EEG anticipatory activity depends on sensory modality

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Abstract

Perceptual anticipation is known to have an impact on the reaction time of decisions. While anticipatory brain activity patterns have been identified in human EEG, in particular in the form of Contingent-Negative Variations (CNV), the single-trial neural signature of anticipation remains unexplored. Similarly, past studies have underlined an effect of pre-stimulus alpha-band activity on reaction times. Still, it remains unknown whether this activity is stimulus-specific or rather acts as a general indicator of readiness. This study aimed to decipher whether human participants expected a visual or an auditory stimulus at the single-trial level in both cued and uncued trials. We show that the CNV entails information about the expected upcoming stimulus, and the information content can be extracted at the single-trial level. Behavioral analyses additionally indicate the correct classification of uncued trials.

1 Introduction

Perceptual anticipation is the expectation of an upcoming stimulus to which participants are ready to respond (Poulton, 1950). Anticipating upcoming stimuli is relevant when making decisions because it directly impacts behavior. Typically, correctly anticipating stimuli results in faster and more accurate decisions (Petro et al., 2019; Poulton, 1950). Moreover, pre-stimulus brain states were shown to impact confidence in judgment (Samaha, Iemi, and Postle, 2017) and the visibility of visual stimuli (Railo, Piccin, and Lukasik, 2021). Therefore, understanding perceptual anticipation is paramount to understanding decision-making at the single-trial level.

While other aspects of decision-making are starting to be well documented, pre-stimulus states such as anticipation remain broadly unexplored due to the experimental challenges they pose. First, in traditional analyses of brain recordings, brain activity is recorded relative to a specific event in time. However, anticipatory processes can begin any time before stimulus onset. While aligning all trials to a consistent point in time is a notoriously difficult task in the case of well-identified brain activity (Barthélemy et al., 2013), it becomes highly challenging for modeling unconstrained patterns. Second, analyses that consist in classifying brain activity patterns between different types of tasks typically require the knowledge of a ground truth. In contrast, anticipation is mainly unconscious (Koch and Preuschoff, 2007), meaning that participants themselves may not be aware of what they are expecting. Asking them directly is asking for a decision, and is therefore likely to change the type of brain activity required (Trevena and Miller, 2002). To address both of these issues, several studies have used cues in their experiment paradigm in order to induce specific expectations and to pinpoint in time its beginning (Petro et al., 2019; Chavarriaga et al., 2012). It is noteworthy however that perceptual decisions in ecological contexts may need to be made in the absence of cue. Electroencephalography (EEG) is a neuro-recording technique of choice for this problem thanks to its fine temporal precision and its capability to capture both conscious and unconscious cortical activity. It has already been used to uncover several pre-stimulus brain activity patterns, which we detail in the following.

A neuronal component of expectation, called the Contingent Negative Variation (CNV), has been extensively studied in the context of temporal expectations. A CNV is a type of event-related potential (ERP) that emerges after a cue announcing a target stimulus is displayed. It takes the shape of a linearly increasing potential that reaches its maximum when the contingent stimulus is expected (Walter et al., 1964). Upon several presentations of this association of stimuli the CNV is created, and a weakening of the association, for example with jitters in the temporal relationship between the two events, the CNV disappears. Therefore, the CNV was originally established as a neural marker of temporal expectation.

It has been shown that the CNV is both associated with stimulus expectation and with motor preparation. Works led by Chavarriaga and collaborators (Garipelli, Chavarriaga, and Millan, 2009; Garipelli, Chavarriaga, and Millan, 2011; Khaliliardali et al., 2012; Chavarriaga et al., 2012; Khaliliardali et al., 2015) have shown that it is in fact possible to distinguish different forms of CNVs. These works used a Go/NoGo task, which consisted for participants in taking an action or remaining still depending on an imperative stimulus. The contingent stimulus was displayed at a fixed interval before the imperative stimulus. In these works, they tried to detect whether participations anticipated the need for a response or not. For example, Garipelli, Chavarriaga, and Millan (2009) and Garipelli, Chavarriaga, and Millan (2011) presented sequentially two dots S1 followed by S2, and a motor response had to be produced upon S2 presentation if S1 was green and withhold response if it was yellow. They were able to classify anticipation with an above-chance performance for some participants, reaching up to 80% classification accuracy. About half of the participants seemed to demonstrate different brain activity patterns during anticipation. Chavarriaga et al. (2012), Khaliliardali et al. (2012), and Khaliliardali et al. (2015) implemented more ecological versions of this task by

immersing the participant in a maze (Chavarriaga et al., 2012) or in a simulated driving scenario (Khaliliardali et al., 2012; Khaliliardali et al., 2015). We note that these studies focused in particular on whether participants expected that an action was required or not. While these advances are particularly relevant for brain-computer-interface applications, the question of whether the semantic content of anticipation can be decoded at the single-trial level remains open. More specifically, we are interested in determining whether the CNV depends on the sensory event expected by the participant when there is always an action to perform and if these variations can be detected at the single-trial level.

Besides the CNV, other components of brain activity in the pre-stimulus period have been shown to have an effect on subsequent behavior. Among them, the activity in the alpha band ($8 - 13$ Hz) has received a lot of interest, because it is thought to be representative of the gating of sensory information in the brain Jensen and Mazaheri (2010) and Jensen, Bonnefond, and VanRullen (2012). Moreover, pre-stimulus alpha power has been associated with top-down processing (Min and Herrmann, 2007). It remains however unclear how this pre-stimulus oscillatory activity influences decision-making. In particular, pre-stimulus alpha activity could modulate sensory sensitivity, sensory selectivity, or higher cognitive processes involved in decision-making, such as evidence integration or internal evaluation of decision performance. Iemi et al. (2017) and Samaha, Iemi, and Postle (2017) have shown in complementary studies that the confidence rating correlated with the alpha band activity in a visual classification task, whereas the perception of the stimulus itself, as assessed by the classification performance of participants, remained unaltered. Similar findings have been established in the auditory modality (Wöstmann, Waschke, and Obleser, 2019). In contrast, Barik et al. (2019) have shown that face pareidolia is related to certain levels of alpha activity, supporting that alpha activity at the single-trial level relates to the formation of decisions. Other studies have associated with sensory processes. Lou et al. (2014) suggested that pre-stimulus alpha power modulated the encoding of sensory information, since it correlated with the amplitude of stimulus-specific post-stimulus EEG activity. This finding is supported by the theory of selective attention carried by alpha oscillations (Foxe and Snyder, 2011). While the pre-stimulus effects have been studied, it remains to be shown whether this alpha-band activity is a neural correlate of anticipation, i.e. if it is specific to the anticipated stimulus.

Computational modeling of decision-making has provided insight into its processes, from sensory encoding to motor response. In particular, the Diffusion-Decision Model (DDM) (Ratcliff, 1978; Ratcliff and Tuerlinckx, 2002; Ratcliff and McKoon, 2008) explains response times and accuracy as the result of a linear accumulation of sensory evidence until a decision boundary which represents the speed-accuracy trade-off. The accumulation rate, called the drift, and the starting point of the accumulation are particularly interesting parameters when it comes to assessing the impact of prior expectations on decisions (Urai et al., 2019; Bode et al., 2012). Ratcliff and Tuerlinckx (2002) also introduced inter-trial variability for these parameters to account better for possible fluctuations. However, whether anticipation modulates the starting point, as classically believed (Bode et al., 2012; Grosjean, Rosenbaum, and Elsinger, 2001), or the drift rate, i.e. the evidence accumulation stage (Urai et al., 2019), remains debated.

In this work, we show that it is possible to distinguish between anticipation of visual and auditory stimuli at the single-trial level. We implemented an EEG

experiment where participants had to decide at each trial whether the stimulus they were presented with was an image of a face or a sound, and are cued as to which stimulus will be displayed in one part of the recording session. After confirming that anticipatory processes are present in our data, we performed a cluster-based analysis on EEG grand-averaged activity to underline differences between temporal expectation and perceptual anticipation. The next and main part of this study aims at differentiating EEG activity depending on what each participant has expected (a sound or an image), based on the cued trials only and using different components of the EEG activity (late ERP, spectral activity in the alpha band). We then applied the classifiers to uncued data, using the classifiers trained on cued data on the one hand and predictions made on post-stimulus activity of uncued trials on the other side. To understand which stage of decision formation is modulated by anticipation on cued trials and assess the classification performance in the absence of ground-truth labels on uncued trials, we related the classification performance and prediction to DDM parameters. This analysis indicates that it is indeed possible to decipher the semantic content of anticipation even on uncued trials.

2 Results

We have analyzed EEG recordings from 42 participants who performed a sensory categorization task. At each trial, participants had to decide whether the stimulus they were randomly presented with was a sound or a visual stimulus consisting of a drawing of a face. The trials were preceded by a pre-stimulus period of 0.9 seconds, and on some trials a cue was presented at the beginning of this pre-stimulus period, indicating with 80% confidence the class of the upcoming stimulus. In that case, the pre-stimulus period was called the *anticipation* period.

Our analyses aimed to characterize the brain activation patterns related to specific stimulus anticipation at the group level and at the single-trial level.

2.1 Behavioral results

The descriptive statistics of response times and accuracies for each condition and stimulus type are summarized in Table S1. We first tested the effects of the stimulus and the condition (i.e. presence or not of an informative cue) on the response times and accuracy at the group level using ANOVA. We observe a significant effect of the stimulus ($RT_{\texttt{auditory}} = 526ms, RT\texttt{visual} = 462ms, F_{1,41} = 119.783, p < 0.001$) and the condition ($RT_{cued} = 470ms, RT_{uncued} = 526ms, F_{1,41} = 70.304, p < 0.001$) on the response time. We also note an interaction effect between stimulus and condition ($F_{1,41} = 30.024, p < 0.001$), with responses of cued visual trials faster than any other trial type ($p < 0.001$), and uncued visual trials significantly faster than uncued auditory trials ($t = 12.236, p < 0.001$), but not than cued auditory trials ($t = 1.058, p = 0.293$). The accuracy however was impacted by neither the stimulus type or the presence of the cue (see Figure S2). Note that there is no interaction effect of the two factors on the accuracy. These results show that the presence of the cue effectively reduced the response times (see also Figure S1).

