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# Time for What? Dissociating Explicit Timing Tasks Through Electrophysiological Signatures

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3  
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38 **Abstract**

39 Estimating durations between hundreds of milliseconds and seconds is essential for  
40 several daily tasks. Explicit timing tasks, which require participants to estimate durations  
41 to make a comparison (time for perception) or to reproduce them (time for action), are  
42 often used to investigate psychological and neural timing mechanisms. Recent studies have  
43 proposed that mechanisms may depend on specific task requirements. In this study, we  
44 conducted electroencephalogram (EEG) recordings on human participants as they  
45 estimated intervals in different task contexts to investigate the extent to which timing  
46 mechanisms depend on the nature of the task. We compared the neural processing of  
47 identical visual reference stimuli in two different tasks, in which stimulus durations were  
48 either perceptually compared or motorically reproduced in separate experimental blocks.  
49 Using multivariate pattern analyses, we could successfully decode the duration and the  
50 task of reference stimuli. We found evidence for both overlapping timing mechanisms  
51 across tasks as well as recruitment of task-dependent processes for comparing intervals  
52 for different purposes. Our findings suggest both core and specialised timing functions are  
53 recruited to support explicit timing tasks.

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55

## 56 **Introduction**

57 Interval timing, the ability to estimate durations in the hundreds of milliseconds to  
58 seconds, is essential for daily tasks. Although this ability is commonly treated as a single  
59 skill, recent studies have proposed that how we process temporal durations may depend  
60 on how we use this information (Breska and Ivry, 2016; Coull and Nobre, 2008; Lewis and  
61 Miall, 2003; van Wassenhove et al., 2019).

62 One organising principle of timing tasks is how temporal information will be used  
63 and measured (Coull and Nobre, 2008; Shalev et al., 2019). A major distinction is between  
64 implicit and explicit timing tasks (Coull and Nobre, 2008). Implicit timing tasks do not  
65 require participants to report temporal durations; however, time impacts performance on  
66 another task-relevant factor. For example, temporal cues can facilitate sensory and motor  
67 performance (Rohenkohl et al., 2012; Rohenkohl et al., 2014; Nobre and van Ede, 2018). In  
68 explicit timing tasks, temporal durations are the main objective, and participants report  
69 them in some fashion. Convergent evidence from lesion and correlational studies suggests  
70 that different neural systems contribute to implicit vs. explicit timing functions (Coull and  
71 Nobre, 2008; Breska and Ivry, 2016).

72 Although explicit timing tasks have traditionally been treated as a homogeneous  
73 category, how participants provide explicit reports can differ significantly across tasks. For  
74 example, in motor tasks, participants estimate durations to execute timed actions, while in  
75 perceptual timing tasks, they estimate durations to assess or compare them with a  
76 reference. If explicit timing relies on a shared common mechanism that serves various  
77 types of explicit reports, then temporal encoding should unfold similarly regardless of the  
78 motor or sensory demands of the task. In contrast, differences in temporal encoding as a  
79 function of task demands would suggest heterogeneous and highly specialised local  
80 temporal encoding mechanisms. Identifying differences in temporal encoding could also  
81 have broader implications for interpreting temporal processing differences in explicit vs.  
82 implicit tasks since the demands often differ in these two classes of tasks. Explicit timing  
83 tasks often rely on perceptual timing judgments, whereas implicit timing tasks rely on  
84 speeded motor actions. The possibility remains that differences attributed to explicit vs  
85 implicit timing may, at least partly, reflect differences in reporting demands instead.  
86 Understanding whether the perceptual and motor demands of tasks lead to neural  
87 differences would thus help qualify interpretations regarding the factors determining  
88 neural processing of timing.

89 Previous studies exploring perceptual and motor temporal judgments have  
90 primarily relied on behavioural (Keele et al., 1985; Ivry and Hazeltine, 1995; Merchant et al.,

91 2008a; Merchant et al., 2008b; Rammsayer and Troche, 2014) and fMRI measures (Buetti et  
92 al., 2008; Wiener et al., 2010; Nani et al., 2019; Naghibi et al., 2023). Both methods suggest a  
93 combination of general and goal-directed processes involved in perceptual and  
94 sensorimotor timing. However, while behavioural findings can offer insight into how we  
95 express our time estimations, they do not let us compare whether or how different  
96 temporal processing stages are affected by task requirements. Similarly, functional brain  
97 imaging can identify common and distinct brain areas activated depending on the task  
98 goals but without indicating whether the dynamical patterns of activations within and  
99 across regions are comparable.

