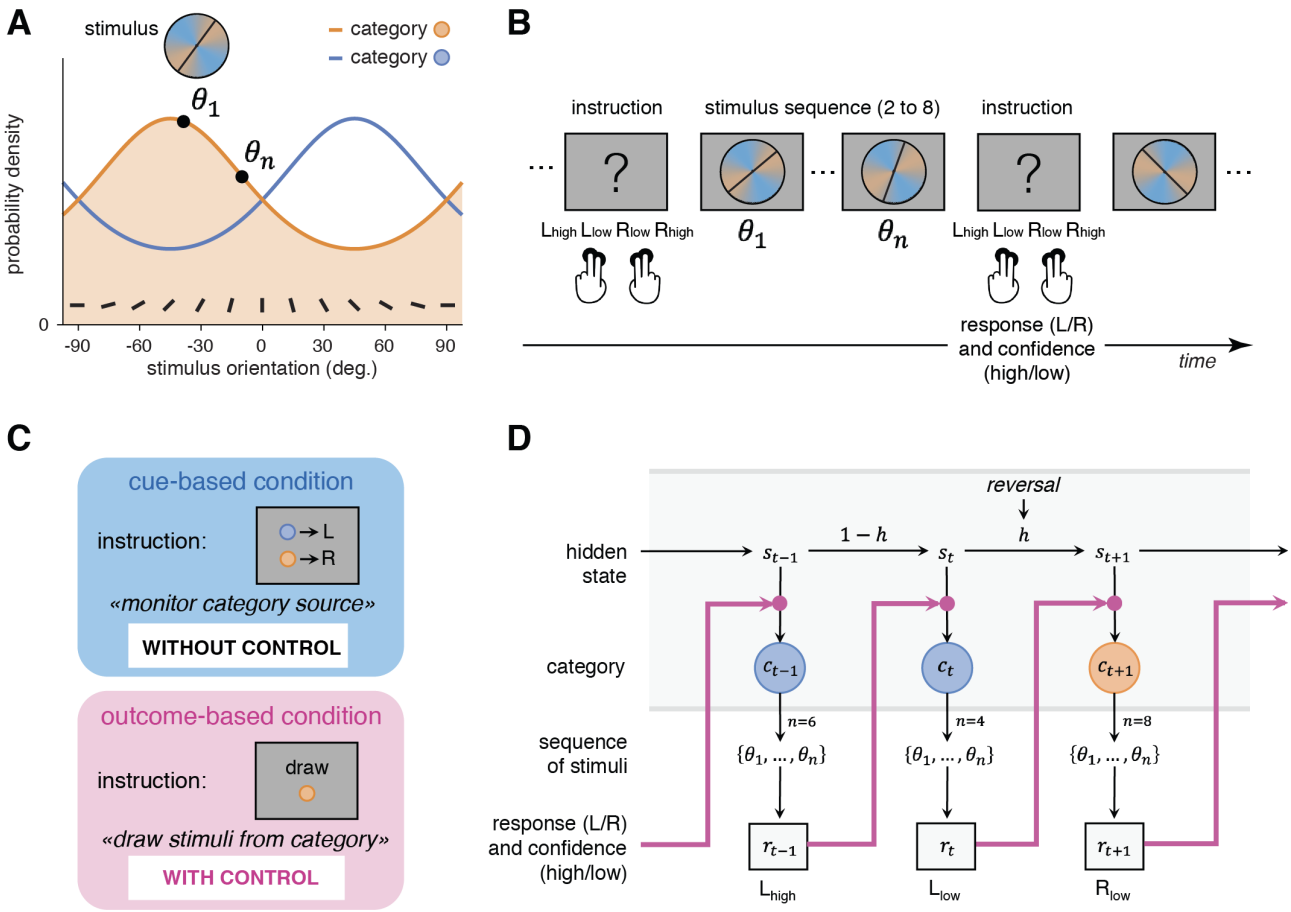

Figure 1. Experimental paradigm probing changes-of-mind across two controllability conditions
A) Stimuli were oriented bars drawn from either of two categories (orange and blue). The generative probability distributions of drawn orientation for each category are depicted. The two category means are orthogonal to each other. **B**) On each trial, participants were presented with sequences of 2 to 8 stimuli drawn from either color category, and were asked to indicate their response and the associated confidence (high, low) using four response keys. Confidence keys (low, high) were assigned to the inner and outer keys of each choice. **C**) Participants underwent two experimental conditions that varied only in the degree of control over stimuli. In the cue-based condition (blue), observers were asked to monitor the category from which stimuli were drawn. In the outcome-based condition (pink), agents were asked to select an action that will produce stimuli from either category. The evidence available for each choice, but also all stimulus and response properties of the task were tightly matched across conditions (see Methods). **D**) Graphical description of the task structure. The hidden state reversed unpredictably after a pseudo-random number of trials. In the cue-based condition, the category drawn at trial *t* only depends on the hidden state s_t. In the outcome-based condition, the category drawn at trial *t* depends on both the hidden state s_t and the previous response r_{t-1}, as indicated by pink arrows.

Psychometric analyses of choice and confidence

By examining differences between conditions, we first established that participants adapted their behavior after a reversal to select the response corresponding to the new hidden state (Fig. 2A). We found that participants were slower to adapt in the Ob condition, with psychometric fits indicating a higher reversal time constant in this controllable condition (t_{32}=5.0, p=1.95×10^{-5}; see Methods). Participants also reached a higher asymptotic reversal rate in the Ob condition (t_{32}=6.3, p=4.0×10^{-7}; Fig. 2B and Supplementary Results), replicating earlier findings (Weiss et al., 2021).

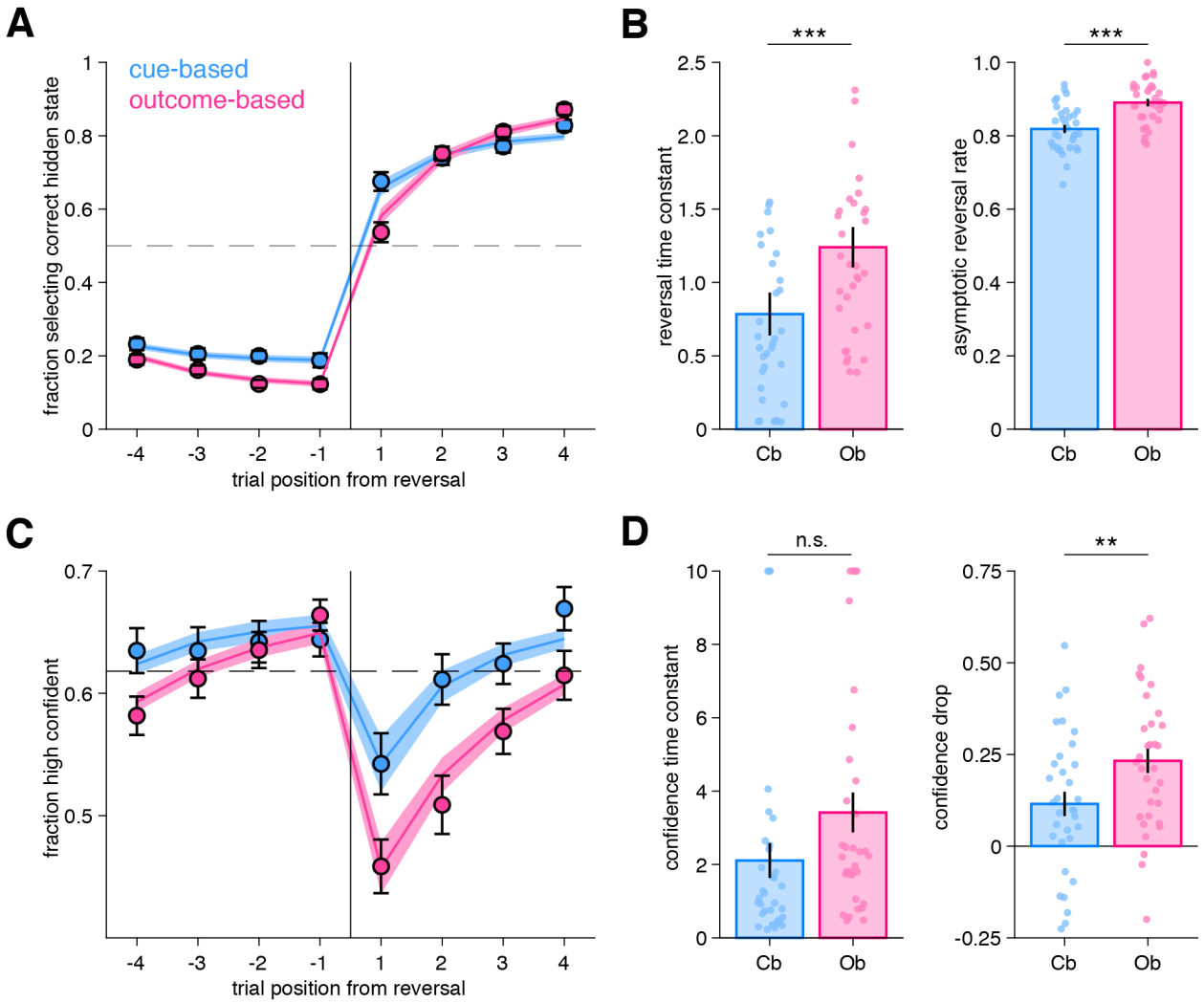

Figure 2. Behavioral reversal curves characterizing participants' responses and their confidence in cue-based and outcome-based conditions.
A) Fraction of hidden state correctly reported as a function of trial number before and after a reversal. Vertical lines indicate the position of reversals. Horizontal dotted lines indicate chance level. Circles and error bars indicate mean and SEM across participants (*N*=33). Shaded areas indicate mean and SEM of psychometric predictions from the best-fitting truncated exponential functions. **B**) Psychometric parameters 'reversal time constant' and 'asymptotic reversal rate' characterizing the fitted response reversal curve in A (see Methods). Circles indicate individual participants and bars and error bars indicate the mean and SEM across participants. ***p<.001, paired t-tests. **C**) Fraction of high confidence responses as a function of trial number before and after a reversal. Horizontal dotted lines indicate mean confidence. Circles and error bars indicate mean and SEM across participants (*N*=33). Shaded areas indicate mean and SEM of psychometric predictions from the best-fitting sigmoid functions. **D**) Psychometric parameters 'confidence time constant' and 'confidence drop' for the fitted confidence reversal curve in B (see Methods). Circles indicate individual participants and bars and error bars indicate the mean and SEM across participants. **p<.01, n.s. not significant, paired t-tests.