Then, we tested the effect of a congruent or incongruent cue and the stimulus on the response times and mean accuracy (the descriptive statistics can be found in Table S2) within the cued condition using ANOVA. We observed that incongruent trials had a significant effect on both the response time ($RT_{\texttt{congruent}} = 452ms, RT_{\texttt{incongruent}} = 558ms, F_{1,41} = 131.890, p < 0.001$) and the accuracy ($A_{\texttt{congruent}} = 99.1\%, A_{\texttt{incongruent}} = 91.1\%, F_{1,41} = 31.140, p < 0.001$), and observe as previously that the stimulus type had an effect on the response times ($RT_{\texttt{auditory}} = 496ms, RT\texttt{visual} = 445ms, F_{1,41} = 67.009, p < 0.001$, see also Figure S3) but not on the accuracy (Figure S4). We observed no interaction effect on either the response times or the accuracy. These results show that the cue was considered informative by the participants.

Together, these results support the emergence of anticipatory effects after the presentation of an informative but partially unreliable cue, which validates the experimental paradigm implemented here.

2.2 Anticipatory activity is different from baseline activity

We first compared the electrical brain activity of the anticipation period to baseline brain activity. Since the duration of the baseline period was jittered across trials, we defined two periods of interest in the baseline period. The "early baseline" corresponded to the period $[0, 900]$ ms from the beginning of the baseline period, and the "late baseline" corresponded to a period of 900 ms preceding the pre-stimulus period.

On the grand average activity of all electrodes, we observe that the anticipation activity is significantly different from both early (cluster test, $p = 0.03$ in $[-900 : -794]$ms pre-stimulus, $p = 0.004$ in $[-629 : 0]$ms pre-stimulus) and late baseline activity ($p = 0.004$ in $[-817 : 0]$ms pre-stimulus).

Qualitatively, we observe that the anticipation period entails oscillations at a frequency of 10Hz, stronger than what is typically observed in brain activity. This is simply due to the design of the pre-stimulus period. Indeed, we showed participants 10 frames of random dots, which effectively trigger such patterns.

2.3 Anticipatory activity is distinct from temporal expectation

Next, we wanted to show that the anticipation activity is distinct from temporal expectation of the coming event. Therefore, we compared at the group level the brain activity in the anticipation period to the activity in the pre-stimulus period of uncued trials.

Grand average ERPs (Figure 3) show a significant difference in two time periods: $[-718 : -546]$ms pre-stimulus ($p = 0.017$) and $[-268 : 0]$ms pre-stimulus ($p = 0.023$).

The first one corresponds to the visual-evoked potential due to the presentation of the cue and is not relevant for our next analyses because it is not related to anticipation but rather to the sensory processing of information. The second one, however, is quite similar to the Contingent Negative Variation (CNV) that appears during temporal expectations. Since this signal is significantly different from the uncued one, where little perceptual anticipation can be made, and

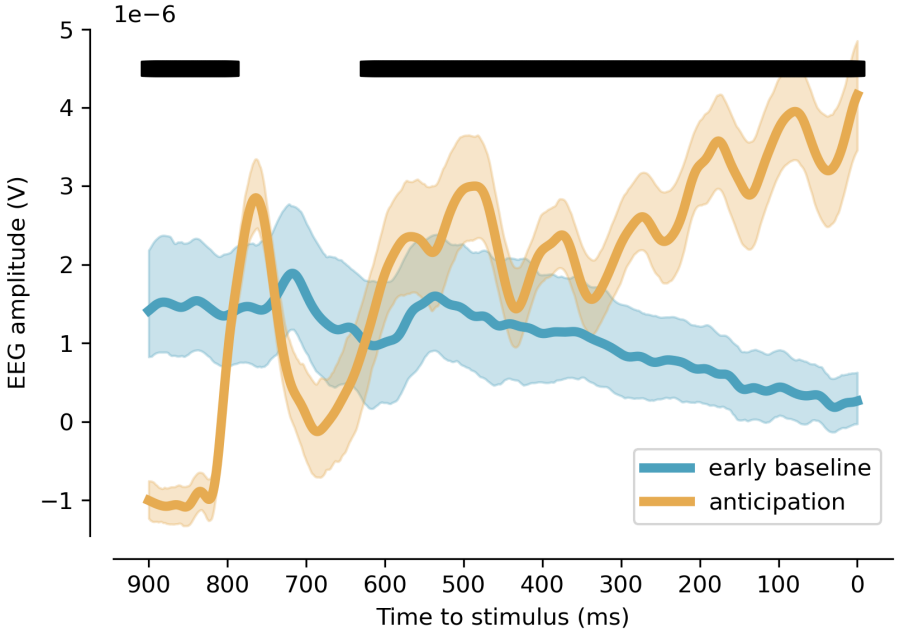


Figure 1: Grand average of early baseline and anticipatory EEG activity over all participants and channels, with 95% confidence interval over participants. The black lines denote the clusters of significant differences between anticipation and early baseline activity, as computed with a $p = 0.05$ threshold.

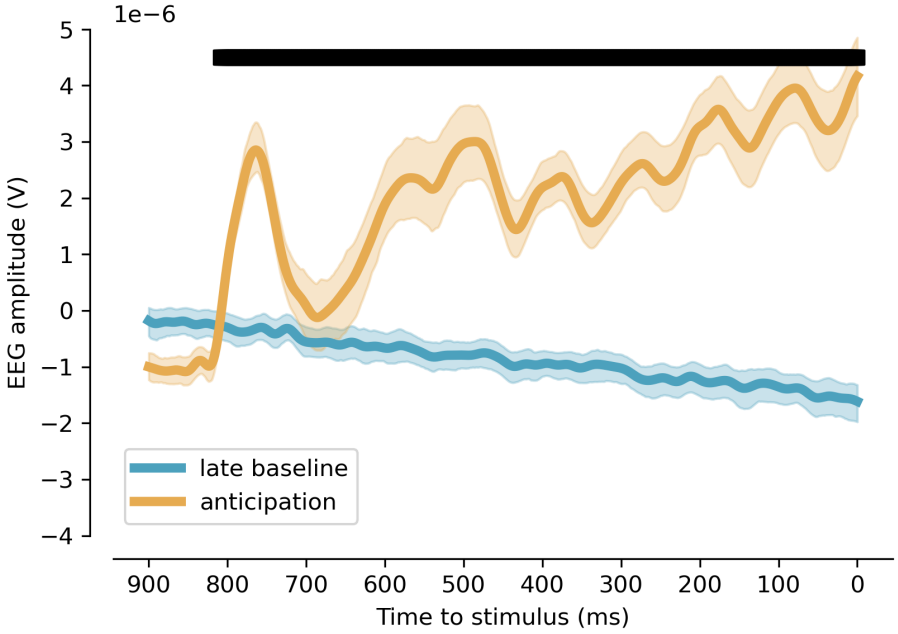


Figure 2: Grand average of late baseline and anticipatory EEG activity over all participants and channels, with 95% confidence interval over participants. The black lines denote the clusters of significant differences between anticipation and late baseline activity, as computed with a $p = 0.05$ threshold.

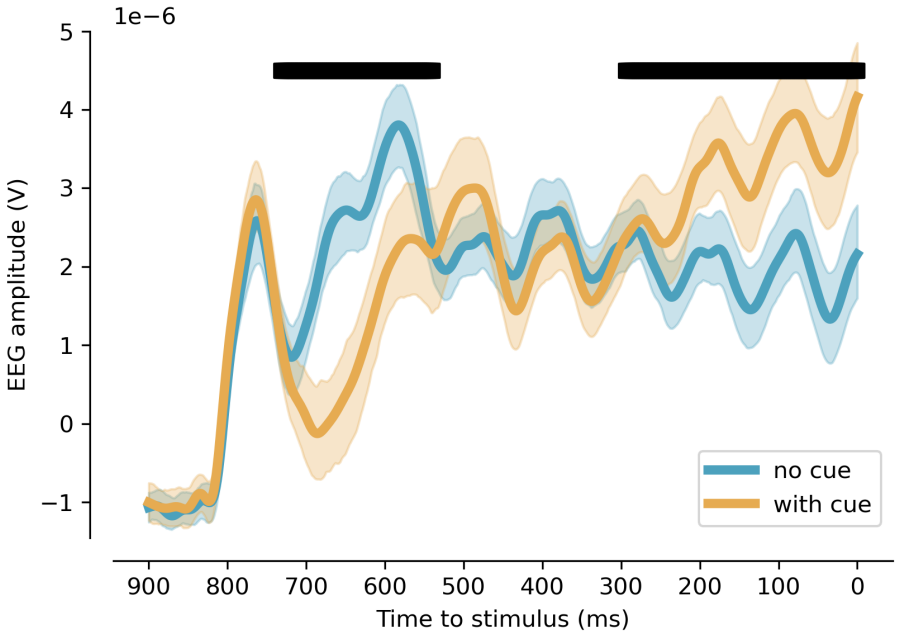


Figure 3: Grand average of anticipatory EEG activity in cued and uncued trials over all participants and channels, with 95% confidence interval over participants. The black lines denote the clusters of significant differences between cued and uncued pre-stimulus activity, as computed with a $p = 0.05$ threshold.

temporal expectation should prevail, it indicates that the content of anticipation shapes the related brain activity.

Figure 4 shows the areas involved in anticipation by representing the difference of evoked activity in the pre-stimulus period in the calibration versus test phase, i.e. with and without an informative cue. We observe a general ramping of EEG activity, and a more positive difference in the central areas. These observations are consistent with the definition of the CNV. Later activity is dominated by occipital activation, again due to the presence of SSVEPs, which, in addition to the global ramping of activity, bestride activity in other channels.

2.4 Discriminating anticipation-specific neural signatures

We first tried to test whether the pre-stimulus ERP could be distinguished at the group level between visual and auditory anticipation, that is, whether the pre-stimulus ERP differed at the group level when an eye and an ear cue were presented. As shown in Figure 5, we observed no significant difference between the two ERPs.