100         Electrophysiological studies in humans using EEG can offer valuable additional  
101 insights into how intervals are encoded and how task demands can influence different  
102 temporal processing stages. Many studies have investigated event-related potentials and  
103 timing (for a review, see Kononowicz, van Rijn, and Meck, 2018), most focusing on a single  
104 task or comparing the activity between temporal and non-temporal tasks. Recent  
105 developments in multivariate pattern analysis (MVPA) have demonstrated that EEG data  
106 also contain rich spatial information that can be used to decode neural states (Stokes et  
107 al., 2015). These methods have started to be applied to temporal tasks, revealing how task  
108 goals and context can influence how time is encoded in brain activity (Bueno and Cravo,  
109 2021; Damsma et al., 2021).

110         This study investigated whether multivariate analysis of time-resolved EEG signals  
111 can distinguish between explicit timing of durations in tasks stressing perception vs. action.  
112 We designed an experiment in which participants viewed a reference interval in each trial  
113 and, in different blocks, had to reproduce the duration or compare it to a probe. The visual  
114 stimulus and set of durations/intervals were identical between conditions, enabling us to  
115 explore how EEG signals during and after the reference interval were modulated by the  
116 stimulus duration, task, and interaction. With this approach, we aimed to advance the  
117 understanding of the neural mechanisms underlying perceptual and motor timing and how  
118 they differ and overlap.

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## 122 **Materials and Methods**

### 123 **Data availability**

124 All materials resulting from this study are openly available. Please see ([link](#)) to access the  
125 task, analysis code, and raw and pre-processed data.

### 126 **Participants**

127 The experimental protocol was approved by The Research Ethics Committee of the Federal  
128 University of ABC (UFABC), where the study took place. Study implementation followed  
129 approved guidelines and regulations (CAEE: 03607118.4.0000.5594).

130 Thirty-three human volunteers participated in the study after giving informed  
131 consent. Data from a final sample of twenty-nine volunteers were fully analysed (mean age  
132 23 y.o., age range of 18-35; 14 females). Data from the four additional participants were  
133 excluded from the analysis. The reasons included: loss of data due to an energy blackout  
134 during the experiment; loss of data due to computer memory issues during data collection;  
135 computer memory issues and excessive noise during data collection; and excessive data  
136 loss (19%) during artefact removal (see below). All participants had normal or corrected  
137 vision and declared being free from psychological or neurological diseases.

### 138 **Stimuli and Procedures**

139 The experiment consisted of two computerised tasks presented in different blocks,  
140 temporal discrimination and temporal reproduction (Fig. 1a), combined with EEG  
141 recordings. The stimuli were presented using Psychtoolbox (Brainard, 1997) v.3.0 package  
142 in Octave on a ViewPixx monitor with a vertical refresh rate of 120 Hz, placed at  
143 approximately 52 cm from the participant. Responses were collected via a response box  
144 with nine buttons (DirectIN High-Speed Button; Empirisoft). In the discrimination task,  
145 participants used the index fingers of both hands to respond with the extreme left and  
146 extreme right buttons. In the reproduction task, they used the right index finger and the  
147 extreme right button.

148 The experiment was divided into 16 short blocks of 32 trials each. Discrimination  
149 and reproduction tasks alternated from one block to another, and their order was  
150 counterbalanced between participants. A written cue presented for two seconds instructed  
151 and reminded participants about the task before each block started. The word  
152 'JULGAMENTO' preceded the discrimination task ('judgement' in Portuguese), and  
153 'REPRODUÇÃO' preceded the reproduction task ('reproduction' in Portuguese). For both  
154 tasks, trials consisted of two visual stimuli (filled circles of 1 visual-degree radius)  
155 presented sequentially on a grey screen.

156 Before each trial started, there was a blank screen (grey background) with a white  
157 fixation point at the centre ( $1/6$  visual-degree radius) that could last between 900 and 1200  
158 ms. The first stimulus (S1) was a light-blue-filled circle that could last one of four possible  
159 logarithmically spaced intervals: 750, 1042, 1442, or 2000 ms. The four intervals occurred  
160 equally frequently over the experiment. The order of the intervals presented at S1 was  
161 random, with the constraint that a given interval could not occur in more than three  
162 consecutive trials. After the first stimulus, another blank screen with a fixation point was  
163 shown (600 to 900 ms). We categorised this segment as the S1-offset epoch.

164 The second visual stimulus differed according to the task. In the temporal-  
165 discrimination blocks, the second stimulus (light-green-filled circle) lasted 40% less or 40%  
166 more than the first stimulus. After 600 ms from the offset of the second stimulus, a  
167 response screen appeared, prompting participants to indicate if the second stimulus was  
168 shorter (left button) or longer (right button) than S1. Responses were unspeeded. In the  
169 temporal-reproduction blocks, the second stimulus (S2) had the same light-green colour,  
170 but the participant controlled its duration. Participants were instructed to press the right  
171 button when they thought the reference (S1) duration had elapsed. The answer was  
172 considered correct if the reproduced duration was longer than half of the reference  
173 intervals and less than two times the reference. Feedback was provided for both tasks in  
174 every trial. The fixation point turned green if the answer was correct or red otherwise (for  
175 350 ms duration).