As expected, participants' confidence decreased after a reversal in both conditions (Fig. 2C). However, confidence decreased more sharply in the Ob (Fig. 2D), an observation confirmed by psychometric fits of a confidence 'drop' parameter (t_{32}=3.59, p=.0011; see Methods). In addition, the confidence time constant characterizing the slope of confidence increase after a reversal was different across conditions (paired t-test, t_{32}=-1.9, p=.064; sign-rank test, z=-2.65, p=.008), indicating that in the Ob condition, participants reached a higher asymptotic performance

(Fig. 2D). Together, these findings indicate that participants adapted their behavior more slowly and their confidence dropped more strongly in the Ob, controllable condition (Fig. 2).

To better understand these differences, we re-analyzed participants' choices and confidence as a function of the objective evidence available in favor of repeating their previous choice ("consistent evidence") vs. switching away from their previous choice ("inconsistent evidence"; Fig. 3). In both conditions, we found that the stronger the consistent evidence, the more often participants repeated their previous choice (Fig. 3A). Crucially, psychometric fits revealed a difference in the point of subjective equivalence (choice-PSE) between conditions (t_{32}=-7.83, p=6.2×10^{-9}; Fig. 3B). The choice-PSE parameter reflects the amount of evidence required for a participant to switch away from their previous choice more often than repeat it. This difference means that participants needed more evidence against their previous decision for switching in the Ob condition. In contrast, participants were equally sensitive to the available objective evidence across conditions (t_{32}=1.09, p=.28; Fig. 3B).

We analyzed confidence reports using the same procedure. As expected, confidence increased with the strength of consistent evidence in both conditions (Fig. 3C). By contrast, participants were considerably less confident in their choices following inconsistent evidence in the Ob condition (Fig. 3C). To quantify these effects, we fitted two sigmoid functions to switch and repeat choices separately, each sigmoid being characterized by an offset and a slope (see Methods). Based on these fits, we estimated the quantity of evidence for which confidence is equal for repeat and switch decisions (confidence-PSE, Fig. 3C). We found a significant confidence-PSE difference between conditions (Wilcoxon signed rank test, z=-2.89, p=.0038; Fig. 3D), indicating participants needed more inconsistent evidence to be equally confident in switch and repeat decisions in the Ob condition. We also found that the sensitivity of confidence reports to evidence (slope) was smaller in the Ob than in the Cb condition on switch decisions (t_{32}=5.1, p=1.6×10^{-5}; Fig. 3D).

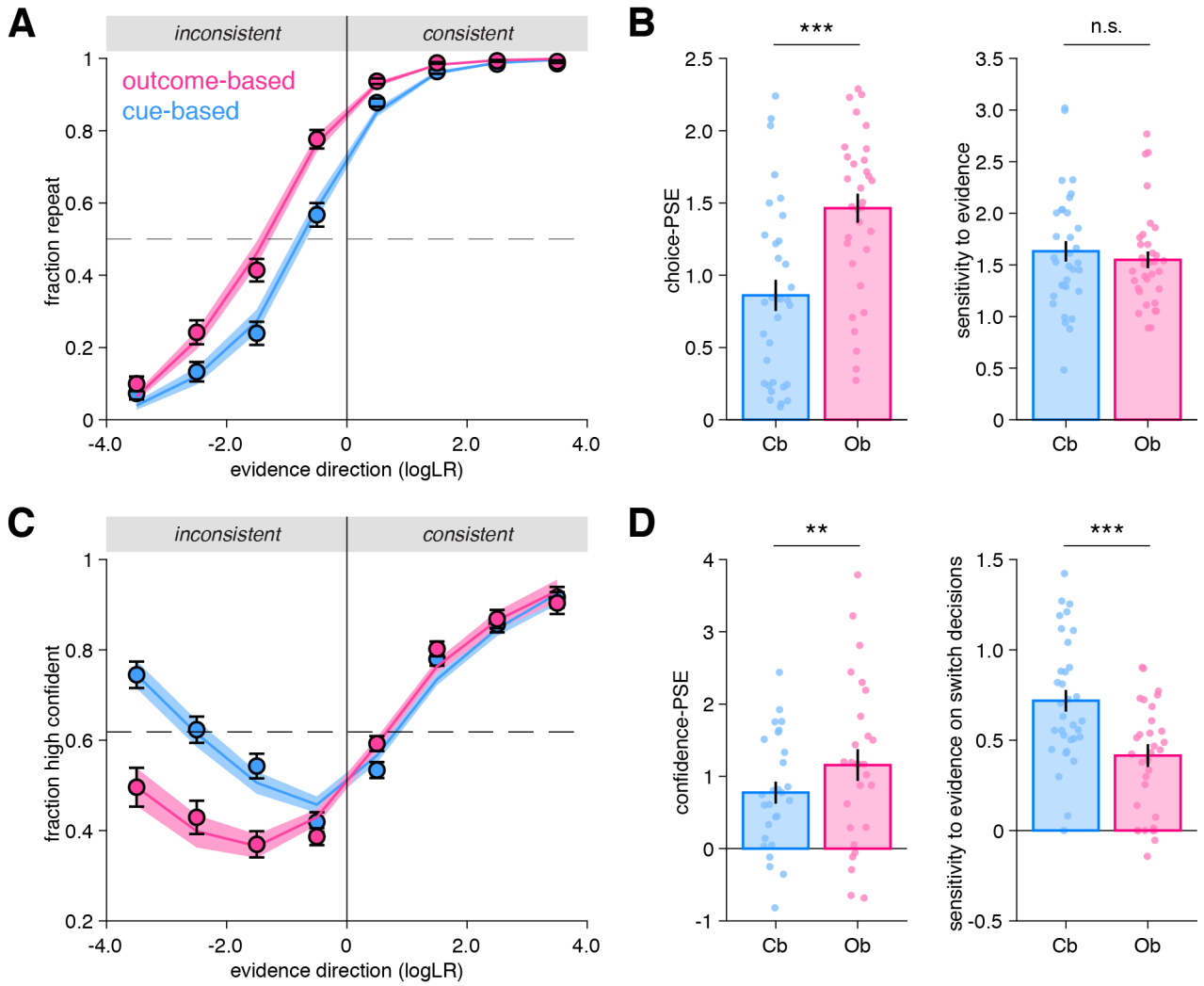

Figure 3. Behavioral repetition curves characterizing participants' responses and their confidence. **A**) Fraction of response repetitions as a function of whether the evidence was consistent (in favor of repeating) or inconsistent with the previous choice. Circles indicate human data (*N*=33) and error bars display SEM across participants. Shaded areas indicate mean and SEM of psychometric predictions from the best-fitting truncated exponential functions (see Methods). **B**) Psychometric parameters 'point of subjective equivalence' (choice-PSE) and 'sensitivity to evidence' (slope) characterizing the response repetition curves in A. ***p<.001, n.s. not significant, paired t-tests. **C**) Fraction of high confidence responses as a function of whether the evidence was consistent or inconsistent with the previous choice. Circles indicate human data (*N*=33) and error bars display within-participant SEM Within-participant error bars are represented to allow a comparison between conditions without an influence of inter-individual variability about the use and calibration of the high and low confidence responses. Shaded areas indicate mean and SEM of psychometric predictions from the best-fitting mixture of two sigmoid functions for repeat and switch trials respectively (see Methods). **D**) Psychometric parameters characterizing the confidence repetition curves in C. Left panel: 'confidence-PSE' (point of subjective equivalence) representing the quantity of evidence for which participants are as confident in their repeat decisions as in their switch decisions. **p<.01, Wilcoxon signed rank test (see Methods). Right panel: 'sensitivity to evidence' for the switch trials. ***p<.001, paired t-test. Circles indicate individual participants and bars and error bars indicate the mean and SEM across participants. In all panels, cue-based (Cb) condition is in blue and outcome-based (Ob) condition in pink.

Ruling out alternative accounts of differences between conditions

Although the degree of control over information sampling is the key difference between conditions, we sought to examine two alternative interpretations for this difference. First, we examined whether the temporal direction of inference could explain the observed differences between conditions: prospective in the Ob condition (by predicting which key would draw from the target category on the next trial), and retrospective in the Cb condition (by identifying the category of the last sequence of stimuli) in a new Experiment 3 (see Methods). Participants were now asked to guess which category the computer *drew* from when they saw the sequence of stimuli (retrospective condition), or to guess which category the computer *will draw* from based on what they saw (prospective condition). Neither condition conferred any control to participants. We found no difference in confidence drop (t_{24}=.89, p=.38), and no difference in the sensitivity to evidence parameter on switch decisions (t_{24}=0.95, p=.35), in contrast to the original conditions of Experiments 1 and 2A (Fig. S1 and Supplementary Results). These results provide evidence that the differences between the original Cb and Ob conditions were not due to a retrospective or prospective temporal orientation, and suggest instead differences due to the degree of control over evidence sampling.

Second, we examined whether the maintenance of a constant (fixed) category goal across trials was critical for participants to experience a different degree of control between conditions (Experiment 2B). We created a condition in which the instructions (which category to draw from in the Ob condition, which category/action mapping to use in the Cb condition) changed on a trial basis, instead of on a block basis (see Methods). We found that confidence on trials with inconsistent evidence was less different between conditions (Fig. S4), and the confidence increase after a reversal was similar across conditions (t_{17}=-1.01, p=.33), in line with Experiments 1 and 2B. Moreover, there was a difference in PSE between conditions (t_{17}=-6.4, p=6.4×10^{-6}), revealing that participants needed more evidence to change their mind in the Ob condition, again in line with Experiments 1 and 2A (Fig. S4 and Supplementary Results).

Separable effects of confidence and controllability on changes-of-mind

We have seen that participants changed their mind less often in the Ob condition. Following a switch decision, we found that participants were generally less confident when they switched than when they repeated their previous response (main effect of RESPONSE TYPE, $F_{1,32}$=55.8, p=1.7×10^{-8}), and were also less confident in the Ob as compared to the Cb condition (main effect of CONDITION, $F_{1,32}$=17.9, p=.00018; Fig. 4A). We further identified a significant interaction between RESPONSE TYPE and CONDITION ($F_{1,32}$=18.9, p=.00014), indicating a more pronounced decrease in confidence on switch decisions in the Ob as compared to the Cb condition.