Qualitatively, however, we note a difference between the two grand averages, which indicates that some participants may display stronger differences between the two types of anticipation. The topographies also present some differences (Figure 6). We note a difference over the central areas, suggesting a difference between the CNVs and indicating that the CNV holds information about the

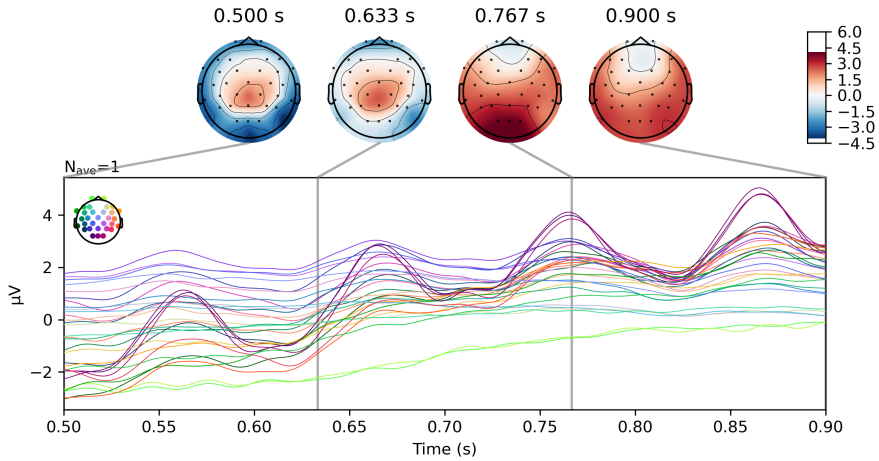


Figure 4: Difference of EEG activity evoked in the pre-stimulus period upon cue presentation and without the cue, over the lest 400ms before stimulus onset. The central areas seem to hold differences, consistent with the definition of CNV.

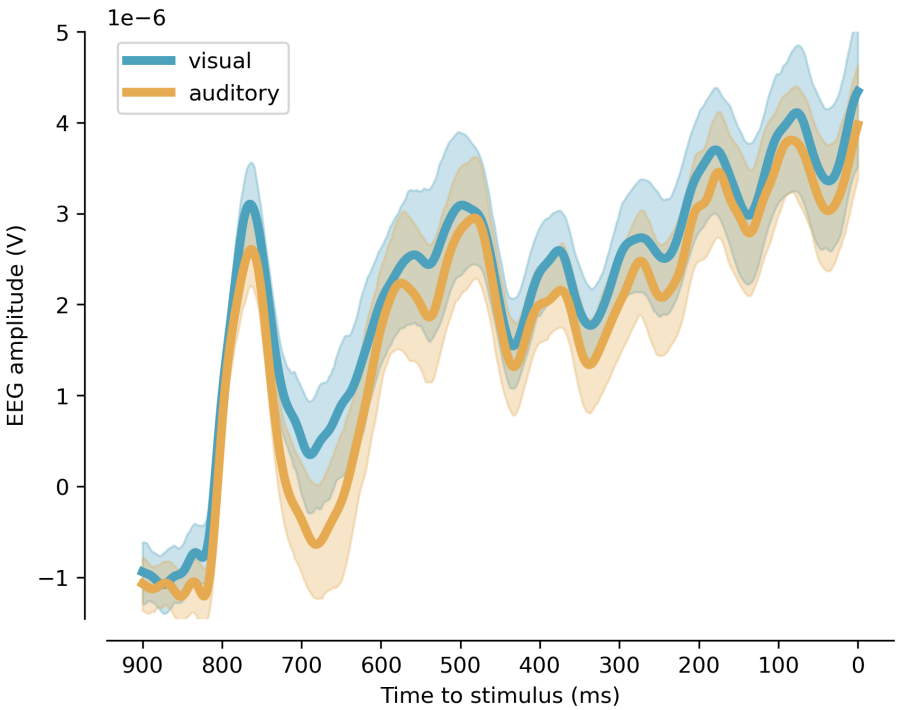


Figure 5: Grand average of anticipatory EEG activity grouped by the type of cue over all participants and channels, with 95% confidence interval over participants. Visual anticipation trials were cued by an eye icon, while auditory anticipation trials were cued by an ear icon.

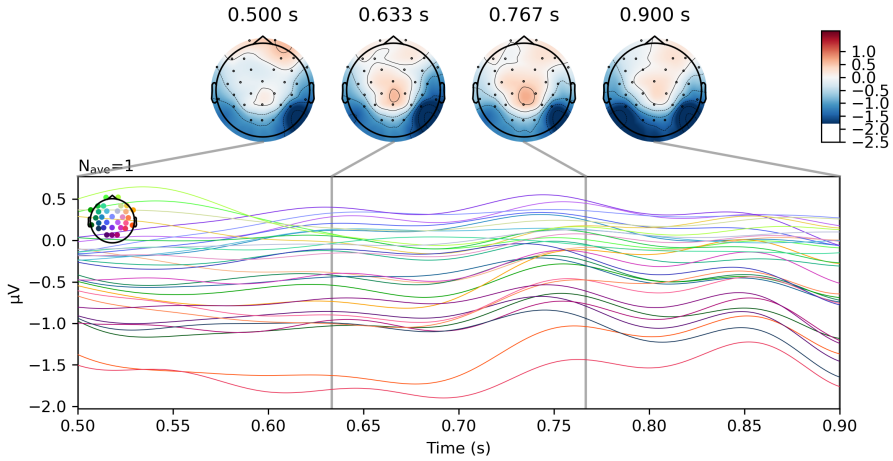


Figure 6: Difference of pre-stimulus evoked activity between ear-cued and eye-cued trials, announcing respectively an upcoming auditory and visual stimulus, over the last 400ms before stimulus onset.

type of expectation, but also a difference in the parietal-occipital electrodes. This difference might be due to a pre-activation of sensory areas in preparation of the upcoming stimulus.

2.5 Single-trial decoding of anticipation

2.5.1 Decoding anticipation from the CNV is feasible on some participants on cued trials

The core test of this study was to determine whether single-trial anticipation could be classified. In the context of our experiment, we hypothesized that participants would display differences in their CNV component depending on whether they expected a sound or a visual stimulus. To this aim, we filtered the signal to keep frequencies between 1 and 4 Hz, hence keeping only the lower frequency signals that characterize the CNV. As a first step, we only considered cued trials, as they allow for direct computation of the classification accuracy.

The table of classification performances is shown Table S3. Out of the 42 participants, 26 displayed classification accuracies, as computed from a $10-$fold cross-validation procedure, above their individual empirical chance level. We found that the classification accuracies were significantly above chance level at the group level, (Fisher test, $\chi^2 = 265.5, p < 0.0001$). It is therefore possible to classify anticipation states in the pre-stimulus period at the single-trial level.

As the CNV appears after several presentations of the cue-stimulus association, we assess the effect of the condition order on the classification performance. We observed no significant difference between the two groups in the classification accuracy (Welch t-test, $p = 0.341$, $df = 40$). This result was expected since all the participants received 60 trials of training prior to the cued condition.

2.5.2 Alpha-band activity for estimating the single-trial anticipation class

Following the results of past studies, we also assessed whether the alpha-band power spectral density could characterize anticipation at the single-trial level. Using the 8 most discriminative electrodes (selected by the Fisher rank, see Methods for more details) and a Support Vector Machine classifier, we found that they significantly differed from the empirical individual chance level at the group level (Fisher test, $\chi^2 = 115.7, p = 0.012$), although only 5 participants showed above-chance classification accuracies. We conclude therefore that the alpha-band activity is different between the two classes of anticipation, although this difference is visible in fewer participants than differences in CNV.

We also tried to classify the ERP within the alpha frequency band using the same classification pipeline as for the CNV classification, this time filtering the raw signal between 8 and 13Hz. We found that 10 participants showed above-chance classification accuracies, representing again a smaller proportion of all participants compared to the classification of ERPs. Moreover, the classification accuracy was higher than chance at the group level (Fisher test, $\chi^2 = 175.5, p < 0.0001$).

Given the better results obtained using ERP classification, the analyses performed on uncued trials are using the pipeline described in the ERP section.

2.6 Towards decoding single-trial anticipation on uncued trials

On uncued trials, we do not have the ground truth about what the participant expected. Therefore, a behavioral proxy for anticipation is necessary to check the validity of our classification. From the behavioral analyses, we found that incorrect anticipation led to longer response times, as seen in the effect of catch trials on the response times. Therefore, we assume in the following that incorrect anticipations lead to longer correct responses, while correct anticipations lead to shorter reaction times on correct responses. Uncued trials were classified for each participant using two pipelines. We first describe how post-stimulus activity was used to infer a ground truth for the state of anticipation. We additionally applied the classifier trained on the covariance matrices of ERPs of cued trials.

2.6.1 Using post-stimulus brain activity to decipher anticipation

Post-stimulus activity holds information about the prior expectations about the stimulus. We therefore trained a classifier to detect when the anticipation did not match the stimulus, using the same pipeline as previously.

The classification performance on cued trials was significantly above chance level (mean AUC across participants: 0.79 ± 0.12), with trials of one participant classified under chance level. Given the satisfactory results of the classification on cued trials, the classifiers were trained again on all the cued trials for each participant and applied to uncued data. The labels thus obtained were converted to anticipation labels, themselves used as the ground-truth labels of anticipation for classification. Applying the same pipeline as described earlier on CNV classification, we computed a classification score for each participant

and then combined the $p-$values across participants using a Fisher test. The classifiers yielded above-chance classification accuracy for 5 participants, resulting in above-chance classification performance at the group level (Fisher test, $\chi^2 = 121.1, p = 0.005$).

We expected a predicted correct anticipation rate close to 50% for all the participants. However, we obtain that participants anticipate the trials correctly $31 \pm 5\%$ (mean$\pm$standard deviation) of the time, which is significantly different from 50% (one-sample $t-$test, $t(41) = -27.6, p < 0.001$).

In the following, we will refer to this pre-stimulus classification pipeline as "post-stimulus"-based.