176 Responses exceeding 11.2s (four times the longest interval for S2 in the  
177 discrimination task) were considered a timeout for both tasks. In such cases, no response  
178 was registered, negative feedback was provided, and the trial was considered lost. No trials  
179 were lost for any participant for reaching the timeout. For the data analysis of the  
180 discrimination task, the mean proportion of “longer” responses was calculated separately  
181 for trials shorter/longer than the reference and for each reference. For temporal  
182 reproduction, trials reproduced more than two times or less than half the presented  
183 interval were removed from further behavioural analysis. A linear regression between the  
184 presented and produced interval was estimated for each participant.

185 Before the experiment started, all participants completed a training session  
186 consisting of one block of each task. If the participant failed to achieve at least 75%  
187 accuracy in either task, the training session would be repeated up to three times. Only two  
188 participants required an extra training session.

## 189 **EEG recordings and pre-processing**

190 EEG was recorded continuously from 64 ActiCap Electrodes at 1000 Hz by a QuickAmp  
191 amplifier (Brain Products). Data were high-pass filtered online (0.01 Hz) to avoid  
192 electrodermal fluctuations. All electrode sites were referenced to FCz and grounded to AFz.  
193 The electrodes were positioned according to the International 10-10 system, except for the  
194 TP9 and TP10 electrodes in the earlobes. Additional bipolar electrodes recorded the  
195 electrooculogram. Data pre-processing was carried out using the FieldTrip toolbox for  
196 MATLAB (Oostenveld, Fries, Maris and Schoffelen, 2011). Offline filters were applied to the  
197 continuous data with a bandpass of 0.1 Hz to 30 Hz (Butterworth filter, order 3), and all data  
198 were re-referenced to the average activity of the earlobe electrodes and downsampled to  
199 250 Hz. Channels with missing data due to problems in acquisition or channels with  
200 excessive noise were interpolated using the FieldTrip channel-repair function. Data from  
201 most volunteers required no interpolation (14 participants) or up to two channels  
202 interpolated. Two participants had 3, and one participant had four channels interpolated.

203 Independent component analysis (ICA) was performed for eye-movement artefact  
204 detection and rejection. Eye-related components were identified with the help of SASICA,  
205 available for FieldTrip (Chaumon, Bishop and Busch, 2015), by visually inspecting  
206 topographies and time series from each component. We used 9-second segments from S1  
207 onset to identify eye movement-related components to be rejected in later analysis  
208 relevant segments. Using these long segments for the ICA, we excluded periods between  
209 blocks from the continuous EEG data in which participants could move and interfere with  
210 the electoral signal and detection of eye-related components. From this point forward, we  
211 used data from 62 channels, excluding bipolar and reference electrodes on the earlobes  
212 (TP9 and TP10).

213 The analyses focused on the processing of the first stimulus. Critically, the first  
214 stimulus in both tasks was identical, and participants were not required to make any  
215 responses during this phase of the trial. We segmented the data relative to S1 onset (from  
216 150 ms before to 2700 ms after) and S1 offset (from 150 ms before to 1 s after). Baseline  
217 correction used the periods from 150 ms before reference stimulus onset for S1-onset  
218 epochs. and 50 ms before to 50 ms after offset for S1-offset epochs. Baseline correction for  
219 S1-offset epochs was calculated around the 100 ms (-50 ms to 50 ms) from reference  
220 stimulus offset to remove any potential contribution from the classification related to the  
221 preceding final segment before offset. We evaluated interval and task decoding during  
222 three critical periods: from 0 to 750 ms after S1 onset (since this was the shortest possible  
223 S1 duration and therefore present for all trials); at the mean of the last 100 ms before S1  
224 offset; and from 0 to 600 ms after S1 offset (since this was the shortest interval following

225 S1) (Fig. 1b). Trials were rejected from the analysis if segments exceeded 150  $\mu\text{V}$  or the  
226 amplitude range was greater than 250  $\mu\text{V}$  in any of the 62 channels. The same segmentation  
227 for S1 and the final 100 ms was used for rejecting noisy trials. The percentage of rejected  
228 trials was 2.3% (range between 0% - 11.1%) for S1-onset segments (or the last 100 ms  
229 segments) and 0.7% for S1-offset segments (0%- 5.9%).

### 230 **Multivariate pattern analysis**

231 We investigated differences between tasks and intervals in the time-resolved EEG using a  
232 supervised learning classification approach. We used a Linear Discriminant Analysis (LDA)  
233 as implemented in the MVPA-Light toolbox for MatLab (Treder, 2020) combined with custom  
234 scripts. The multi-class classification was performed using the MVPA-Light package.  
235 Regularised multi-class was based on Linear Discriminant Analysis (LDA). The training data  
236 is first projected onto a  $(C-1)$ -dimensional discriminative subspace, where  $C$  is the number  
237 of classes. A test sample is assigned to the class with the closest centroid in this subspace.  
238 Decoding performance was estimated using accuracy. For ease of interpretation,  
239 classification accuracies were subtracted from chance levels: 0.5 for the two-label task  
240 classification and 0.25 for the four-label interval classification.