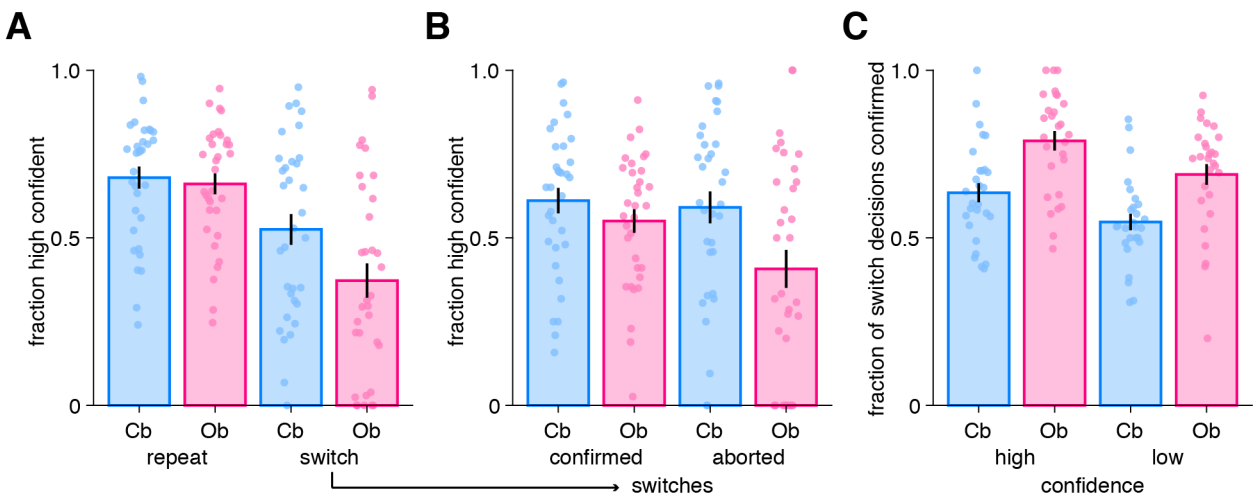

Figure 4. A role for confidence in changes-of-mind
A) Fraction of high confidence responses as a function of whether participants repeated their previous choice ("repeat") or changed their mind ("switch") in the cue-based (Cb, blue) and outcome-based (Ob, pink) conditions. **B**) Fraction of high confidence responses following switch decisions that were confirmed or aborted i.e. when participants return back to their previous response in the two conditions. Bars and error bars indicate mean and SEM across participants and circles indicate individual data points (*N*=33). **C**) Fraction of switch decisions confirmed on the next trial (see Methods) as a function of whether the change-of-mind was performed with high or low confidence, for each condition. Bars and error bars indicate mean and SEM across participants (*N*=28, due to some participants not exhibiting all types of responses (see Methods); note that jackknifed statistics with all 33 participants provided virtually identical results).

After changing their mind, participants could either confirm their category choice on the next trial ("confirmed" switch), or return back to the category selected before the switch occurred ("aborted" switch). We found that after a switch decision, participants were less willing to go back to their previous response in the Ob condition, with 72.7% of switches being confirmed, but only 58.9% in the Cb condition (t_{32}=-8.19, p=2.4×10^{-9}). This is consistent with a stronger stickiness tendency observed in the Ob condition, suggesting a reluctance to switch back and forth when participants were in control, and instead a willingness to test again their new category choice. Moreover, participants were more confident on trials in which switch decisions were confirmed as compared to aborted ($F_{1,32}$=10.3, p=.0030), and more confident in the Cb than in the Ob condition ($F_{1,32}$=20.6, p=.0001), with an interaction between these factors ($F_{1,32}$=10.7, p=.0026), due to participants' confidence decreasing on aborted switches as compared to confirmed switches in the Ob condition (Fig. 4B). When they are not in control, participants may be more flexible and switch back and forth more easily, as indicated by a similar level of confidence for switches confirmed and aborted in the Cb condition.

Similarly, we examined whether switch decisions performed with high (resp. low) confidence more often led to choices being confirmed (resp. aborted) in each condition (Fig. 4C). We found a main effect of CONFIDENCE on the fraction of switches confirmed ($F_{1,27}$=30.4, p=7.8×10^{-6}), meaning that participants confirmed their switch more often when it was made with high confidence. This suggests a causal role for confidence in controlling changes-of-mind. Switch

decisions were more often confirmed in the Ob condition ($F_{1,27}$=47.8, p=1.98×10^{-7}), consistent with a higher flexibility of responses in the Cb condition, without an interaction between CONFIDENCE and CONDITION ($F_{1,27}$=.093, p=.76). Together these findings reveal that participants (i) changed their mind less often in the Ob condition; (ii) did so with reduced confidence; (iii) were afterwards more willing to confirm a change-of-mind than returning to their previous response, as compared to the Cb condition.

Computational model with inference noise and metacognitive noise

To further characterize the mechanisms underpinning choice and confidence differences between conditions, we developed a normative Bayesian model (Fig. 5A). In line with previous work on a closely related task, we endowed it with noisy inference (Drugowitsch et al., 2016) (see Methods). We observed a similar amount of inference noise between conditions (t_{32}=1.45, p=.16), indicating that evidence was integrated equally well across conditions, in line with psychometric results (Fig. 3). We found a lower perceived hazard rate in the Ob relative to the Cb condition (t_{32}=7.46, p=1.7×10^{-8}), indicating that participants perceived the environment as less volatile when being in control (Fig. 5B).

To capture the patterns of confidence responses, we further introduced three additional parameters: a confidence threshold, a metacognitive noise, and a confidence gain associated with switch trials, all capturing unique aspects of confidence response patterns (see Methods and Fig. 5A). In line with model-free analyses indicating a difference in the fraction of high confidence responses between conditions, we found a lower confidence threshold in the Cb condition, which corresponds to more high-confident responses, as compared to the Ob condition (t_{32}=-4.3, p=1.3×10^{-4}), together with no difference in metacognitive noise (t_{32}=-0.29, p=.76), or confidence gain for switch trials (t_{32}=.10, p=.92; Fig. 5B). Using best-fitting parameters fitted to individual participants, we validated our model by simulating choice and confidence responses, and analyzed the simulated data in the same way as human data (Palminteri et al., 2017; Wilson and Collins, 2019). We show that simulations provided an accurate fit to participants' choice and confidence responses (Fig. S2). We further validated the independent role of each parameter by median-splitting the participants into groups of high and low hazard rate (Fig. S3A), high and low confidence threshold (Fig. S3B) and high and low confidence gain for switches (Fig. S3C), each of these parameters having a selective influence on choices and confidence. Even when parameters were similar across conditions (e.g. confidence gain), there was still a substantial inter-individual variability that had a visible effect on participants' confidence (Fig. S3C), indicating the necessity of each parameter in capturing qualitative signatures participants' choices and confidence. Model simulations also reproduced very well the fraction of switch decisions confirmed on the next decision and their associated confidence (Fig. 4).

We next examined whether our computational model could not only predict choice and confidence (Fig. S2), but also predict effects on the next decision. We re-fitted the psychometric choice-PSE (Fig. 3B) separately for subsamples of trials, for both human data and simulated choice data from the best-fitting parameters (see Methods). For human choices in the Cb condition, we found a higher PSE following a repeat as compared to a switch trial, indicating that more evidence was required to switch away from the current best option (t_{32}=3.2, p=.0033), whereas in the Ob condition, PSEs were similar after repeat and switch trials (t_{32}=.08, p=.93; Fig. 5C, bars). In the Cb condition, the PSE pattern predicted by the model matched human choices (t_{32}=5.4, p=7.0×10^{-6}), with a smaller PSE after a switch than after a repeat trial (Fig. 5C, squares). By contrast, in the Ob condition, the PSE pattern predicted by the model showed the same difference between repeat and switch trials (t_{32}=8.9, p=3.3×10^{-10}), unlike what was observed for human choices (interaction between DATA TYPE (human, model) and RESPONSE TYPE (after a repeat, after a switch) $F_{1,32}$=16.94, p=.000025; Fig. 5C). This deviation from model predictions indicates that participants required more evidence to switch back following a change-of-mind in the controllable Ob condition.

We further investigated whether confidence had a role in this deviation. We again fitted choice-PSEs separately for trials following a high or a low confidence response, in each condition (Fig. 5D). As expected, PSEs were lower following a low confidence response, indicating participants are more willing to change their minds after a low-confident response. Importantly, and unlike what was observed when comparing responses following repeat and switch trials, we observed a similar qualitative pattern for human and model choices (Fig. 5). This indicates that the difference in PSE following switches in the Ob condition cannot be due to the model having miscalibrated confidence, because the differences in PSE observed for human choices across confidence levels and between conditions were adequately captured (Fig. 5D and S2).