2.6.2 Using the CNV classifier trained on cued trials

While further qualitative assessment of the classification performance is given later in the "Brain and behavior" results section, the rate of predicted-correct anticipations can quantitatively indicate the quality of the fit, as we expect again that around 50% of the trials are correctly anticipated. We observed that $53 \pm 4\%$ of the trials are correctly anticipated by each participant on average, according to the classifiers. This value also significantly differed from 50% (one-sample $t-$test, $t(41) = 4.746, p < 0.001$).

However, when taking the "ground-truth" labels of anticipation on uncued trials as obtained through the post-stimulus classification, we observed that the classification accuracy lied at chance level. This could indicate either a failure of the post-stimulus classification or a failure of this pre-stimulus classification, although it is not possible to conclude on that based on the results presented above. The next analysis, whose results are presented thereafter, compared the classification predictions to behavioral observations to substantiate these results.

In the following, we will refer to these classification results as "cued-pre-stimulus"-based.

2.7 Relation to behavior

2.7.1 Behavioral predictions

Behavior in decision-making tasks is characterized by the mean response time of correct and incorrect responses and the response accuracy. The previous analyses yielded four different anticipation determination method: on cued data, we either used the cue as the class of anticipation (the "ground" method) or the label predicted by the classifier (the "classifier" method). On uncued data, we either trained the classifiers on pre-stimulus uncued data using labels predicted on post-stimulus activity (the "post-stimulus" method) or used the classifiers created during the "classifier" method trained on cued data to generate the anticipation labels of the uncued trials (the "cued-pre-stimulus" method). For each anticipation determination method, we therefore computed these quantities for each participant separately. The mean and standard deviation of these values across participants are presented Table 1.

We additionally performed repeated measures ANOVAs on the response times and response accuracy, taking Response (correct or incorrect), Anticipation (correct or incorrect) and Anticipation determination method (Ground,

	Cued		Uncued	
	Ground	Classifier	Post-stimulus	Cued-pre-stimulus
Correct anticipation				
RT correct	450 ± 76	463 ± 76	480 ± 76	526 ± 77
RT incorrect	750 ± 490	596 ± 397	569 ± 422	542 ± 219
Response accuracy	99.1 ± 1.0	97.8 ± 1.7	98.1 ± 2.1	97.8 ± 1.8
Incorrect anticipation				
RT correct	564 ± 98	474 ± 82	544 ± 81	523 ± 85
RT incorrect	522 ± 310	576 ± 398	556 ± 161	563 ± 232
Response accuracy	91.1 ± 9.1	$97.6\pm$	97.5 ± 1.8	97.5 ± 2.2

Table 1: Mean response times on correct and incorrect responses (in ms) and response accuracy (in %) depending on the correctness of the anticipation and the anticipation determination method. In each cell, the mean within participant and then across participant $\pm$ the standard deviation across participants is presented. On cued trials, the "Ground" anticipation determination method corresponds to the hypothesis that the cue is the anticipation class, while the "Classifier" method means that anticipation labels are the ones returned by the CNV classifier. On uncued trials, the anticipation label is always obtained from pre-stimulus CNV classification. The "Post-stimulus" method is the one where the classifier is trained on uncued data using the labels obtained by the post-stimulus classification, while the "Cued-pre-stimulus" is the method where the classifier was trained on the pre-stimulus activity of cued trials and then applied to uncued data.

Classifier, Post-stimulus or Cued-pre-stimulus) as within-subject factors. On response times, we observed a significant impact of anticipation ($F(1, 41), p = 0.01$), as well as an interaction effect of anticipation and response ($F(1, 41), p = 0.02$). Post-hoc analyses revealed that on correct responses, incorrect anticipations yielded significantly longer response times than correct anticipations ($t(41) = 4.302, p_{Holm} = 0.003$). On response accuracy, we observed an effect of both the anticipation ($F(1, 41) = 30.329, p < 0.001$) and the anticipation determination method ($F(3, 123) = 17.692, p < 0.001$), as well as an interaction effect of those two factors ($F(3, 123) = 26.045, p < 0.001$). Post-hoc analyses revealed that only incorrectly-anticipated cued trials, as determined by the Ground method, were responded to less accurately than any other trial type ($p_S < 0.001$).

2.7.2 Distribution of anticipation and behavioral outcomes in response time quantiles

For each participant, the trials were split into three groups depending on their tercile of response times. These terciles were computed individually, so that each participant had the same number of short, medium, and long response times. We then also assessed whether trials were anticipated correctly (i.e. if the anticipation and stimulus labels matched) and if they were responded to correctly (i.e. if the stimulus and response labels matched), yielding four pairs of possible anticipation-behavior outcomes.

Figure 7 represents the distribution of anticipation-behavior outcomes in

each response time tercile when the anticipation label is drawn directly from the cue label ("ground" method) (Figure 7a), on cued trials when the anticipation is predicted by the classifier (Figure 7b), on uncued trials using the post-stimulus method (Figure 7c), and on uncued trials using the cued-pre-stimulus method (Figure 7d).

On cued data (Figure 7a), we observed that, among correct responses, correct anticipations were prominently represented among shorter reaction times relative to longer ones, while on the contrary incorrect anticipations were denser on long reaction times. On the other hand, error responses tended to be more represented among longer reaction times relative to shorter reaction times regardless of whether the anticipation was correct or not. Only the proportion of incorrectly-anticipated correctly-responded trials was significantly higher in the third quantile than in the first ($t = 12.816, p < 0.001$) and second ($t = 10.125, p < 0.001$) quantiles, and correctly-anticipated incorrectly-responded trials were significantly more represented in the third relative to the first quantile of response times ($t = 5.227, p < 0.001$). These global trends were also found using the classifier method instead of the ground method on cued trials (Figure 7b). However, these differences were not significant at the group level.

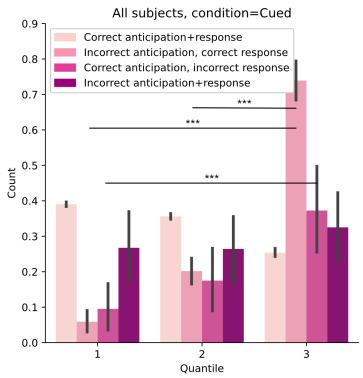
On uncued data, the two sources of anticipation labels yielded qualitatively different results. While anticipation predicted by the post-stimulus method raised qualitatively similar results to those obtained on cued data, the trends are reversed when using anticipation predicted by the cued-pre-stimulus method. In particular, correct anticipations with correct responses qualitatively display longer reaction times while incorrect anticipations with correct responses tend to be shorter. Note that the post-stimulus-based classifier yielded that correctly-anticipated correctly-responded trials were significantly more represented in the first quantile than in the third ($t = -6.310, p < 0.001$). The same qualitative difference can be observed on the ground-truth cued trials (Figure 7a), although not significant.

These observations lead us to the interpretation that the post-stimulus method may have performed better than the cued-pre-stimulus method.

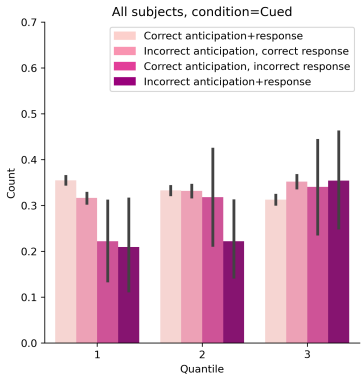
An interesting difference that emerges between cued and uncued trials lies in the distribution of correctly-anticipated error trials. These tend to have longer reaction times in the cued condition while they are more represented among the shorter reaction times in the uncued condition (Post-stimulus-based classifier: first-second quantile: $t = 5.608, p < 0.001$, first-third quantile: $t = 5.720, p < 0.001$; cued-pre-stimulus-based: first-second quantile: $t = 4.356, p = 0.014$). While it is possible that the classification algorithms failed on uncued trials, we propose the alternative view that error trials on correct anticipations result from different mechanisms depending on the condition: in the cued condition, these errors emerge when there is doubt either on the cue that has been seen or the motor command corresponding to the matching response. In contrast, as no indication about the upcoming stimulus is provided to the participant in uncued trials, shorter reaction times and errors could emerge in a repetitive task when motivation drops.

2.7.3 Anticipation and diffusion-decision models

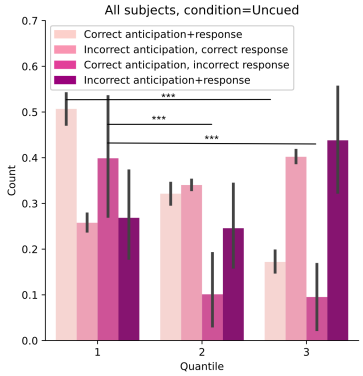
We fitted the DDM to individual behavioral data in the cued condition to assess the mechanism by which response times and response accuracy are improved



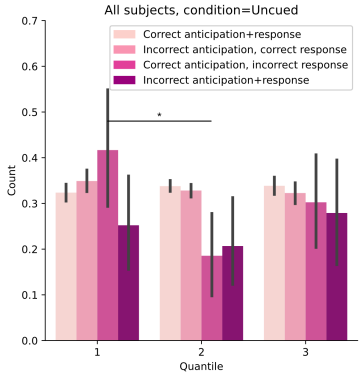
(a) Cued trials, anticipation=cue label



(b) Cued trials, anticipation predicted



(c) Uncued trials, anticipation predicted by classifier trained on uncued data



(d) Uncued trials, anticipation predicted by classifier trained on cued data

Figure 7: Distribution of trials within each anticipation-behavior outcome type across response time terciles, for cued (a, b) and uncued (c, d) trials. In each plot, the anticipation label was extracted differently. (a) anticipation labels correspond to cue labels ("ground" method). (b) anticipation labels are the ones predicted by the classifier ("classifier" method). (c) anticipation labels are the ones predicted from pre-stimulus activity by the classifier trained on uncued data: the training was done using post-stimulus-predicted labels to build the "ground-truth" labels of anticipation ("post-stimulus" method). (d) anticipation labels are the ones predicted from pre-stimulus activity by the classifier trained on cued data ("cued-pre-stimulus" method).

upon correctly anticipating the upcoming stimulus. For this, the boundary $a = 1$ and non-decision time $T_0 = 0.3$s were fixed for all participants, while the drift ν and starting point z_r was fitted for each participant depending on whether the cue matched the stimulus or not. This resulted in 2 drifts and starting points per participant.