241 For the time-resolved classification, data from individual trials were smoothed  
242 using a moving average with a 40-ms window. We used a four-fold cross-validation for task  
243 classification (reproduction or discrimination). Each fold consisted of eight blocks, four of  
244 each task. For example, in the first fold, the test data consisted of blocks 1 to 8 (four blocks  
245 of each task), and the training data consisted of the remaining blocks (9 to 32, twelve blocks  
246 of each task). In the second fold, test data consisted of blocks 9 to 16, and so on  
247 successively. Four-fold cross-validation was also used for interval classification within a  
248 task, each with two blocks of the task. For example, in the first fold, the test data consisted  
249 of the first four blocks of a given task, and the training data consisted of the other twelve  
250 blocks; in the second fold, the test data consisted of blocks 5 to 8 of that task, and so on  
251 successively. Lastly, we also performed a between-task classification for intervals, with  
252 training data consisting of 12 blocks of a task and the test data consisting of the other 4  
253 blocks of the other task, following the same logic as the within-task classification. Cross-  
254 validation is not necessarily needed for the between-tasks classification, given that the  
255 training and test data come from different tasks and blocks. However, we kept the cross-  
256 validation so that a single model trained on the same data was tested on the same or the  
257 other task. This makes results more comparable within and between tasks.

258 At each time point, all 62 EEG sensors were used as features. The analysis was  
259 conducted at each time point (4 ms apart after downsampling). We evaluated whether

260 accuracy was above chance levels using a permutation test-based control of the familywise  
261 error rate for multiple comparisons (Groppe, Urbach and Kutas, 2011). This method  
262 guarantees a strong control of family-wise error rate (the same degree of false discovery  
263 control as Bonferroni correction) but is generally more powerful. Permutation-based strong  
264 control of family-wise error rate is one of the best methods to establish reliable lower  
265 bounds on the onset and offset of effects when apriori boundaries are unavailable  
266 (Groppe, Urbach and Kutas, 2011). In short, permutations are constructed by flipping the  
267 sign of a random set of participants and calculating new t-scores under this rearrangement.  
268 For each permutation ( $n=10000$ ), a tmax score is calculated (the most extreme positive or  
269 negative value of the t scores across all time points) and stored. Critical t-values and p-  
270 values are estimated from these tmax distributions. For each test, we report the t-max  
271 value (the estimated t-value for  $p=0.05$ ). All tests were one-sided t-tests compared with  
272 zero with an alpha level of 5% for significance level. For time point-by-point classification  
273 accuracy measures, we considered time points in which the t-values exceeded the  
274 empirical critical t calculated in the permutation test. Whenever relevant, we show  
275 univariate F-values for differences between experimental conditions to illustrate effects.

276

## 277 **Results**

### 278 **Behavioural Results**

279 Participants performed well on both tasks. Using the feedback levels as a measure of  
280 accuracy, the mean accuracy for the discrimination task was 91.6%, ranging between 77.3%  
281 and 98.0%. The mean accuracy for the reproduction task was 95.7%, ranging between 84.8%  
282 and 100%.

283 For the following behavioural analyses, statistics were calculated using JASP (2022).  
284 In the discrimination task (Fig. 1c), the proportion of longer responses was submitted to a  
285 2 (shorter/longer than reference)  $\times$  4 (S1 duration: 750/1042/1442/2000 ms) repeated  
286 measures ANOVA. There was a main effect of shorter/longer, with participants responding  
287 "longer" more often when S2 was longer than S1, as expected ( $F(1,28) = 1845.78$ ,  $p < .001$ ,  $\omega^2$   
288 = 0.98). Additionally, there was a higher proportion for "longer" responses for longer  
289 durations of S1 ( $F(1.741, 48.736) = 59.90$ ,  $p < .001$ ,  $\omega^2 = 0.51$ , Greenhouse-Geisser sphericity  
290 correction). Finally, we also found a significant interaction between these factors ( $F(2.091,$   
291  $58,536) = 14.77$ ,  $p < .001$ ,  $\omega^2 = 0.18$ , Greenhouse-Geisser sphericity correction), indicating that  
292 the effect of duration on bias was stronger on both extreme intervals.

293 For the reproduction task (Fig. 1d), participants systematically produced longer  
294 responses as S1 duration increased. However, they tended to underestimate longer

295 durations and overestimate shorter ones. The linear regression between the sample and  
296 reproduced intervals shows positive slopes ( $0.69 \pm 0.03$ , mean  $\pm$  s.e.m, one-sample t-test  
297 against zero:  $t(28)=22.5$ ,  $p<.001$ ). Despite performing the task well, the pattern of  
298 participants' responses followed the central tendency effect (Jazayeri and Shadlen, 2010).