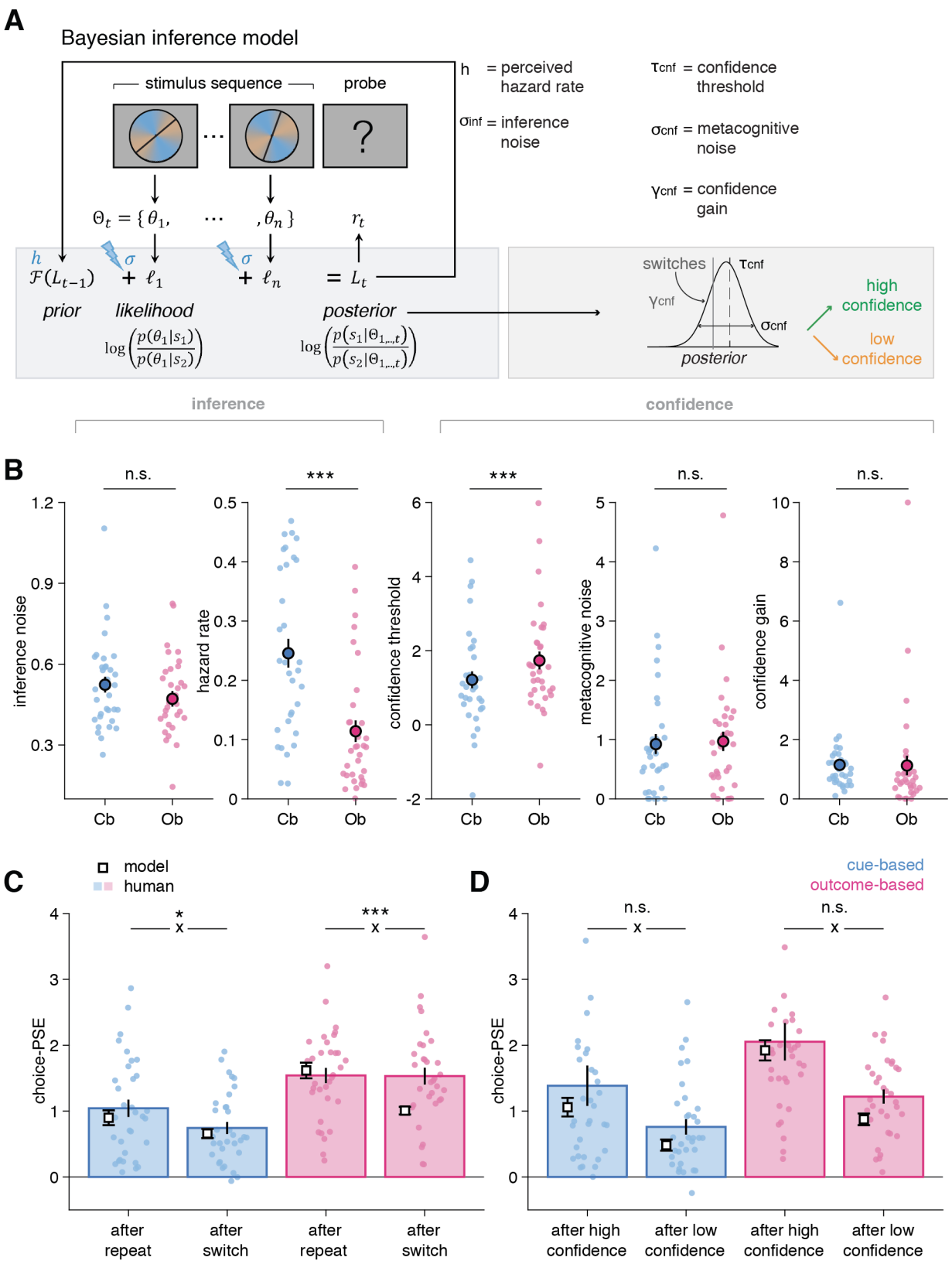

Figure 5. Bayesian normative model describing choices and confidence

A) Model schematic of computations. The model updates a belief about category from the evidence acquired through the sequence of stimuli, additionally corrupted by inference noise that scales with sequence length, and with a hazard rate controlling reversal occurrence. Based on the strength of the belief about category, responses above (resp. below) a confidence threshold are given with high (resp. low) confidence, with choices and confidence therefore being based on the same posterior belief. An imperfect readout of the posterior belief is modelled by metacognitive noise, and a confidence gain parameter selectively applied of

switch trials (see Methods). **B**) Best-fitting model parameters: inference noise, hazard rate, confidence threshold, metacognitive noise and confidence gain in the cue-based (Cb, blue) and outcome-based (Ob, pink) conditions. Circles and error bars indicate mean and SEM across participants (N=33) and small circles indicate individual parameter values. ***p<.00001, n.s., non-significant, paired t-tests. **C**) Psychometric parameter choice-PSE (point of subjective equivalence) fitted separately on trials following a repeat vs. a switch in each condition. Statistical significance is indicated for the interaction (cross) between RESPONSE TYPE (after a repeat, after a switch) and DATA TYPE (human, model). *p=.027, ***p=.000025, n.s., non-significant. **D**) Psychometric parameter Choice-PSE fitted separately on trials following a high confidence vs. a low confidence response in each condition. Small circles indicate individual data points, bars and error bars indicate mean and SEM for human data. White squares and error bars indicate mean and SEM for model simulations of different participant sessions.

Neuromagnetic signatures of information seeking during changes-of-mind

We examined whether the aforementioned features of switch decisions in the Ob condition were related to changes in cortical, subcortical and peripheral systems. First, we analyzed fluctuations in spectral power of brain signals recorded in MEG in the alpha band (Experiment 4), a frequency range known to be associated with changes in attentional and arousal systems (Corbetta and Shulman, 2002).

We computed a “repeat minus switch” contrast in the alpha-band power at [–4,+4] seconds around the response probe onset in all channels. Then, we clustered the channels according to the strength of pairwise correlations of time courses of this contrast across channels (Fig. 6A). This analysis identified two main spatial clusters of channels: an occipital cluster and a frontal cluster. Inspecting time courses of the “switch minus repeat” contrast (thereafter, “switch effect”; Fig. 6B) revealed that the switch effect occurred earlier in the occipital cluster (time from trial onset, occipital: 1.450 +/- 0.229 s, frontal: 2.099 +/- 0.243 s, jackknifed mean +/- SEM; jackknifed t_{23}=3.1, p=.005) and peaked before the response probe onset (time from probe onset, occipital: -0.393 +/- 0.028 s; jackknifed t_{23}=-14.2, p<.001). In contrast, the switch effect started later and peaked after the probe onset (+0.958 +/- 0.032 s; jackknifed t_{23}=29.6, p<.001) in the frontal cluster (Fig. 6B). The two clusters were therefore defined by two distinct time windows. The occipital switch effect was larger than the frontal effect before the response probe onset (during the sequence, peak t_{23}=6.0, cluster-level p<.001), whereas the frontal effect was larger than the occipital effect after the probe onset (during and after the response, peak t_{23}=7.5, cluster-level p<.001; Fig. 6C).

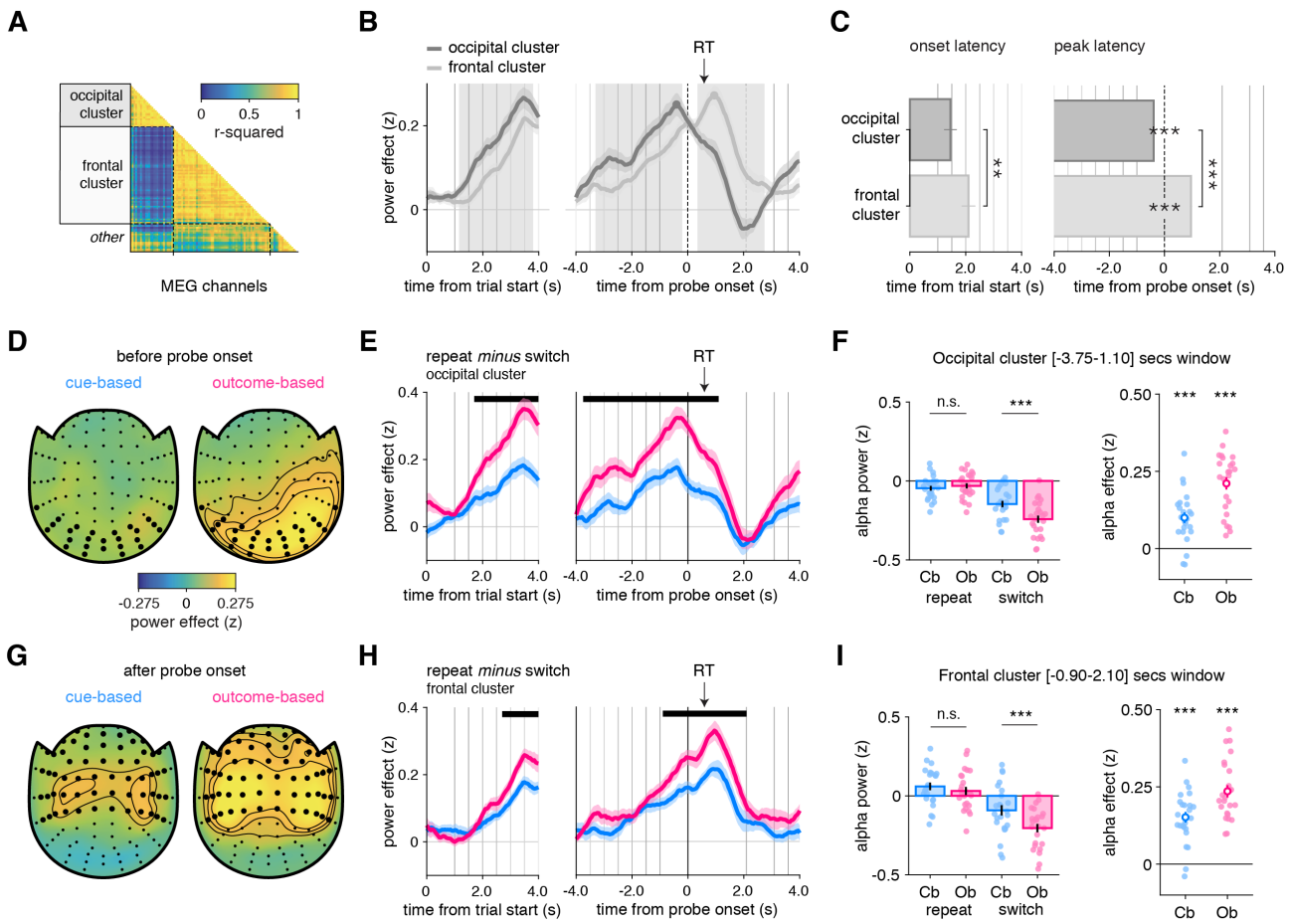

Figure 6: Alpha-band MEG as a window onto the neural basis of changes-of-mind (Experiment 4)
A) Pairwise correlation matrix of time courses of alpha-band contrast between repeat and switch trials across all MEG channels, grouped into two main clusters, labeled as occipital and frontal based on their localization. **B**) Average time course of alpha-band contrast between repeat and switch trials for the occipital (dark gray) and frontal (light gray) clusters, time-locked at trial onset (left panels) or response probe onset (right panels). Shaded areas indicate time windows (1: before probe onset, 2: after probe onset) in which time courses in the two clusters significantly differ. **C**) Left panel: onset latency of the contrast between repeat and switch trials, locked to trial onset. Right panel: peak latency of the contrast between repeat and switch trials, time-locked to response probe onset. Bars and error bars indicate jackknifed means and SEM. **D, G**) Spatial topography of the contrast between repeat and switch trials in the time window (1) before probe onset (D) and in the time window (2) after probe onset (G), in the cue-based (left) and outcome-based conditions (right). **E, H**) Contrast of repeat against switch trials in the cue-based (blue) and outcome-based (pink) conditions time-locked at the trial onset (left panels) or response probe onset (right panels). Horizontal lines indicate statistical significance at $p<.05$ corrected. Vertical lines indicate trial events: probe onset, samples of the sequence and the response probe onset. The black arrow indicates the average response time across conditions and participants. **F, I**) Left panels: stars indicate significance from an ANOVA with CONDITION (cue-based, outcome-based) and RESPONSE TYPE (repeat, switch) as within-participant factors on the time window statistically significant after correction identified in E and H respectively. Right panels: stars indicate significance for paired t-tests of the contrast between repeat and switch trials in each condition separately. *$p<.05$, **$p<.01$, ***$p<.001$. N=24 participants. See also Fig. S5 for raw effects in occipital and frontal clusters.