We first tested whether the drift or the starting point varied significantly depending on the correctness of anticipation. The drift was significantly greater on correctly-anticipated trials compared to incorrectly anticipated trials (paired-sample t-test: $t(41) = 4.322, p < 0.001$, Cohen's $d = 0.667$). We also observed a

significant effect of anticipation correctness on the starting point value, whereby the starting point was closer to the correct decision boundary when the stimulus was correctly anticipated (paired-sample t-test: $t(41) = 2.465, p = 0.018$, Cohen's $d = 0.380$).

We then tested whether these differences also related to the classification accuracy on cued trials. We observed that participants that displayed above-chance classification performances had a significantly more positive difference in starting point between correctly and incorrectly-anticipated trials, compared to participants whose classification performance remained at chance-level (independent sample t-test: $t(40) = 2.102, p = 0.042$, Cohen's $d = 0.668$). Moreover, we noted a significant correlation between classification accuracy and difference in starting point (Pearson's r: 0.346, $p = 0.025$). Note that neither analysis revealed a significant relation between drift difference and classification accuracy.

Applying these results to assess classification performance on uncued data of the post-stimulus-based and the cued-pre-stimulus-based pipelines, we repeated the subjective fitting, this time using uncued trials. We then computed the difference between parameters of correctly and incorrectly-anticipated trials, and compared the differences within and across classification pipelines. Within pipeline, none of the pipelines returned a significant difference between parameters, which we could allocate to a poor fitting compared to cued trials. However, the comparison of these differences across pipelines signals that the cued-pre-stimulus-based pipeline returns significantly more positive starting point differences than the post-stimulus-based pipeline (Shapiro-Wilk test: $W = 0.615, p < 0.001$, Wilcoxon signed-rank test: $W = 346, p = 0.02$, Cohen's $d = 0.488$). Given our analysis on cued trials, a better pipeline should display a more positive starting point difference, indicating that the cued-pre-stimulus-based pipeline could have been more accurate than the post-stimulus-based one.

3 Discussion

In this article, we sought to underline the neural correlates of anticipation in human EEG data evoked by both cued and uncued decisions. We showed that central ERPs, that we identified as the CNV, was not a general marker for unspecific anticipation but rather contained information about the expected stimulus at the single-trial level on cued trials. The classification performance was indeed robust on cued trials across participants. We subsequently attempted single-trial decoding of anticipation on uncued trials using two techniques: the first one used the classifiers trained on cued data, while the second involved a second classifier trained on cued trials to detect incorrect anticipations from post-stimulus activity. The classification performance on the latter was above chance level for 5 out of 42 participants, which is above chance at the group level, although there is a clear degradation of classification performance compared to the classification on cued trials. DDM modeling also allowed to associate anticipation with a shift of the starting point towards the associated decision boundary and an increase of the drift rate upon correct anticipation. Moreover, a better subjective classification performance of pre-stimulus EEG activity relates to an increased difference in starting points between correct and incorrect anticipations. This result also provides a method to assess the classification performance of anticipation on

uncued trials.

In this work, we assessed the selectivity of the CNV and of pre-stimulus alpha-band power to specific perceptual anticipation. The CNV showed to be particularly indicative of the anticipated stimulus as 26 out of 42 participants displayed above-chance classification performance with the pipeline implemented here. Past literature associated the CNV to non-specific temporal expectation (Walter et al., 1964) or temporal estimation Kononowicz and Penney (2016). More recently, works have shown that it was possible to distinguish anticipation in Go/NoGo tasks at the single-trial level, that is, to distinguish anticipation between trials where a movement is required relative to when movement has to be withheld (Garipelli, Chavarriaga, and Millan, 2009; Garipelli, Chavarriaga, and Millan, 2011; Chavarriaga et al., 2012; Khaliliardali et al., 2012; Khaliliardali et al., 2015). While Chavarriaga et al. (2012) emancipated their analyses from motor preparation by requiring no motor output in one of their tasks, the authors argued that the differences are ascribable to attentional changes following an erroneous proposition. The present work goes further by showing that the CNV is specific to the anticipated type of stimulus. Whether this can be used for brain-computer interface applications remains to be investigated, as online control requires additional temporal constraints that were not considered here. Our experiment additionally provided a fixed time window for anticipation, making the stimulus temporally predictable. In ecological situations, events may not have such a regular temporal structure, and future works could focus on detecting anticipation onset.

The second feature explored is pre-stimulus alpha power. In the past, alpha activity was shown to be an important marker in the pre-stimulus period. While we did observe significant differences in alpha-band activation between the two types of anticipation in this study, the single-trial classification performance using alpha-band activity yielded poorer results than CNV-based classification. Several reasons could explain this. First, the alpha band activity was thought in the past to be related to a passive gating of sensory information and global mental states (Pfurtscheller, Stancák, and Neuper, 1996). This was referred to as an "idling" state. This, however, contradicts more recent evidence that sensory gating is made specifically for each sensory modality, and in a targeted fashion (Jensen and Mazaheri, 2010; Jensen, Bonnefond, and VanRullen, 2012), or that attention is selective to specific stimuli (Foxe and Snyder, 2011). The second explanation, which we believe is the most likely, is that the paradigms implemented in previous studies used stimuli at different perception levels, including stimuli close to the individual perception threshold of each observer (Bode et al., 2012; Barik et al., 2019; Samaha, Iemi, and Postle, 2017). In these instances, stimulus perception would be highly dependent on the network excitability, represented by the alpha-band activity level. Here, we used clearly distinguishable stimuli. Samaha, Iemi, and Postle (2017) have however shown that the alpha-band activity biased the confidence ratings of participants and not the behavioral performance, which would mean that regardless of their alpha activity, participants could still sense the visual information they were presented with. In the same line, Benwell et al. (2021) showed that discrimination accuracy was unaltered by fluctuations of pre-stimulus alpha power while subjective ratings of awareness correlated negatively with alpha power. This is still compatible with our explanation, as it would mark a difference between sensed and perceived information, the latter requiring a conscious grasp of the stimulus.

The DDM analyses revealed that correct anticipation resulted both in a shift of the starting point toward the correct decision boundary and an increase in the drift rate. This is consistent with both the theory of premature sampling, whereby information is integrated before the stimulus appears (Laming, 1979a; Laming, 1979b; Grosjean, Rosenbaum, and Elsinger, 2001), and the idea of sensory facilitation (Walz et al., 2015), whereby information is more easily integrated when it is expected. Premature sampling results in a starting point shift, while sensory facilitation could explain the increased drift rate. Interestingly, only the difference in starting point between correct and incorrect anticipation significantly varied between participants whose CNVs were classified with above-chance accuracy and participants with chance-level classification accuracy. In that sense, the classifier could have captured premature sampling more efficiently in those participants with good classification performance compared to those for which the classifier yielded chance-level classification accuracy. We further used this result to infer the classification performance of pre-stimulus activity of uncued trials. Classifying uncued pre-stimulus activity is particularly challenging due to the lack of ground-truth information regarding the class of anticipation. The DDM analysis on these trials revealed that the difference in starting points between correct and incorrect anticipations (as predicted by either classifier) was greater when the anticipation class was predicted using a classifier trained on cued data and applied directly on uncued data ("cued-pre-stimulus" pipeline) than when it was predicted from a classifier trained on uncued data, using labels predicted from post-stimulus EEG activity ("post-stimulus" pipeline). However, upon comparing the distribution of anticipation and behavioral outcomes across response time quantiles, we observed that the "post-stimulus" pipeline yielded patterns more similar to cued trials than the "cued-pre-stimulus" pipeline, suggesting conversely a better performance of the "post-stimulus" pipeline. Note however that this analysis is qualitative, and that some uncertainty remains, as a quantitative assessment of the quality of the classification of anticipation based on post-stimulus activity on uncued data is equally difficult and was not performed here.

A variety of factors could be at the origin of anticipation. Among them, sequential effects have been shown to have an impact on subsequent decisions (Yu and Cohen, 2008; Bode et al., 2012; Abrahamyan et al., 2016; Palminteri et al., 2017; Urai et al., 2019). Our experiment was designed in such a way that the stimuli were presented randomly to each participant at each trial, with a 50% chance of either stimulus being presented at each trial. Moreover, the stimuli were well distinguishable, reducing the uncertainty. It has however been shown that past stimuli and decisions had an impact on subsequent decisions even when sequences are absent from the experiment design (Yu and Cohen, 2008). We did not consider such effects here, in particular not in the cued experiment, where we implicitly assumed that the effect of the cue was greater than possible sequential effects. Indeed, the presence of the cue reduces the perceived uncertainty compared to uncued trials, as underlined by the reduction of response times in cued trials compared to uncued trials. We argue however that these effects should be considered in more uncertain contexts, for example when attempting to classify uncued pre-stimulus periods, or if the stimuli are closer to the perceptual threshold. The effect of global levels of attention on subsequent behavior could also be evaluated, as drowsiness is reflected in post-stimulus EEG patterns, possibly reflecting an alteration of the evidence integration stage

of decision-making (Jagannathan, Bareham, and Bekinschtein, 2022). Future studies could weigh the contribution of the specific anticipation, sequential effects, and attention on behavior, and in particular response times, by means of regression analyses for instance.

It is very likely that the anticipatory processes we uncovered are implicit for the main part. Indeed, while our experiment did not include a feedback questionnaire, some participants reported that they deliberately ignored the cue in the calibration phase to avoid making mistakes. However, our behavioral analysis has shown that participants were systematically faster in the calibration phase compared to the test phase, regardless of the order in which the blocks were performed. The accuracy however did not decrease with increasing speed, although the cue was faulty in approximately 20% of the cases. It indicates that the participants finalized their decisions upon stimulus presentation, but still considered the cue as informative, as they tended to make more mistakes in catch trials, i.e. when the cue and the subsequent stimulus did not match. A deeper analysis, which could include for example a scaling of the reliability of the cue combined with an analysis of how behavior and subjective ratings of the usefulness of the cue, could be useful to investigate this effect.