299 We compared performance between tasks using two different approaches. In a first  
300 analysis, we investigated whether participants with a higher accuracy in discrimination also  
301 performed better in the reproduction task, as measured by the root-mean-square error  
302 (RMSE). The RMSE measures how far the interval reproductions are from the presented  
303 interval, with larger values indicating worse performance. Participants who performed  
304 better in one task were also better in the other task. We used a robust skipped correlation  
305 to protect against bivariate outliers (Pernet, Wilcox and Rousselet, 2013) and observed a  
306 significant negative correlation between discrimination accuracy and reproduction RMSE  
307 (robust skipped Spearman correlation,  $r = -0.62$ , 95% Confidence Interval:  $-0.78 -0.33$ ,  $p<.001$ ,  
308 Fig. 1e). Using Spearman's correlation yielded equivalent results (Spearman correlation,  $r =$   
309  $-0.62$ , 95% CI:  $-0.79 -0.37$ ,  $p<.001$ ).

310 In a second analysis, we investigated whether participants were consistent in  
311 under/overestimating the duration of S1 between the two tasks. We correlated the average  
312 "longer" responses in the discrimination task and the bias in the reproduction task  
313 (calculated as the average difference between reproduced and reference intervals). There  
314 was a significant negative correlation between these measures, indicating that participants  
315 who reproduced intervals as longer tended to judge the second interval as being "shorter"  
316 in the discrimination task (robust skipped Spearman correlation,  $r = -0.42$ , 95% CI:  $-0.67 -$   
317  $0.06$ ,  $p = 0.02$ , Fig. 1f). Using Spearman's correlation yielded equivalent results (Spearman  
318 correlation,  $r = -0.42$ , 95% CI:  $-0.69 -0.09$ ,  $p = 0.02$ ).

## 319 **Electrophysiological Results**

### 320 *Timing task modulates EEG signals during S1*

321 The first analysis focused on the differences in the EEG signal between tasks. We analysed  
322 the first 750 ms from S1 onset from all non-rejected trials. Figure 2a shows that the accuracy  
323 for classifying the task was statistically above chance level, with effects starting during the  
324 early stages of the reference intervals (critical  $t = 3.527$ ). For illustrative purposes, we  
325 performed a mass univariate ANOVA<sup>1</sup> with the factors Task (discrimination and  
326 reproduction) and Interval (four possible reference intervals) for each time point and

<sup>1</sup>The ANOVA was performed for illustrative purposes. We plot F-values topographies for the factors Task and Interval in different figures.

327 channel. The topographies for the univariate F-values across sensors in Fig. 2b shows that  
328 differences in the time-resolved EEG between tasks were captured by more frontal and  
329 central sensors, as shown in Fig. 2c. We did not expect any modulation according to the  
330 interval during this initial period of S1 (since differential intervals had not yet elapsed), so  
331 this analysis also served as a sanity check and there were no significant effects of interval  
332 durations (Extended Data Fig. 2-1).

### 333 *Task and interval modulate activity at the end of the S1*

334 Information about the duration of the interval is available at the end reference interval. We  
335 performed two separate analyses to test whether it was still possible to decode the task  
336 and, additionally, decode the duration of the reference interval. Both analyses used the  
337 average signal during the last 100 ms before S1 offset for each electrode as the dependent  
338 variable.

339 Classifying tasks yielded a significant above-chance decoding accuracy ( $t(28) =$   
340  $6.887, p < .0001$ , Fig. 3a). Differences associated with the task were stronger in frontal and  
341 central sensors, as shown by the univariate F-values in Figures 3b and 3c.

342 We used both within- and between-tasks classification approaches to look at  
343 interval classification. In the within-task classification, training and testing data came from  
344 the same task (i.e., discrimination or reproduction). In the between-task classification,  
345 training used data from one task, and testing used data from the other. Significant decoding  
346 accuracy values resulted in all cases (Fig. 4a). Decoding was significant within tasks for  
347 discrimination ( $t(28) = 3.019, p < .01$ ) and reproduction ( $t(28) = 2.377, p = 0.024$ ). Between tasks,  
348 decoding was significant when training on reproduction and testing on discrimination ( $t(28)$   
349  $= 4.596, p < .0001$ ) as well as when training on discrimination and testing on reproduction  
350 ( $t(28) = 5.025, p < .0001$ ). In contrast to classifying the task, information about durations was  
351 most pronounced in central-parietal sensors (Fig. 4b and c).

352

### 353 *Task and interval modulate activity after S1 offset*

354 In a second analysis, we investigated whether information about task and interval could  
355 also be found in the EEG signal after S1 offset. Only at the offset do participants have  
356 complete information about S1 duration. During this period, we found that EEG activity is  
357 modulated by both task and duration.