In the occipital cluster (Fig. 6D), the switch effect was larger in the Ob than the Cb condition (peak t_{23}=6.2, cluster-level $p<.001$), with the largest difference just before probe onset (Fig. 6E, see also Fig. S5A-B for the raw effects). We found no significant difference between conditions on

repeat trials (t_{23}=0.6, p=.528) but a significant one on switch trials (t_{23}=3.9, p<.001; interaction: $F_{1,23}$= 40.7, p<.001; Fig. 6F). The frontal cluster (Fig. 6G) featured a larger (and longer) switch effect in the Ob than the Cb condition (peak t_{23}=4.4, cluster-level p<.001), with the largest difference just after probe onset (Fig. 6H, see also Fig. S5C-D for the raw effects). As for the occipital cluster, we found no significant difference between conditions on repeat trials (t_{23}=1.1, p=.272), but a significant one on switch trials (t_{23}=4.1, p<.001; interaction: $F_{1,23}$=24.6, p<.001; Fig. 6I). Thus, in both clusters, switch decisions are driving the differences between conditions. Since previous work has identified links between motor preparation and alpha-band activity, we further sought to examine whether these switch effects were due to response preparation. For this purpose, we selected a sub-sample of channels sensitive to response-hand selectivity in the frontal cluster. We found no difference in motor lateralization between conditions at a liberal sample-wise threshold p<.05. This suggests that the effects described above are truly about changes-of-mind, not the preparation of a response switch (Fig. S6).

Pupillometric and cardiac signatures of information seeking during changes-of-mind

We analyzed pupil dilation time-locked at the trial onset and at the response probe onset (pooled over Experiments 1 and 2A; see Methods). In both conditions, pupil dilation increased slightly before, but mainly after probe onset, with a first peak around 1s after probe onset and a second peak corresponding to the next trial (see Fig. S5E-F for raw effects). To compare pupil dilation between switch and repeat trials, we compared the time courses of these two trial types in Fig. 7A), and, at each time point, performed a 2 × 2 ANOVA with RESPONSE TYPE (repeat, switch) and CONDITION (Cb, Ob) as within-participant factors. This revealed a large time window (time from probe onset, +0.16 to +5.43 s), in which the interaction between RESPONSE TYPE and CONDITION was significant (p_{corr}<.001; Fig. 7B). Within this time window, pupil dilation differed only marginally across conditions on repeat trials (t_{31}=1.96, p=.059), but was larger in the Ob than in the Cb condition on switch trials (t_{31}=-5.04, p=1.94×10^{-5}). At the trial onset, we also found a time window with a significant interaction between CONDITION and RESPONSE TYPE (time from probe onset, +3.0 to +4.0s; p_{corr}<.001; Fig. 7A).

To investigate whether the peripheral nervous system also contains specific signatures of information seeking, we examined the cardiac interbeat interval (IBI) from electrocardiogram (ECG) signals recorded in Experiment 4. In both conditions, the IBI increased before probe onset, and slowly decreased thereafter (see Fig. S5G-H for raw effects), a dynamic comparable to that of the alpha-band response suppression observed in MEG. This increase was larger on switch than on repeat trials (Cb: t_{23}=3.8, p<.001; Ob: t_{23}=6.5, p<.001; Fig. 7C), an effect that was more pronounced in the Ob than in the Cb condition (main effect of CONDITION: $F_{1,23}$=12.6, p=.002; main effect of RESPONSE TYPE: $F_{1,23}$=34.8, p<.001; interaction RESPONSE TYPE and CONDITION: $F_{1,23}$=5.8, p=.024; Fig. 7D).

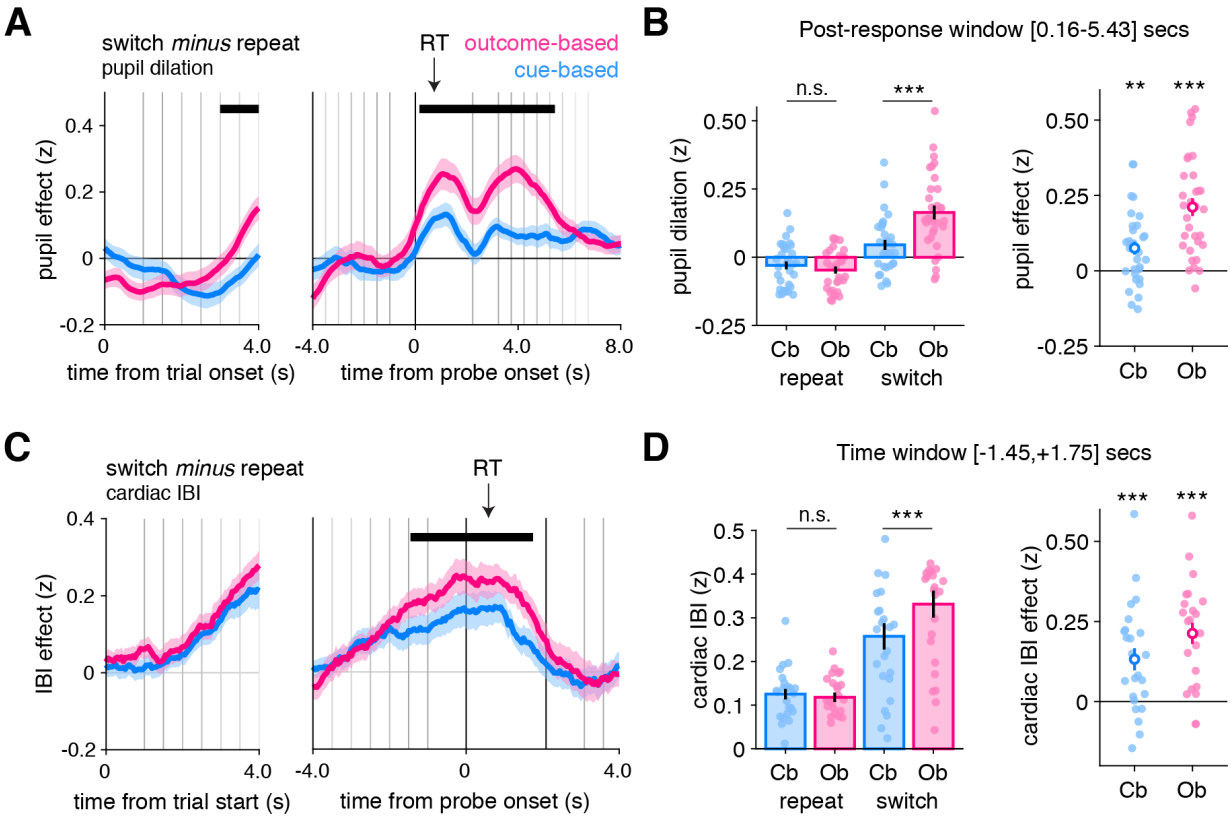

Figure 7: Larger pupil dilation and cardiac interbeat interval (IBI) signals on changes-of-mind
A) Pupil dilation on switch minus repeat decisions time-locked at the trial onset (left panels) and at the response probe onset (right panels). Shaded areas indicate mean and standard error across participants on each time point. The horizontal lines indicate statistical significance at $p<.05$ corrected from ANOVAs with CONDITION (cue-based, outcome-based) and RESPONSE TYPE (repeat, switch) as within-participant factors. The black arrow indicates the average response time across conditions and participants (N=33, pooled across Experiments 1 and 2A). **B**) ANOVA effects on the time windows statistically significant after correction using permutation tests identified in A. Stars correspond to significance of paired t-tests between conditions in the time window, ***$p<.0001$, n.s. not significant. **C**) Cardiac interbeat interval on switch minus repeat decisions time-locked at the trial onset (left panels) and at the response probe onset (right panels). Shaded areas indicate mean and standard error across participants on each time point (N=24, Experiment 4). **D**) ANOVA effects on the time window statistically significant after correction using permutation tests identified in C. In all panels, vertical lines indicate trial events: trial onset, samples of the evidence, and the response probe onset (dotted line). Blue: cue-based condition, pink: outcome-based condition. See also Fig. S5 for raw dynamics of pupil response and cardiac IBI.

We further examined whether these physiological markers of changes-of-mind can indicate when commitments to a change-of-mind occur: whether they accompany the stimulus sequence progression, already ramping up before the response; or whether they occur when the response is provided. We separated physiological data for short (2-4) and long (6-8) stimulus sequences (see Methods). We observed that the alpha-band effects associated with switch responses arose earlier for long as compared to short sequences across conditions, both in the occipital (Fig. S7A) and frontal (Fig. S7B) clusters (main effect of SEQUENCE LENGTH, occipital: peak $F_{1,23}$=25.1, cluster-level $p<.001$); frontal: peak $F_{1,23}$=17.7, cluster-level $p<.001$). Thus, the difference between conditions observed for changes-of-mind starts before probe onset, with participants engaging more attention

early in sequences that eventually lead to a response switch. In contrast, pupil dilation did no differ significantly across the two sequence length groups. In both conditions, pupil dilation on changes-of-mind increased only after the response (Fig. S7C). Finally, the IBI revealed dynamics comparable to those of the alpha-band suppression, with differences between short and long sequences restricted to before the probe onset (main effect of SEQUENCE LENGTH: peak $F_{1,23}$=10.4, cluster-level p<.05; Fig. S7D). Together, these results highlight distinct within-trial dynamics, with alpha-band power and IBI effects of changes-of-mind already starting pre-switch, whereas pupillary effects of changes-of-mind being restricted to post-switch.

Isolating the effects of information seeking from confounding variables

Since changes-of-mind occurred (i) more often when decision evidence was inconsistent with the previous choice (Fig. 3), and (ii) less often when participants' prior beliefs were stronger, we reasoned that these two variables may differently influence changes-of-mind in each condition, which would obscure a pure effect of changes-of-mind. In other words, if decision evidence and prior belief differ across repeat and switch trials, fluctuations in these two quantities may create a confound. We thus sought to examine whether neurophysiological effects in the Ob condition were specifically related to changes-of-mind, over and above (i) the absolute strength of prior belief and/or (ii) the amount of decision evidence signed by the prior belief (thereafter, "prior belief" and "evidence direction"). To account for these two quantities, we relied on the variables inferred from our computational model (see Methods).

First, using particle filtering, we extracted trajectories of these two quantities conditioned on participants' responses and established the statistical relationships between these quantities and changes-of-mind. As expected, we found that absolute prior beliefs were stronger on a repeat than on a switch trial ($F_{1,32}$=59.02, p=9.3×10^{-9}), and higher than in the Ob than in the Cb condition ($F_{1,32}$=72.3, p=1.0×10^{-9}), in line with a lower perceived hazard rate found in the Ob condition, with an interaction between RESPONSE TYPE and CONDITION ($F_{1,32}$=11.7, p=.0017). We also established that evidence direction strongly was positive (resp. negative) on repeat (resp. switch) decisions ($F_{1,32}$=7527.9, p<1×10^{-11}), an effect that was more pronounced in the Ob than in the Cb condition ($F_{1,32}$=52.5, p=3.1×10^{-8}) with an interaction between RESPONSE TYPE and CONDITION ($F_{1,32}$=5.59, p=.024).