In conclusion, the CNV holds information about perceptual anticipation, and it is possible to decipher what is expected from pre-stimulus EEG activity at the single trial level. Future works could deepen the uncovered relations between brain activity and behavioral predictions using modelling techniques to build a more precise description of the influence of anticipation on behavior and, consequently, refine the classification of uncued trials.

Author contributions

Conceptualization, I.H.; Methodology, I.H.; Software, I.H. and S.C.; Formal Analysis, I.H.; Investigation, I.H.; Writing – Original Draft, I.H.; Writing – Review and Editing, I.H., S.C., A.D., and M-A.A.; Funding Acquisition, M-A.A., S.C., and A.D.; Resources, M-A.A. and S.C.; Supervision, S.C., A.D., and M-A.A.

Declaration of interests

The authors declare no competing interests.

4 Materials and methods

4.1 Participants

42 participants (24 males, 18 females; 5 left-handed; aged $20 - 64$, mean: 30.43 ± 10.78) with normal or corrected-to-normal hearing and vision took part in this study. The experiment was approved by the Comité d'Ethique de la Recherche Paris-Saclay, under the application number 321. Each participant was informed about the purpose of the study and signed informed consent forms upon participation. All participants fully completed the experiment.

4.2 Experiment design

The experiment consisted of two parts, denominated "test" and "calibration" phases thereafter, which the participants completed within the same recording session. During the test phase, participants were presented randomly at each trial with either the sketch of a face ("face" trial) or a sound ("sound" trial). They were instructed to respond as fast as possible to each stimulus by pressing with their dominant hand on the right arrow of a keyboard for "face" stimuli and on the left arrow for "sound" stimuli. Each trial started with the apparition of a red cross in the middle of the screen, indicating a 1.5 s rest period to the participant. The cross then became white to instruct participants to start focusing on the task and avoid parasitic movements that can blur EEG signals (blinking, jaw and head movements in particular). This baseline period lasted for 1.5 to 3 seconds, with its duration varying randomly across trials. After that, a square visual noise clip appeared for 0.9 s in the middle of the screen, frames being updated at a rate of 10 Hz. While the last frame remained on the screen until the end of the trial, the stimulus was displayed for 200 ms at the end of the noise clip. The trial terminated upon participant response or after a timeout of 2 s after stimulus onset.

Trials in the calibration phase were identical to those in the test phase, with the addition that a cue appeared for 200 ms at the beginning of the noise clip, indicating which stimulus would be displayed. A pictogram of an eye indicated a "face" trial, and an ear icon indicated a "sound" trial. To eliminate the possibility of having created a delayed response instead of sensory anticipation, we set the cues to be inaccurate in 20% of the cases, excluding the ten first trials. We chose this catch probability according to the threshold at which oddball paradigms function, hence ensuring that the cue was still reliable (Ehrlich and Cheng, 2018; Chavarriaga, Sobolewski, and Millan, 2014). A summary of the sequence of a trial for these two phases is given Figure 8.

Participants performed 3 test and 4 calibration blocks of 60 trials each, resulting in 180 test trials and 240 calibration trials. 20 training trials preceded the test phase, and 60 training trials were performed before the calibration phase. The training phase preceding the calibration phase was longer so that participants had time to learn the impact of the cue, the correct response to each target stimulus, and to avoid making mistakes in catch trials. Half of the participants performed the test blocks first, while the other group of participants started with the calibration blocks to prevent any influence of the order of the phases. Participants were free to take a break between each block and could decide when to continue with the next one. The experiment was performed in a dark room to enhance the sight of the visual stimulus.

4.3 Stimuli

Target stimuli consisted of a sound pulse at 1000 Hz for the sound stimulus, and a sketch of a face for the visual stimulus. The sketches were generated by Yang et al. (2020) from the Radboud Faces Database (Langner et al., 2010). Cue stimuli consisted of an open-source drawing of an eye and one of an ear, displayed at the center of a screen over a random dot square cloud. All stimuli lasted for 200 ms.

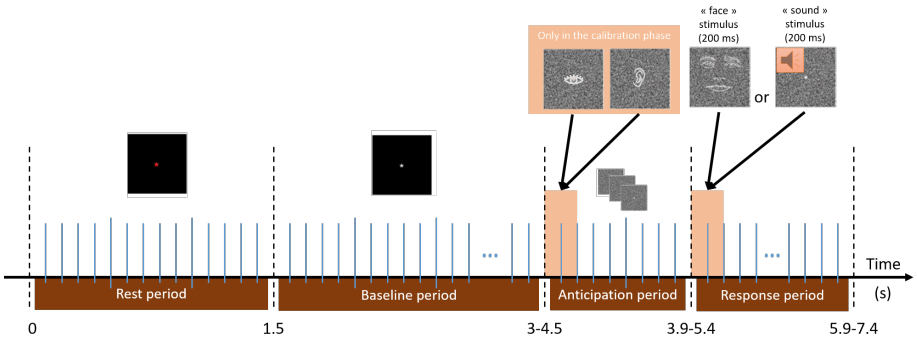


Figure 8: Summary schematic of the sequence of a trial

4.4 EEG data acquisition

EEG signals were recorded at 1000 Hz using 32 active AgCl electrodes, and the actiCHamp Plus amplifier (Brain Products GmbH, Gilching, Germany). The electrodes were placed according to the 10/20 international system. Electrode Fz served as the reference electrode upon acquisition.

To avoid contamination by stimulus-related activity, we applied offline a non-causal finite impulse response band-pass filter with cut-off frequencies 0.1-35Hz to remove high-frequency artifacts (muscle activity in particular) and low-frequency artifacts, such as sweat. Data was subsequently epoched on the relevant periods of interest (see below).

4.5 EEG data comparisons: periods of interest

We wanted to see if we could distinguish the ERP forms between anticipation versus baseline, anticipation and no anticipation (i.e., pre-stimulus period with and without a cue), and visual versus auditory anticipation. The pre-stimulus period was defined as the window $[-400 : 0]$ ms preceding the target stimulus for both stimuli and in both cued and non-cued conditions. It can equivalently be defined as the $[500 : 900]$ ms time window following the onset of the noise clip and cue. Since the duration of the baseline period was randomly varied across trials, we defined two time intervals of interest in the baseline period: $[500 : 900]$ ms after the beginning of the baseline period and $[-400 : 0]$ before cue onset. 4 comparisons were hence performed: early-baseline vs. anticipation, late-baseline vs. anticipation, anticipation vs. no anticipation, and visual vs. auditory anticipation.

4.6 Computing ERP components

For the initial investigation of significant differences between the different periods of interest described above, ERP components were computed by averaging trials within category (early/late baseline, cued trials, uncued trials, face anticipation and sound anticipation). A comparison of the grand average was performed, averaging the signal both across trials and channels within participants.

4.7 Classification pipelines

4.7.1 Classifying ERPs using covariance matrices

The CNV is a candidate for discriminating the type of anticipation at the single-trial level. To use it as a feature for classification, we first applied a $1-4$Hz band-pass filter on raw calibration data and epoched it from 500 to 900ms after noise clip onset, corresponding to the last 400ms before stimulus onset. Trials were then split into 10 stratified folds, using cue label for stratification to ensure that the label distribution is preserved in each fold. For each cross-validation round, 9 of these folds were used as the train set and the remaining one as the test set, so that each fold was used once as the test set. Using the PyRiemann Python toolbox (Congedo, Barachant, and Bhatia, 2017; Barachant et al., 2023), extended covariance matrices (Barachant and Congedo, 2014) with XDawn components (Rivet et al., 2009) were computed for each class using the train set, selecting 8 components, and the Minimum Distance to Mean was used to assess the class of each trial. Using covariance matrices for EEG activity classification was proven efficient to improve classification accuracy on ERP data (Barachant and Congedo, 2014) and motor imagery (Barachant et al., 2012; Barachant et al., 2013). The classification accuracy was then computed for each test set and then averaged across test sets within participant.

4.7.2 Classifying pre-stimulus alpha-band power

As pre-stimulus alpha-band power has been shown to be predictive of behavior in other works (Iemi et al., 2017; Samaha, Iemi, and Postle, 2017; Barik et al., 2019; Bode et al., 2012; Wöstmann, Waschke, and Obleser, 2019; Railo, Piccin, and Lukasik, 2021; Lou et al., 2014; Min and Herrmann, 2007; Min et al., 2008; Petro et al., 2019; Dijk et al., 2008), we used it as a feature to classify single trials according to the type of anticipation (face vs. sound anticipation). Alpha power is computed using a multitaper in the frequency band $[8-13]Hz$ over the time window of interest $[-400, 0]$ms before stimulus onset. The powers thus obtained are averaged over frequencies, resulting in 31 features, one per acquisition electrode.

The data used for fitting consists of the cued trials for each participant, i.e. 240 trials. To reduce the dimensionality of the feature space and avoid the "curse of dimensionality", the 8 most discriminative features are selected using Fisher ranking (Gu, Li, and Han, 2012): for each feature i, a score is computed using the following equation (Equation 1):

$$F(i) = \Sigma_{j \neq i} \frac{(\mu_j - \mu_i)^2}{\sigma_i^2 + \sigma_j^2} \tag{1}$$

The 8 features with the highest score are selected. A SVM classifier is fitted over the cued trials using a 3-fold cross-validation, and the mean classification accuracy is used as a metric for classification assessment.

4.7.3 Classifying pre-stimulus activity of uncued trials

The afore-described classification pipelines are supervised. However, the ground-truth label of anticipation is unknown on trials of the test phase of the experiment, i.e. on uncued trials. To circumvent this issue, two solutions are proposed

here. First, if we assume the stationarity of the anticipation phenomenon across tasks, the brain activity patterns of anticipation over uncued trials should be similar to those found on the cued trials. Therefore, classifiers trained on cued data can be applied on uncued data of the same participant. We hence retrained the classifiers obtained on all the trials of the calibration phase of the experiment for each participant, and predicted the corresponding anticipation class using the thus trained classifier on uncued trials.