358 The MVPA classifier decoded which task participants performed early after S1 offset  
359 (Fig. 5a, critical  $t = 3.500$ ). Importantly, the data for this analysis were baseline corrected  
360 around the S1 offset, eliminating the effect reported for the last 100 ms of S1 task  
361 classification. Figures 5b and 5c show the evolution of EEG differences driven by task as  
362 illustrated by univariate F-values and the average signal at distinct electrodes.

363 Decoding of intervals was done within and between tasks. Above-chance decoding  
364 levels were observed in both (Fig. 6). For the within-task classification, decoding was  
365 significant within tasks for discrimination (critical  $t = 3.588$ ) and reproduction (critical  $t =$   
366  $3.493$ ). Between tasks, decoding was significant when training on reproduction and testing  
367 on discrimination (critical  $t = 3.613$ ) and when training on discrimination and testing on  
368 reproduction (critical  $t = 3.625$ ). Interestingly, looking at Figures 6b and 6c, two patterns  
369 emerge concerning the coding of intervals. An early posterior effect (100 to 300 ms) in which  
370 the amplitude is lower for shorter intervals and a later frontal effect ( $>300$  ms) in which  
371 shorter intervals show a higher amplitude.

372

### 373 *Task-dependent time coding after S1 offset*

374 Our final analysis investigated whether intervals are differently encoded between tasks. So  
375 far, we have shown that both task and time modulate EEG activity. Our previous analyses,  
376 in which time was trained and tested in different tasks, emphasised the commonalities for  
377 interval coding between tasks. In this last analysis, we investigated whether revealing  
378 selective, task-dependent processing of temporal intervals was also possible.

379 Our strategy was to use the difference in amplitude from the longest to the shortest  
380 interval and test whether MVPA can distinguish whether these differences come from  
381 performing different tasks. To increase the number of trials for the classifier, we created  
382 pseudo-trials comprising these differences. For each pseudo-trial, we draw four trials from  
383 the 2000-ms interval (longest) and four from the 750-ms interval (shortest) without  
384 replacement. We averaged the signal for each interval and the difference between the  
385 longest and shortest signal. Pseudo-trials were created using the same four-fold cross-  
386 validation strategy, so training and test pseudo-trials came from different folds. In the final  
387 step, a similar task classification was used on the pseudo-trials, investigating whether the  
388 classifier could successfully decode the task from the different subtractions. Creating  
389 pseudo-trials and classification was repeated 100 times for each participant, and the  
390 average accuracy was estimated.

391 Task-dependent differences in duration processing appeared after the offset of S1.  
392 No differences occurred during the last 100 ms of each interval (mean accuracy of 0.014,  
393 standard error of the mean: 0.018; test difference from zero:  $t(28) = 0.747$ ,  $p = 0.461$ ).  
394 Differences after S1 offset are shown in Figure 7a. The periods in which the MVPA accuracy  
395 was above chance (critical  $t = 3.388$ ) overlapped with periods in which we also observed  
396 common interval-duration coding between tasks. Figures 7b (discrimination) and 7c  
397 (reproduction) show the average differences from the longest to the shortest interval for  
398 discrimination and reproduction tasks, respectively, when the classifier accuracy was  
399 significantly above chance (from 378 ms to 414 ms). Figure 7d depicts the difference  
400 between discrimination and reproduction topographies (discrimination - reproduction).

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## 409 **Discussion**

410 Using multivariate pattern analysis, we revealed a set of overlapping neural signals for  
411 encoding the duration of temporal intervals for explicit perceptual judgement and motor  
412 reproduction. The different task demands also activated task-specific processes across  
413 various time scales, both during the interval itself and after its offset, revealing possible  
414 parallel states of motor versus perceptual preparation. Lastly, we also found evidence that  
415 task demands can interact with duration estimation. Despite analysing brain activity during  
416 periods with identical stimulation and timing demands, neural signals discriminating  
417 between the future task demands of perceptual judgement vs. motor reproduction were  
418 also prevalent across the various time scales analysed, ranging from early during the  
419 encoding interval to after the offset of the reference interval.

420 Task-specific EEG activity at the early stages of interval processing differed between  
421 encoding durations for subsequent perception- or action-based tasks, suggesting that  
422 timing unfolds in different neural contexts depending on future task demands. Within these  
423 different contexts, not only was it possible to decode timing within each task, but decoding  
424 generalised between tasks, suggesting a common activity pattern that covaried with time.  
425 This common encoding of time was observed during both periods in which timing  
426 information was available - at the end of the reference interval and after its offset. After  
427 the interval offset, the decoding of intervals was significant from early periods, including  
428 early differences over posterior sensors and later effects distributed over frontal sensors.