In both conditions, both prior belief and evidence direction showed strong and sustained correlations with alpha power suppression in occipital and frontal clusters (Fig. 8A). In the occipital cluster, when controlling for the effects of both model variables, the Cb switch effect disappears before probe onset, but remains afterwards. By contrast, the Ob switch effect remained present, albeit smaller, before and after probe onset (residual variance, Fig. 8B). Importantly, the difference between conditions remained significant when accounting for these two model variables (peak

t_{23}=5.8, cluster-level p<.001), meaning that the original difference between conditions (Fig. 6) cannot be explained away by different prior beliefs or decision evidence. In the frontal cluster, all effects fully remained after controlling for prior belief and decision evidence, with a significant difference between conditions (peak t_{23}=4.0, cluster-level p<.001; residual variance, Fig. 8B).

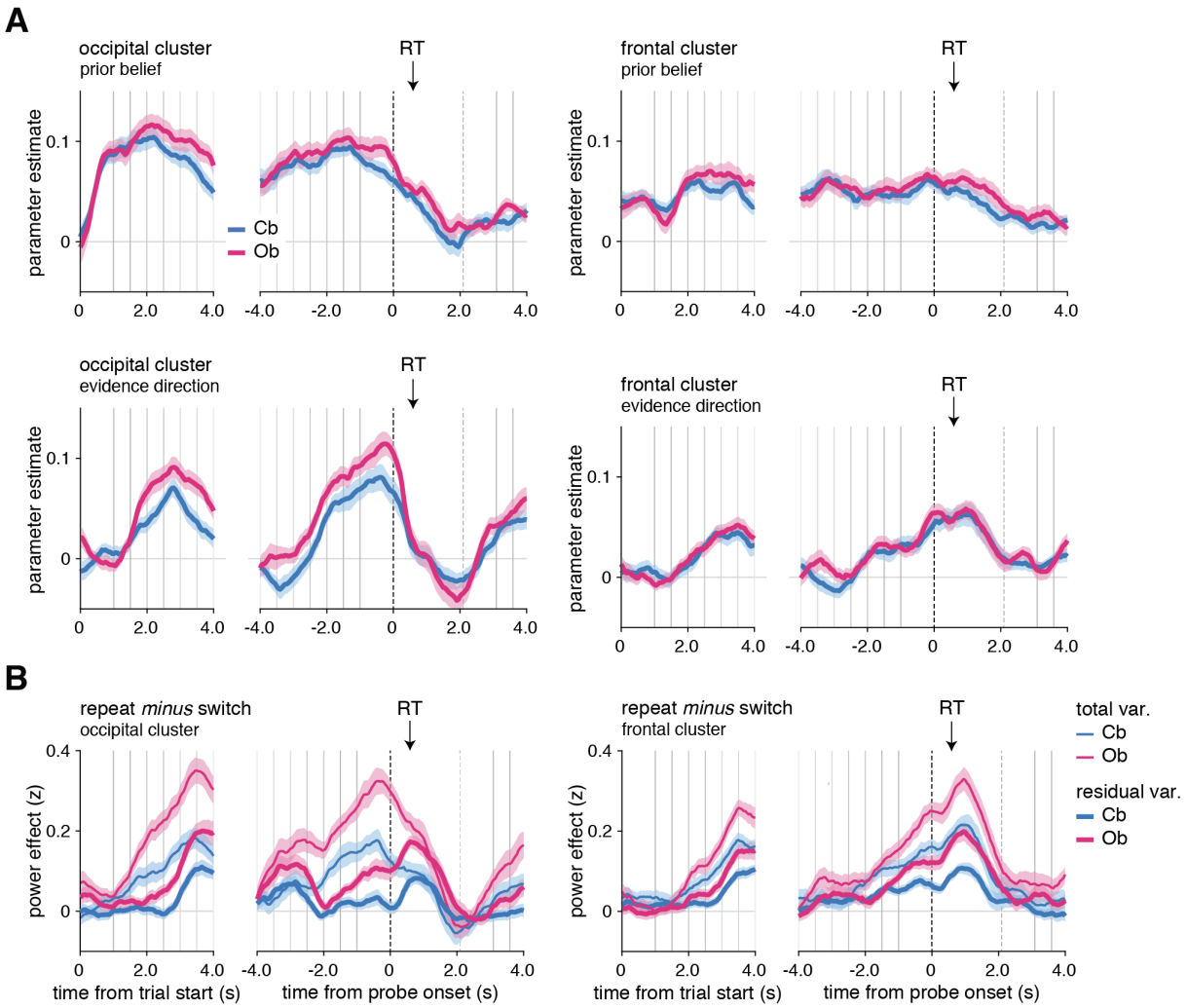

Figure 8: In controllable environments, changes-of-mind effects cannot be explained away by fluctuations in prior beliefs or evidence direction. For MEG alpha-band power in the occipital cluster (**A**) and in the frontal cluster (**B**), pupil dilation (**C**) and cardiac IBI (**D**), contrast between repeat and switch trials time-locked at the trial onset (left panels) or at the response probe onset (right panels) after removing the variance due to fluctuations in prior belief and evidence direction (thick lines, residual variance) in the cue-based (blue, Cb) and outcome-based (pink, Ob) conditions. Raw contrasts are displayed for comparison (thin lines, total variance). Vertical lines indicate trial events: probe onset, samples of the sequence, and response probe onset (dotted line). The black arrow indicates the average response time across conditions and participants. total var.: total variance; residual var.: residual variance after accounting for the two model variables, prior belief and evidence direction.

Discussion

Accurate decisions in uncertain environments require forming and updating beliefs through efficient information sampling. Previous studies of human decisions and confidence have often relied on tasks in which participants have no control over the sampling of information (Fleming et al., 2018; Murphy et al., 2016; van den Berg et al., 2016). However, outside the laboratory, we usually have some control over information sampling: which way to look, which food to try, which person to listen to. We do not passively *receive* information but rather actively *seek* information for decision-making (Gureckis and Markant, 2012; Sharot and Sunstein, 2020). Here, we reasoned that control is necessary for information seeking, which we used to dissociate information seeking from changes in beliefs and behavior. Across several variants of the same task tested with and without control over information sampling, we obtained converging evidence that information seeking is associated with decreased confidence and drives active hypothesis testing. At the physiological level, information seeking is associated with stronger and longer-lasting correlates of attention and arousal.

In previous work, information seeking has often been studied and theorized in the context of 'exploration-exploitation' dilemmas (Costa et al., 2019; Daw et al., 2006). In these tasks, participants are typically immersed in controllable environments, and asked to sample one among several options to maximize reward. Therefore, they have to choose between exploiting a currently rewarding option, and foregoing rewards to explore alternative options to seek information about their associated rewards (Rich and Gureckis, 2018; Wilson et al., 2014). This cognitive trade-off raises the issue that exploration and exploitation not only differ in terms of information seeking, but also in terms of other cognitive and behavioral events. In particular, three main events co-occur during an exploratory decision: 1. a covert change-of-mind about the expected reward of the current option, 2. an overt change in behavior (e.g., a response switch), and 3. information seeking, i.e., an active search for information about the new option being considered. The latter is only possible in the outcome-based condition, allowing us to isolate information seeking by comparing response switches between the two conditions.

We fitted a Bayesian inference model to participants' choices, and extended our model to predict confidence reports. Simulations with best-fitting parameters of individual participants confirmed that each parameter captures a specific behavioral gradient matching participants' psychometric signatures (Fig. S3). First, we replicate our previous finding of a lower perceived hazard rate in the outcome-based condition (Fig. 5B), corresponding to participants perceiving contingencies as more stable in controllable environments (Weiss et al., 2021). This lower perceived hazard rate contributes to explaining a larger loss of confidence on changes-of-mind in the outcome-based condition. In the model, the lower perceived hazard rate creates stronger prior beliefs, such that more inconsistent evidence is required for them to be reversed. This mechanism

predicts lower confidence during changes-of-mind despite stronger evidence in favor of a change-of-mind in the current trial. This increase in the magnitude of prior beliefs also explains why participants confirm more often their changes-of-mind in the outcome-based condition, despite lower confidence in these changes-of-mind.

In both conditions, our model predicts that the quantity of inconsistent evidence required for participants to change their minds (reflected in choice-PSE estimates) should be smaller following a switch than a repeat decision (Fig. 5C). This prediction was verified in the cue-based condition. By contrast, in the outcome-based condition, participants violated this prediction by showing similar choice-PSEs following repeat and switch decisions (Fig. 5C). This deviation between model and data in this condition where changes-of-mind are associated with information seeking could reflect at least two cognitive effects. First, participants may believe a new reversal in task contingencies to be less likely just after a perceived reversal. Second, participants may engage in an active form of hypothesis testing – i.e., testing that the new action draws from the target category. Such instrumental hypothesis testing is by definition only possible in the outcome-based condition, where participants can actively sample the environment to confirm or discard their new hypothesis (Collins and Frank, 2013; Markant and Gureckis, 2014). Hypothesis testing is known to be particularly valuable in environments with many choice options (Gureckis and Markant, 2012), but the fact that we observe it in a condition with only two options suggests that it is a constitutive feature of information seeking.

The notion of controllability bears a partial resemblance with the distinction between learning under selection vs. reception (Gureckis and Markant, 2012), and between free vs. forced choices (Chambon et al., 2020; Ligneul, 2021; Sidarus et al., 2019; Wilson et al., 2014). Performance benefits have been identified in selection contexts and free choice contexts, where participants can maximize the informativeness of their choices (Freeman et al., 2014; J. L. Voss et al., 2010; Xu and Tenenbaum, 2007). However, in these previous studies, sequences from selection and reception (and, likewise, from free and forced) choices vastly differ, which make it difficult to separate the specific effects of controllability from its consequences on the evidence available for subsequent choices. Instead, the current paradigm carefully matched the amount of evidence provided in both controllability conditions. Furthermore, we sought to validate controllability as the true cause of differences between conditions. In Experiment 3, we show that a distinction in temporal focus (prospective instead of retrospective inference in an uncontrollable context) cannot account for the differences between the original conditions (Fig. S1). In Experiment 2B, when the instructions changed unpredictably across trials instead of blocks, participants still perceived the outcome-based condition as more stable, providing evidence that the specificity of this condition arises from the controllability of information sampling experienced (Fig. S4).