The second solution consists of analyzing the post-stimulus effects of anticipation. Indeed, challenged expectations should result in potential variations in the post-stimulus period (Kappenman and Luck, 2011; Lou et al., 2014). Consequently, detecting mismatch signals in the post-stimulus ERP should indicate the type of anticipation produced by the participant in the pre-stimulus period, hence providing "ground-truth" labels on the type of anticipation on uncued trials. We therefore trained a classifier to detect incorrect anticipations in the post-stimulus period of the cued trials, using the same pipeline as described in "Classifying ERPs using covariance matrices". The ROC curves were plotted for each participant to verify the correctness of the classification, then the classifiers were trained again over all cued trials and were subsequently used to detect incorrect anticipations on uncued trials. The anticipation labels were then obtained by combining the stimulus labels and the labels obtained from this pipeline. These labels were then used as the cue labels in the pipelines described earlier.

The different pipelines used to generate the classes of anticipation on both cued and uncued trials are summarized Figure 9. In the following, we will refer to the anticipation on cued trials as "ground" anticipation when the cue label is used as the anticipation class, or as "classifier" when the anticipation class is the one predicted by the pre-stimulus classifier. On uncued trials, we will refer to "cued-pre-stimulus" anticipation when the anticipation is the one predicted by the aforementionned classifier trained on cued trials, or to "post-stimulus" when this anticipation is the one predicted by the pre-stimulus classifier trained using the labels predicted by the post-stimulus classifier trained on cued data and subsequently applied to uncued trials.

4.8 Linking brain and behavior

One of the main assumptions of the effects of anticipation on behavior is the reduction of response times and error rate subsequent to correct anticipations. If the classification algorithm was indeed trained to distinguish the type of anticipation, we should observe that correct anticipations are more represented among shorter reaction times relative to long ones. Conversely, incorrect anticipations should result in longer reaction times.

4.8.1 Response time quantiles

We first split the predicted anticipations depending on their correctness and behavioral outcome: the anticipation can either match the stimulus or not, corresponding to correct and incorrect anticipations respectively, and the response can match the stimulus or not, corresponding to correct and incorrect responses respectively. In addition, the trials were split into three groups depending on their response time: for each participant, we computed the 33th and 66th per-

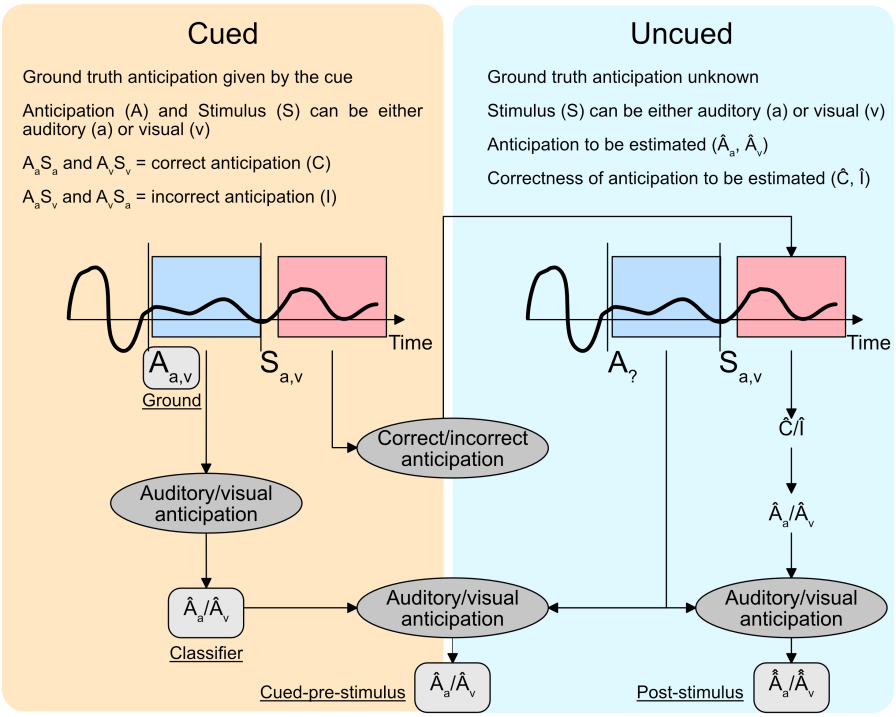


Figure 9: Different anticipation generation methods, on cued and uncued trials. We use two types of classifiers, symbolized by grey ellipsoids: a classifier trained to detect whether the anticipation is visual or auditory based on pre-stimulus EEG activity, and a classifiers trained to detect whether the anticipation was correct or incorrect (i.e. whether anticipation matched the following stimulus or not) based on post-stimulus EEG activity. The final labels that were used as the anticipation class are frames in light grey, with their denomination in the article underlined in the vicinity.

centiles of response times and hence split the trials into short, medium, and long response times. We then studied the distribution of each of the four pairs of anticipation+response outcomes across response time quantiles. This was done separately for cued and uncued trials in order to compare the results on uncued trials to the more reliable ones over cued trials.

4.8.2 DDM fitting

To further analyze the effects of anticipation on behavior, we fitted diffusion decision models (DDMs) (Ratcliff, 1978; Ratcliff and Tuerlinckx, 2002; Ratcliff and McKoon, 2008) to behavioral data. According to DDMs, sensory evidence is accumulated linearly from a starting point z_r until reaching a fixed decision boundary a, at which time a decision is made. The DDM is defined by the equation:

$$dx = \nu dt + N(t) \tag{2}$$

where the decision variable x varies by dx in infinitesimal time dt. The decision state can be viewed as a particle subject to Brownian motion with drift ν, Gaussian white noise term N(t). Additionally, a non-decision time T_0 is fitted to account for biological delay of sensory encoding and motor preparation explaining the difference between the decision time and the observed response time.

Our DDM analysis aimed at identifying whether changes in anticipation resulted in changes in the accumulation rate ν, or rather in a bias in the starting point z_r. More specifically, correct anticipation resulting in faster and more correct decisions than incorrect anticipation, one could expect that correct anticipation either increases the rate of evidence accumulation, or that the decision is initially biased towards the correct decision.

One cued data, two hypotheses were tested:

1. correct anticipations should result in larger drifts or larger starting points than incorrect anticipations

2. participants who displayed above-chance classification performance should also display a larger parameter difference between correct and incorrect anticipations

To test these hypotheses, we fitted a DDM for each participant, fixing the boundary $a = 1$ and non-decision time $T_0 = 0.3$s for all participants. This was necessary in order to compare model parameters across participants, since these parameters are interdependent with the drift and the starting point. For each participant, both the drift term and the starting point were fitted separately depending on whether ground-truth anticipation was correct or incorrect. Starting point, drift, and non-decision time variability were additionally fitted for each subject, but not further analysed. The software fast-dm Voss and Voss (2007) was used, using the Kolmogorov-Smirnov fitting method.

To test hypothesis 1, we performed paired-sample t-tests to assess whether the drifts and starting points significantly depended on the correctness of anticipation. To test hypothesis 2, we followed two complementary approaches. First, we performed independent sample t-tests to assess whether the parameter difference was significantly greater on participants displaying above-chance classification accuracies. Second, we performed a correlation analysis to assess a

possible linear dependency of classification accuracy on either of the parameter difference.

The same DDM fitting was performed on uncued data, using this time the anticipation class predicted by either classifier (i.e. using "cued-pre-stimulus"- and "post-stimulus"-based labels) to assess the correctness of anticipation. This time, we assessed whether a method provided a greater parameter difference than the other. Based on the DDM analysis of cued trials (see Results), this measure would indicate a better classification performance from one classifier or the other.

4.9 Statistical procedures

4.9.1 Behavioral effects

We first tested at the group level the effects of the presence of the cue and the stimulus on the response time and accuracy using a multivariate ANOVA procedure. We further tested the effect of congruent and incongruent cues and stimuli on the response time and accuracy on the cued condition only, using a multivariate ANOVA again. Note that the tests were done separately due to the unbalanced number of trials in each condition.

4.9.2 Significance of ERP differences

To test the group-level effects of anticipation on time series, we performed cluster-based permutation testing. The idea of this type of testing is explained in Maris and Oostenveld (2007), and the methodology is summarized here. This analysis aims to test the statistical significance of effects appearing in ERPs, all while correcting for multiple comparisons. Since the number of tests to perform is very big (901 time points, or pixels), classical corrections such as the Bonferroni correction are not adapted as they would result in meaningless reference thresholds. F-statistics of each pixel are computed to identify clusters of (uncorrected) significant activity. The pre-cluster threshold is set to $p < 0.05$. The signals are then shuffled and the statistics are computed again on the permutation. The statistics of the bigger cluster thus obtained are stored, and the whole process is repeated over several iterations to form the null-hypothesis distribution, against which all the clusters identified in the original signals are tested. We performed 256 permutations. This number allowed us to obtain stable null hypothesis distributions while remaining time-efficient.

4.9.3 Significance of classification performance

We compute a mean classification score from the k-fold cross-validation for each participant and pipeline. The classification scores are compared to chance level that we obtained through permutation testing over 100 iterations. At each iteration, the labels are shuffled, and the classifier is re-run to compute the classification accuracy over the randomly labeled data. The null-hypothesis distribution of the chance level classification performance is thus obtained for each participant, and the classification performance is compared against this distribution. The p-value of the classification accuracy against the null-hypothesis distribution is computed for each participant and further compared across all participants using a Fisher test.

Supplemental information

A Behavioral data

In this section, we noted the visual and auditory stimuli 0 and 1 respectively.

Description of overall behavior (see also Figures S1 and S2):

Table S1: Summary statistics of participant behavior across conditions
Per condition (cued or uncued) and stimulus type (0: visual, 1: auditory).