429 There has been an increase in studies that use multivariate pattern analysis to  
430 investigate EEG activity. Using such methods has several advantages, as they can naturally  
431 account for and leverage the multivariate nature of the signal (Michel and Murray, 2012;  
432 Stokes et al., 2015) while also effectively addressing the statistical challenge of multiple  
433 comparisons. In our study, we capitalised on these methods as a data-driven approach to  
434 look for possible differences between tasks and at similar covariations of neural activity as  
435 a function of time across them. This brings essential advances, given that previous studies  
436 have focused on looking for differences rather than possible similarities when comparing  
437 activity across tasks. However, we have also examined the underlying event-related  
438 potentials across conditions to compare our findings with previous results.

439 For the interval onset period, differences between tasks were driven by an early  
440 activity and followed by what resembles a contingent negative variation (CNV) in frontal  
441 sensors, with a stronger CNV in the reproduction task. One possibility for the observed  
442 difference between tasks is that the reproduction task is more difficult than the comparison

443 task. However, previous studies that have looked at the CNV during the encoding of an  
444 interval found differences in the CNV even when tasks had similar performance (Schlichting  
445 et al., 2020) or displayed no CNV differences when one task was easier than another (as  
446 found in Bueno & Cravo, 2021). Another possibility is that the motor component in the  
447 reproduction task might play a role in modulating the CNV, given the intrinsic relationship  
448 between time and motor regions (De Kock et al., 2021). These results strengthen the  
449 possibility that the brain can tap into a common repertoire of processes to different extents  
450 depending on the task demand. Future studies combining a wider range of temporal and  
451 non-temporal tasks with different motor demands will be essential to explore these  
452 relationships further. Lastly, the term CNV has been used for a wide variety of different  
453 brain activities and tasks. In explicit timing tasks, it often refers to EEG activity during the  
454 presentation of the target duration, which participants have to judge as shorter/longer  
455 than a reference (Bueno et al., 2017; Kononowicz & van Rijn, 2014; Ng et al., 2011; Macar &  
456 Vidal, 2003; Pouthas et al., 2000; Gontier et al., 2009). Studies that have looked at CNV-like  
457 activity during the encoding of an interval are less frequent and present mixed findings,  
458 with some studies finding more negative CNV for timing tasks compared to number tasks  
459 (Schlichting et al., 2020). In contrast, others do not find CNV differences for tasks in which  
460 participants encode time or colour (Bueno & Cravo, 2021; Kulashekhar et al., 2016).

461 For the offset period, we also found both task decoding and time decoding that  
462 generalised across tasks. Specifically, we found a consistent duration decoding starting at  
463 approximately 200 ms post offset for reproduction and 300 ms for discrimination. The early  
464 activity was more present in posterior sensors, resembling a P2, while the late activity was  
465 more concentrated in central sensors, resembling a P300 or a late positive component  
466 (LPC). There has been an increase in studies that have looked at post-offset EEG activity in  
467 timing tasks. These studies have focused on early post-offset activity (Kononowicz and van  
468 Rijn, 2014), and, more recently, on the LPC (Wiener and Thompson, 2015; Bannier, Wearden,  
469 Le Dantec and Rebaï, 2019; Baykan and Shi, 2022; Ofir and Landau, 2022; Baykan et al., 2023;  
470 Özoğlu and Thomaschke, 2023). As with the CNV, the term LPC has been used for various  
471 post-offset activities that vary in sensors and periods, making it hard to pinpoint whether  
472 different studies capture activity from similar processing stages. Critically, and similar to  
473 the CNV, most studies have looked at the LPC during the target interval presentation and  
474 not during its encoding.

475 To our knowledge, only three other studies have looked at post-offset activity  
476 during interval encoding (Bueno and Cravo, 2021; Damsma et al., 2021; Kruijne et al., 2021).  
477 In our previous study (Bueno and Cravo, 2021), a similar pattern, although smaller, was

478 found only for the later activity starting at about 300 ms after the interval offset in frontal  
479 sensors. EEG correlates with duration were also reported after the offset of auditory-  
480 marked durations (Damsma et al., 2021). In this case, effects also resembled a P2 with larger  
481 amplitudes for longer intervals, similar to our parietal P2. Finally, Kruijne and colleagues  
482 did not find duration effects on either P2 or LPC, although they focused their analysis on  
483 central sensors while using visual targets (Kruijne et al., 2021). The different topographic  
484 distributions of the results suggest that the earliest effects after offsetting a reference  
485 stimulus include sensory processing involving central sensors for the auditory task and  
486 posterior sensors for our visual task. Future studies could test for systematic variations in  
487 early timing-related signals depending on the sensory modality of the reference and test  
488 intervals.