At the neurophysiological level, we observed a stronger suppression of neuromagnetic alpha-band activity in the dorsal attention networks during the last seconds preceding and following response switches, in both conditions (Fig. 6). This observation suggests that uncertainty at the time of a change-of-mind is associated with participants being more strongly oriented towards the presented evidence before the response switch occurs. Critically, this finding does not merely reflect greater attention or engagement in the outcome-based condition, which would have suggested general differences in task processing between conditions across repeat and switch decisions. Previous work using fMRI showed that task switching recruits a similar dorsal frontoparietal network involved in attentional control (Corbetta and Shulman, 2002), whereas response switching recruits a frontal network involved in executive control (Daw et al., 2006; Donoso et al., 2014; Findling et al., 2019). However, the use of MEG here allowed us to reveal largely anticipatory activations preceding response switches. Our results are also generally consistent with medial frontal activations during hypothesis testing (for a review, see (Monosov and Rushworth, 2021)) and in non-instrumental information sampling, where the gathered information affords to predict but does not influence future outcomes (White et al., 2019). The temporal dissociation between switch effects observed in the occipital and frontal clusters suggests that changes-of-mind are preceded by a state of increased attention toward external (here, visual) evidence. This first stage is followed by a covert change-of-mind, and ends with an overt response switch reflected in strong alpha-band suppression overlying frontal cortex (Fig. 6 and S5).

In contrast to MEG dynamics, phasic pupil dilation revealed noradrenergic responses starting after the response probe onset and remained during presentation of the outcomes (Fig. 7). This pattern of findings suggests a functional dissociation between alpha-band correlates of attention and pupil-linked arousal during changes-of-mind. The pupil-linked arousal associated with response switches is consistent with previous evidence for an association between pupil response and belief updating in uncertain environments (Filipowicz et al., 2020). Our results are also consistent with a previous study providing evidence that pupil-linked arousal following decision uncertainty increased participants' tendency to switch their choice on the next trial (Braun et al., 2017). The fact that the pupil effect extends well into the next trial suggests that participants pay attention to the consequences of their changes-of-mind well into the next trial, particularly so in the outcome-based condition where they are in control of the upcoming sequence of evidence. This again stands in contrast to alpha suppression that was mostly anticipatory, a distinction between pupil dilation and alpha-band suppression previously observed in relation to attention (Whitmarsh et al., 2021). An additional difference between switch and repeat trials was further observed in the cardiac interbeat interval, with similar dynamics as the alpha-band suppression. This increased slowing of heartbeats preceding response switches could partly reflect, but are unlikely to entirely reduce to, changes in respiration (Park et al., 2014) – e.g., participants holding their breath before response switches in the controllable condition. Together, these findings indicate that information

seeking is characterized by a specific temporal succession of neurophysiological mechanisms in cortical, subcortical and peripheral nervous systems.

By comparing changes-of-mind occurring in controllable and uncontrollable environments, we identified cognitive and neurophysiological signatures of information seeking that had otherwise proved difficult to isolate. We found that in controllable environments, humans require more evidence to change their mind and do so with reduced confidence but are nevertheless more likely to stick to their decision on the next trial, suggesting a form of hypothesis testing. With computational modelling indicating that participants perceive controllable environments as more stable, we were not only able to explain why information seeking is associated with a higher degree of perceived uncertainty, but also to identify stronger and longer-lasting effects of changes-of-mind on cognition and behavior. Alterations in confidence (Rouault et al., 2018), information seeking (Hauser et al., 2017), and perceived controllability (M. Voss et al., 2017) are associated with various psychiatric symptoms. For instance, participants with OCD typically need to gather more evidence before committing to a decision, while participants with schizophrenia present an inflated sense of agency associated with an inability to accurately update these representations (Metcalfe et al., 2014). By clarifying the effects of controllability on inference and confidence, our study lays the groundwork for explaining how the interplay between perceived control, information seeking, and confidence may go awry in psychiatric conditions.

Methods

Participants

Human participants were recruited in the participant pool from the French platform “Relay for Information about Cognitive Sciences” and provided written informed consent. The study was approved by the Comité de Protection des Personnes Ile-de-France VI, ID RCB: 2007-A01125-48, 2017-A01778-45. *Experiment 1*: 17 participants were originally recruited in Feb-March 2016. One participant was excluded for aborting the experiment before the end and one for performing at chance level, leaving 15 participants for behavioral analyses. *Experiment 2*: 20 participants were initially recruited in Nov-Dec 2016 and in March-May 2017. Two participants were excluded for performing at chance level, leaving 18 participants for behavioral analyses. *Experiment 3:* 30 participants were initially recruited in March 2019. Four participants were excluded for performing at chance level and one participant aborted the experiment before the end, leaving 25 participants for behavioral analyses. *Experiment 4*: 24 participants were tested in Sept-Nov 2015, whose behavior is described in (Weiss et al., 2021).

Behavioral tasks

Experiment 1. Participants performed a reversal learning task similar to that of our previous study (Weiss et al., 2021). Participants were presented with sequences of stimuli drawn from two discrete color categories (Fig. 1A), and were asked to make a decision about the generative category on each trial (each sequence; Fig. 1B). To examine a role for subjective confidence in relation to inference and changes-of-mind about category, in addition to their choice, participants indicated their confidence (high or low) in their response using four response keys (Fig. 1B).

Participants performed two experimental conditions that aimed at examining the influence of the degree of control over stimuli on choice and confidence. In the cue-based (Cb) condition, participants were instructed that the computer draws sequences of stimuli, and were asked to identify the category from which the stimuli were drawn (Fig. 1C). An instruction screen indicated the mapping between response keys and color categories (counterbalanced across blocks). In the outcome-based (Ob) condition, participants were instructed to draw stimuli from a given category (Fig. 1C). An instruction screen indicated the target color category for each block (counterbalanced across blocks). Consequently, the hidden state differed between conditions: participants monitored changes in the category being drawn in the Cb condition, whereas they monitored changes in the response key drawing from the target category in the Ob condition (Fig. 1D). The conditions were otherwise fully symmetric, tightly matched in terms of visual and motor requirements, and the order of condition administration was counterbalanced across participants.

The generating category (hidden state) reversed occasionally and unpredictably at the same rate as in both conditions, with “episodes” (i.e. chunks of trials) during which the hidden-state was fixed (Fig. 1D). Episode duration was sampled pseudo-randomly from a truncated exponential probability distribution (between 4 and 24 trials), resulting in a near-constant hazard rate in each block. Participants completed a total of 576 trials divided into blocks of 72 trials (72 sequences). The detailed instructions provided to participants are reported in (Weiss et al., 2021). To experience the difference between experimental conditions, we provide a short analog toy experiment at infdm.scicog.fr/aodemo/runner.html.

Experiment 2. To examine whether the retention of a category goal over a longer time-scale was critical in the participants’ experience of control, and therefore influenced the results, we introduced a new rule manipulation. In half of the blocks, rules were stable across a block (thereafter, Experiment 2A). Since behavior was virtually identical in this rule condition, we then pooled these data with Experiment 1 for a total of 33 participants. In the other half of blocks, rules were changing on a trial basis instead of a block basis (thereafter, Experiment 2B). The generative structure of the task and all other experimental features remained identical to Experiment 1. We analyzed this experimental data (2B) separately (Fig. S4).

Experiment 3. We reasoned that our Cb and Ob conditions differ in terms of the degree of control that participants experience over stimuli. However, an alternative interpretation of these differences would be in terms of temporal orientation, with the Cb condition being about monitoring past stimuli retrospectively (instruction to “monitor”), whereas the Ob condition would be about producing stimuli prospectively (instruction to “draw”). We set out to test this hypothesis using a modified version of the original conditions. Here, after each sequence of stimuli, participants were asked to guess from which category the computer drew from (retrospective condition), or to guess which category the computer will draw from (prospective condition). All other experimental features remained identical to Experiments 1 and 2A.

Experiment 4. Detailed behavioral, modelling and MEG analyses of this experimental data have been presented elsewhere (Weiss et al., 2021). In short, the experimental design was similar to that of Experiment 1 with the exception that no confidence responses were asked, only category choices.

Stimuli. Stimuli were oriented bars presented on top of a colored circle displaying an angular gradient between orange and blue color categories spaced by $\pi/2$ (Fig. 1A). Stimuli were drawn from either of these two categories (Fig. 1A). On each trial, a sequence of 2, 4, 6 or 8 stimuli was drawn from a von Mises probability distribution centered on either category with a concentration of 0.5, and presented to participants for making a decision about category of origin at the end of the sequence (Fig. 1B). The number of stimuli per sequence was drawn from a uniform distribution and pseudo-randomized across trials. Stimuli were displayed at an average rate of 2 Hz with an

inter-stimulus interval of 500 ± 50 ms. The last stimulus of each sequence was followed by a longer delay of 1000 ± 50 ms, before participants were probed for their response.

Statistical and quantitative analyses

Model-free behavioral analyses. We defined performance as the proportion of choices of the true hidden state (true generative color category). We examined whether mean performance and mean confidence (fraction of high confidence responses) varied across Cb and Ob conditions using paired *t*-tests. To assess how much insight participants had into their performance, we computed discrimination ability for each condition as the difference in confidence in correct and error responses (Supplementary Results). We also computed calibration, another measure of metacognitive ability, that reflects overall how closely participants' confidence matched their performance as the mean performance minus mean fraction of high confidence responses (Supplementary Results).

Psychometric analysis of behavior. We first examined two reversal curves: the proportion of choosing either option (Fig. 2A) and the proportion of high confidence responses (Fig. 2C) as a function of trial number before and after a reversal. We modelled choices using a truncated exponential function characterized by two parameters, an asymptotic level and a (reversal) time constant (Fig. 2B). For confidence as a function of reversal, we also fitted an exponential learning model for which we report two characteristic parameters (Fig. 2D), a (confidence) time constant, and a "confidence drop" parameter reflecting the drop between the lower ($p_{\min}$) and upper ($p_{\max}$) asymptotic levels (corrected by the time constant t), such that:

$$\text{Confidence drop} = p_{\max} - p_{\min} + (p_{\max} - p_{\min}) \times (1 - e^{-1/t})$$

We also examined the proportion of repeating the previous choice (Fig. 3A) as a function of evidence recoded in favor of repeating a previous choice ("consistent evidence") or in favor of switching choice ("inconsistent evidence"). We quantified this by fitting a logistic function to quantify the amount of evidence required to switch a response in each condition (PSE, point of subjective equivalence) and the sensitivity to the evidence (slope of the sigmoid function; Fig. 3B). Similarly, we analyzed the proportion of high confidence responses as a function of consistent vs. inconsistent evidence (Fig. 3C). For confidence, we computed within-participant error bars by removing the mean confidence level across conditions before computing the standard error. This was done to allow a fair comparison between conditions without an influence of inter-individual variability about the use and calibration of the high and low confidence responses. As expected, trials with consistent evidence correspond more often to repeat choices (right part of Fig. 3C), whereas trials with inconsistent evidence correspond more often to changes-of-mind (left part of Fig. 3C). To quantify these findings, we fitted two logistic sigmoid functions, one for repeat and one for switch choices, for each condition separately. The sensitivity to the evidence (slope) parameter

was entered into a 2 × 2 ANOVA with factors CONDITION (Cb, Ob) and RESPONSE TYPE (repeat, switch). We also quantified the evidence level at which the two sigmoid for repeat and switch trials intersect, which corresponds to the quantity of evidence at which participants are equally confident in their repeat and in their switch decisions (Fig. 3D). For all psychometric analyses we compared parameters of best-fitting functions across conditions using paired *t*-tests (Figs. 2B-2D-3B-3D). When individual estimates were too noisy (e.g. for 6/33 participants, confidence was very little modulated by evidence level on switch trials), we performed a non-parametric Wilcoxon signed rank test, and displayed only the participants who did not have extreme values.