	RT				Accuracy			
	Cued,0	Cued,1	Uncued,0	Uncued,1	Cued,0	Cued,1	Uncued,0	Uncued,1
Mean	444.555	495.507	485.856	568.152	0.980	0.976	0.978	0.975
Std. Deviation	89.502	79.152	81.567	86.600	0.021	0.021	0.020	0.023
Minimum	332.390	384.330	353.933	421.945	0.897	0.919	0.908	0.905
Maximum	688.908	795.446	681.172	820.106	1.000	1.000	1.000	1.000

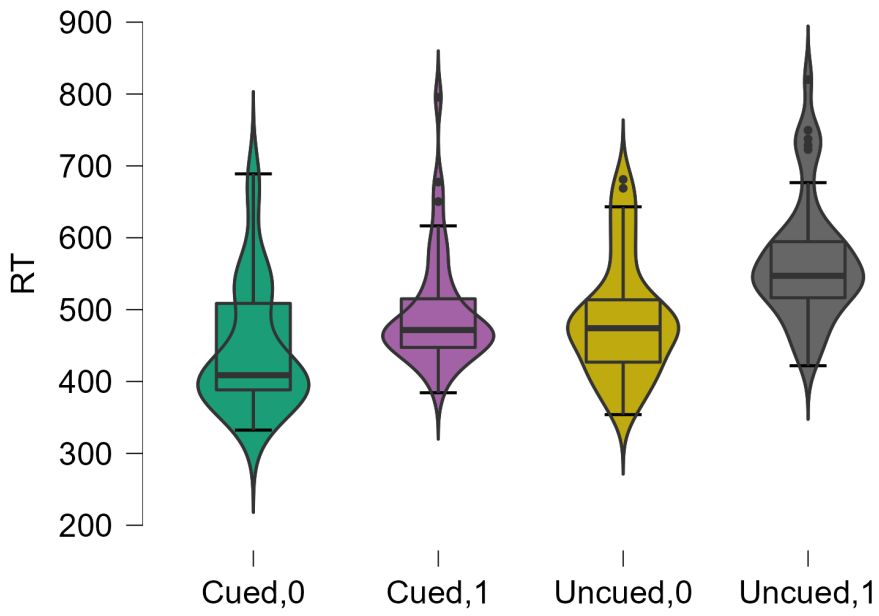


Figure S1: Global mean response times (in ms) per condition and stimulus type

Description of participant behavior on the cued condition only (see also Figures S3 and S4):

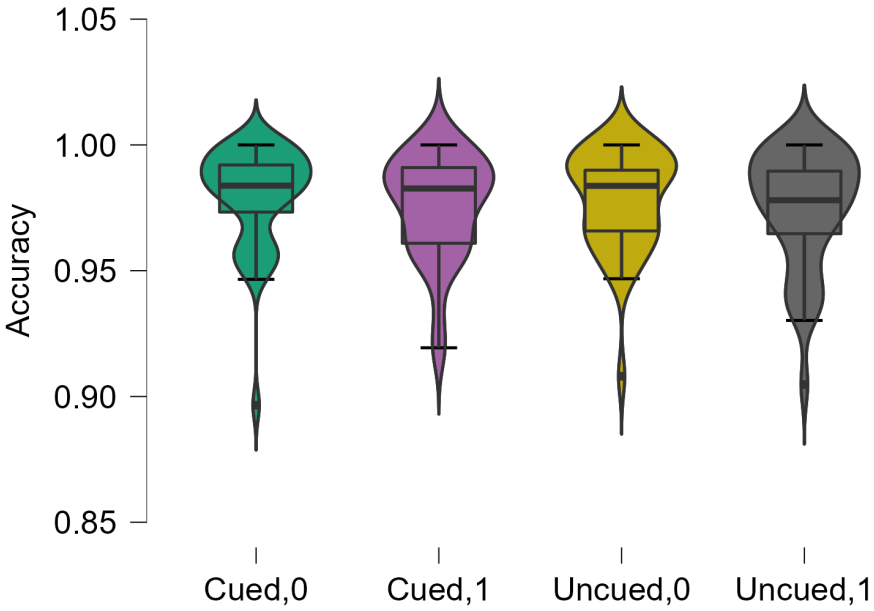


Figure S2: Global mean accuracy rates per condition and stimulus type

Table S2: Summary statistics of participant behavior in the cued condition
Per type of trial (catch: the cue and the stimulus were incongruent, match: the cue and the stimulus were congruent) and stimulus (0: visual, 1: auditory).

	RT				Accuracy			
	Catch,0	Catch,1	Match,0	Match,1	Catch,0	Catch,1	Match,0	Match,1
Mean	529.921	587.475	427.233	476.674	0.927	0.896	0.990	0.992
Std. Deviation	104.551	116.259	89.232	76.800	0.102	0.106	0.014	0.011
Minimum	367.267	406.120	306.427	374.785	0.474	0.545	0.949	0.944
Maximum	854.700	957.789	659.155	778.446	1.000	1.000	1.000	1.000

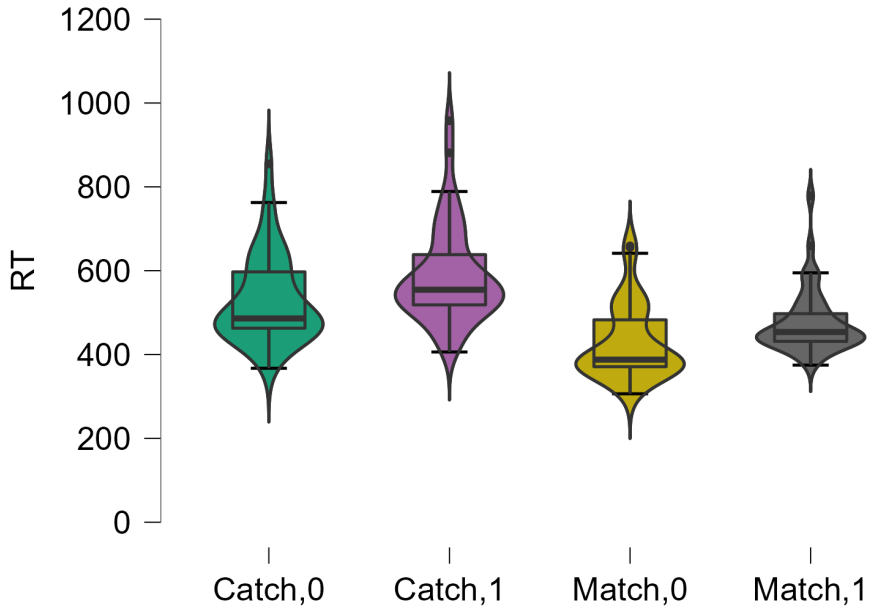


Figure S3: Mean response times (in ms) per type of trial (congruence or incongruence between the cue and the stimulus) and stimulus type

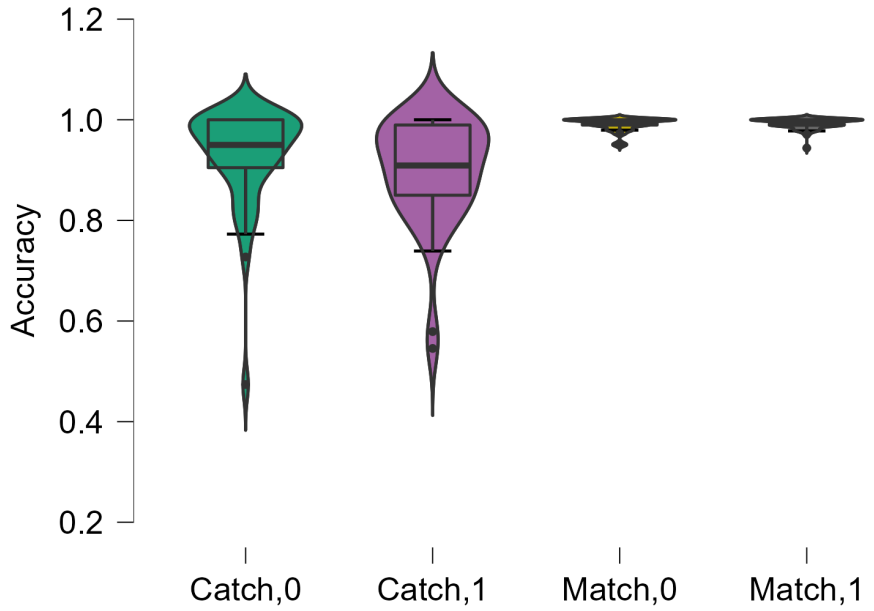


Figure S4: Mean accuracy rates per type of trial (congruence or incongruence between the cue and the stimulus) and stimulus type

B Classification performance

Subject	accuracy	chance (95%)	p-value
pilot3	0.612500	0.558542	0.009901
136	0.595833	0.558542	0.009901
358	0.554167	0.554375	0.099010
916	0.616667	0.554167	0.009901
347	0.629167	0.541875	0.009901
766	0.591667	0.554167	0.009901
661	0.520833	0.562500	0.257426
959	0.562500	0.562708	0.079208
205	0.604167	0.558542	0.009901
400	0.666667	0.546250	0.009901
756	0.525000	0.554167	0.207921
897	0.516667	0.554583	0.376238
420	0.479167	0.562708	0.663366
804	0.608333	0.566875	0.009901
207	0.491667	0.558542	0.574257
196	0.608333	0.566667	0.019802
295	0.604167	0.575000	0.019802
402	0.554167	0.571042	0.118812
722	0.558333	0.566875	0.148515
720	0.529167	0.567083	0.217822
966	0.504167	0.554375	0.475248
568	0.562500	0.558542	0.059406
482	0.470833	0.558542	0.742574
307	0.566667	0.558542	0.049505
730	0.612500	0.558333	0.019802
228	0.595833	0.566667	0.019802
785	0.583333	0.550000	0.009901
640	0.650000	0.558542	0.009901
457	0.558333	0.579375	0.118812
183	0.575000	0.566875	0.049505
759	0.625000	0.558542	0.009901
278	0.562500	0.546458	0.049505
732	0.608333	0.571250	0.009901
441	0.600000	0.571042	0.019802
930	0.562500	0.562500	0.069307
755	0.625000	0.558542	0.009901
689	0.654167	0.562917	0.009901
877	0.529167	0.550000	0.188119
312	0.608333	0.575208	0.009901
751	0.587500	0.558750	0.029703
443	0.529167	0.554375	0.158416
223	0.612500	0.558958	0.019802

Table S3: Classification accuracy obtained from the covariance matrices of the $1-4$Hz-filtered pre-stimulus activity of cued trials ("accuracy"), compared to the empirical chance level ("chance (95%)"). The p-value corresponds to the position of the classification accuracy relative to the empirical distribution of chance level, obtained by permutation.

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