We additionally fitted the PSE on subsamples of trials corresponding to trials following a repeat and a switch decision respectively (Fig. 5C), and for trials following a high or a low confidence response respectively (Fig. 5D). This allowed us to examine how participants adapted their PSE on a dynamic basis, depending on the choice sequence experienced in the task.

Change-of-mind analyses. In Experiments 1 and 2A, we sought to characterize the behavioral properties of changes-of-mind across conditions (Fig. 4). In a 2 × 2 repeated measures ANOVA, we examined the influence of RESPONSE TYPE (repeat, switch) and CONDITION (Cb, Ob) on the fraction of high confidence responses (Fig. 4A, same data as Fig. 3C regardless of evidence level). For switch trials, we further examined confidence on switch trials that were confirmed on the next trial ("change-of-mind confirmed") as compared to switch trials after which participants went back to their previous response ("change-of-mind aborted"; Fig. 4B). Finally, we examined the fraction of changes-of-mind confirmed (over all changes-of-mind) as a function of whether the change-of-mind was done with high or low confidence (Fig. 4C).

In Experiment 2B, we were able to further dissociate true changes-of-mind about category, from motor changes-of-mind related to key presses without a change in belief about category. We report the results for two 2 × 2 repeated measures ANOVAs, one on true changes-of-mind and one on button changes, with RESPONSE TYPE (repeat, switch) and CONDITION (Cb, Ob) as within-participant factors (Fig. S4E).

Computational model

Model structure. We implemented a normative model of perceptual inference in volatile environments with contingency reversals (Glaze et al., 2015). A key aspect of the model is that it operates on the same evidence quantities and in a similar way in both Cb and Ob conditions. Since previous work indicates that inference noise and not selection noise explains most of choice variability in such an inference task (Drugowitsch et al., 2016), we included no selection noise but we introduced inference noise on each sample of the sequence, that scales with sequence length (Weiss et al., 2021). We extended the model in key ways to predict not only choices, but also confidence. First, we introduced a confidence threshold parameter for determining whether the

response will be provided with high or low confidence based on the posterior belief about the chosen category. This parameter captured baseline differences in proportion of high confidence responses between conditions, representing the most parsimonious extension possible to provide a normative confidence response. Second, we introduced metacognitive noise to model an imperfect readout, as previously proposed (Maniscalco and Lau, 2012; Pouget et al., 2016). Third, we introduced a confidence gain parameter on switch trials modelling a differential readout of the posterior belief on changes-of-mind only, as a multiplicative factor on the posterior belief applied on switch trials only.

Model fitting. We fitted the model using a Bayesian Adaptive Direct Search (BADS) with 100 validation samples which provides point estimates for each parameter (Acerbi and Ma, 2017). We used five random starting points and parameters were bounded as follows (hazard rate: range=0.000001-0.999999, inference noise: range=0-10, metacognitive noise: range=0-10, confidence threshold: range=-10,+10, confidence gain for switches: range=0-10). We maximized the likelihood that model choices and confidence reproduce the reversal (Fig. 2) and repetition (Fig. 3) curves of participants, that are the key dimensions of interest for understanding participants' choice and confidence patterns. One participant was excluded for having an unreliable fit. All parameters were allowed to vary between conditions, and we compared the best-fitting parameters using paired *t*-tests.

Model validation. To validate the model, we simulated model choice and confidence from the best-fitting parameters on the same stimuli sequences as participants, and analyzed the simulations similarly as for participants' data (Fig. S2) (Palminteri et al., 2017; Wilson and Collins, 2019). We also performed a median split across participants on the best-fitting hazard rate, confidence threshold, and confidence gain. We then averaged simulations of the model for each subgroup, to further illustrate the independent contribution of each of these parameters (Fig. S3).

Finally, to compare the characteristics of changes-of-mind between model and participants, we reproduced one of the psychometric analyses that fits the choice-PSE separately for trials following a repeat vs. a change-of-mind, and separately for trials following a high vs. a low confidence response. For model simulations, we averaged across 50 simulations per participant session (Fig. 5).

Magnetoencephalography

As reported in our previous study (Experiment 4, (Weiss et al., 2021), we recorded MEG data using a whole-head Elekta Neuromag TRIUX system (Elekta Instrument AB, Stockholm, Sweden) composed of 204 planar gradiometers and 102 magnetometers using a sampling frequency of 1,000 Hz. Prior to the experiment, each participant's head shape was digitized in the MEG coordinate frame. We used four additional head position indicator (HPI) coils, whose positions

were also digitized, to monitor and correct for small head movements across blocks. The movement of HPI coils between blocks remained small (mean: 2.3 mm) was similar across blocks and across conditions (t_{23}=1.6, p=.128).

We first removed magnetic noise from external sources using temporal Signal Space Separation (tSSS), after manually removing detected non-physiological jumps in MEG signals. Stereotyped ocular and cardiac artifacts were corrected using a supervised Principal Component Analysis (PCA). First, the onset of artifacts (either eye blinks or cardiac R-peaks) was automatically detected on auxiliary electrodes (EOG and ECG) synchronized with MEG signals using a threshold-based approach. MEG signals were then epoched from 200 ms before to 800 ms after artifact onsets, and a PCA was used to extract the spatial components of cardiac and ocular artifacts. Typically, one stereotyped PCA component was removed from continuous MEG signals for eye blinks, and two components for heartbeats. Continuous MEG signals were high-pass filtered at 0.5 Hz, down-sampled to 500 Hz, and epoched from 200 ms before to 800 ms after the onset of each stimulus. Finally, epoched MEG signals were low-pass filtered at 8 Hz and their analytical representations (decompositions into real and imaginary parts) were computed using the Hilbert transform, resulting in twice the number of MEG signals (408 from planar gradiometers and 204 from magnetometers).

The spectral power of band-limited MEG oscillations between 8 and 16 Hz was estimated using the 'multitapering' time-frequency transform implemented in FieldTrip (Oostenveld et al., 2011) (Slepian tapers, 8 cycles and 3 tapers per window, corresponding to a frequency smoothing of 25%), in two distinct time windows time-locked either to trial onset (from to 0 to +4 s from trial onset) or to probe onset (from -4 to +4 s from probe onset). We computed the contrast between repeat and switch decisions across conditions at each MEG channel, and examined pairwise correlations of these contrasts across all MEG channels. This analysis identified two main clusters, thereafter labeled 'occipital' and 'frontal' clusters based on their spatial localization. In these clusters, we employed jackknifed statistics to estimate temporal windows of significant differences between switch and repeat decisions, and between conditions (Kiesel et al., 2008).

Pupillometry

To analyze physiological correlates of uncertainty across conditions, we measured pupil dilation at a sampling rate of 1000 Hz in Experiments C, D1 and D2. We preprocessed data with resampling at 100 Hz and corrected for blinks in a window between -100ms and +500ms around the event of interest, using a derivative padding window between -200ms and +200ms and an instantaneous derivative threshold adjusted on participant and block bases. We smoothed the data with a moving average window size of 50ms, detrended slow fluctuations from the signal using a characteristic

time constant of 30s, and z-scored the data. We excluded from the analyses blocks in which participants had more than 50% of low-quality data due to blinks.

We focused our analyses on phasic pupil response time-locked at the trial onset and at the response probe onset. We used an exclusion threshold of 2s (if the window of missing data remained too large). For statistical analyses, we used a first-level uncorrected threshold of 0.05, and further performed correction for multiple comparisons with non-parametric cluster-level statistics computed across adjacent time points (Maris and Oostenveld, 2007). T, F and p-values reported in the main text correspond to corrected statistical values based on permutation tests with 1,000 permutations (Fig. 7B). We report post hoc paired t-tests for comparing pupil dilation between conditions on repeat and switch trials separately, in the time window identified after correction.

Electrocardiography

We extracted the time points of cardiac R-peaks from ECG signals recorded continuously during Experiment 4 using an automatic threshold-based approach (z-score = 3) on band-pass filtered signals between 1 and 16 Hz. We constructed time courses of cardiac interbeat interval from these estimated R-peaks time-locked either to trial onset (from to 0 to +4 s from trial onset) or to response probe onset (from -4 to +4 s from probe onset). We analysed these time courses similarly to time courses of alpha power suppression.

Neurophysiological activity controlled for fluctuations in prior belief and evidence direction

To examine whether the differences between conditions visible in neurophysiological signals remain after controlling for our model variables, we analyzed alpha-band suppression time-locked at the trial onset and at the response probe onset in occipital and frontal clusters. We regressed out the effect of prior belief and evidence direction. We extracted these two variables from our computational model using particle filtering to only extract trajectories consistent with each participant's choice sequence (Fig. 8).

Data and code availability

Participants' data and MATLAB code for behavioral and psychometric analyses of Experiments 1 and 2A are available at https://www.github.com/marionrouault/actobscom/. The repository will be completed upon publication in a peer-reviewed journal. Because tested participants did not provide written consent regarding the posting of their anonymized data on public repositories, the MEG, pupillometric and ECG datasets are available from the corresponding authors upon request.

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Author contributions

Conceptualization: V.W.; Data Collection: A.W., V.C., J.K.L., J.B., Methodology: A.W., V.C., J.D., and V.W.; Formal Analysis: M.R., A.W. and V.W.; Investigation: A.W., J.K.L., V.C., M.R. and V.W.; Writing – Original Draft: M.R. and V.W.; Writing – Review & Editing: M.R., V.C. and V.W.; Supervision: V.W.; Funding Acquisition: J.D. and V.W.

Conflicts of interest

The authors declare no competing interests.