489         Complementing our observation of robust cross-task decoding of temporal  
490 intervals, we also discovered that task demands impacted duration estimation. These task-  
491 dependent temporal encoding effects became apparent only after the offset of the  
492 reference interval. Unlike the common temporal encoding effects, the selective processes  
493 were not observed toward the end of the reference interval. The reason is unclear. Part of  
494 the explanation may rest on the need to derive the differences between stimulus durations  
495 between trials, which may have reduced the sensitivity and power of our analysis.  
496 Alternatively, the stimulus offset may be necessary to increase the readout of neural  
497 differences by acting as a perturbation that makes manifest differences in states that may  
498 otherwise remain encoded in “activity-silent” patterns of synaptic weights (Wolff, Ding,  
499 Myers and Stokes, 2015; Wolff, Jochim, Akyürek and Stokes, 2017). Moreover, after the  
500 interval offset, participants may start transforming and gating the encoded interval  
501 information to guide performance in the specific upcoming task. Such a process is likely to  
502 include the interaction between timing signals and proactive engagement of sensory vs.  
503 motor systems for perceptual judgement vs. motor reproduction, respectively. The  
504 differential encoding and maintenance of temporal intervals depending on how timing  
505 signals will be used are consistent with recent views of how working memory is flexibly  
506 coded depending on future use (Nobre and Stokes, 2019). Theoretical (Orhan and Ma, 2019)  
507 and empirical results in non-human primates (Warden and Mille, 2010) and fMRI in humans  
508 (Muhle-Karbe et al., 2017) have found that how information is maintained may depend on  
509 the expected use.

510         The simultaneous occurrence of an interaction, indicating selective timing-related  
511 computations between tasks, and cross-generalisation, indicating common timing-related  
512 computations across tasks can seem contradictory if one adopts a simple view that brain

513 processing only unfolds sequentially through one single circuit. Our finding, instead,  
514 suggests that timing-related brain processes can unfold in tandem through different  
515 circuits. In this pluralistic scenario, some timing operations may be shared and lead to a  
516 significant degree of (though not absolute) cross-generalisation. In contrast, other timing  
517 operations may be local and selective, leading to a significant degree of (though not  
518 absolute) pattern divergence.

519         There has been an increasing interest in hybrid models for temporal processing,  
520 that propose a combination of local task-dependent areas interacting with partially  
521 distributed timing mechanisms (Merchant, Harrington, and Meck, 2013). Our findings align  
522 with the hybrid model proposal. We found a correlation in performance across tasks in our  
523 behavioural results and similar duration-dependent activity across tasks in our EEG results,  
524 suggesting common processing. However, we also found evidence for task-specific activity  
525 and an interaction of task-dependent activity and durations. These differences do not seem  
526 to be driven by tasks not being equally challenging, given that we found good performance  
527 in both and that we used short and intercalated task blocks to prevent learning or fatigue  
528 from modulating one task more than the other. However, we cannot completely rule out  
529 the possibility that general difficulty or motivation for the different tasks modulated EEG  
530 activity. On the other hand, the observed task-specific encoding of time shows how even  
531 these factors could modulate timing specifically.

532         In conclusion, our findings provide evidence that sensory versus motor demands  
533 may influence time encoding. These differences can have implications for other proposed  
534 categorisations of temporal processes, such as implicit versus explicit tasks. To gain a more  
535 comprehensive understanding of the neural mechanisms involved in temporal processing,  
536 future studies could employ higher spatial and spectral resolution techniques in humans  
537 and non-human animals to investigate these dimensions more systematically. In particular,  
538 modulations of activity in different frequency bands have been noted in timing studies  
539 (Sperduti et al., 2011; Kulashekhar et al., 2016; Wiener et al., 2018; Grabot, 2019; Kononowicz  
540 et al., 2020; Schlichting et al., 2020), but a coherent picture is yet to emerge. Systematic  
541 differences in frequency modulation according to a task's perceptual and motor demands  
542 (e.g., van Ede et al. 2020) would indicate engagement of specialised, local temporal  
543 processing. A combination of spectral analysis and multivariate approaches should provide  
544 a fruitful approach and yield valuable insights into the complex interplay of cognitive and  
545 neural factors that underlie our perception of time.

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739 Fig 1. **Experimental Design and Behavioural Results.** (a) Schematic illustration of the discrimination  
 740 and reproduction tasks. (b) Schematic illustration of the three segments used in the analysis, all relative  
 741 to S1. The light blue area represents the period from 0 to 750 ms from S1 onset, whereas the dark blue  
 742 area represents the final 100 ms before offset for all four sample intervals. The green area depicts the  
 743 period analysed after S1 offset (c) Behavioural results for the discrimination task. The proportion of  
 744 'longer than S1' responses according to S1 interval (750, 1042, 1442, or 2000 ms) and whether S2 was  
 745 shorter (light blue) or longer (grey) than S1. (d) Behavioural results for the reproduction task depict the  
 746 mean of reproduced durations for each S1 interval. For (c) and (d), the light-coloured circles depict each  
 747 participant's values, whereas black circles depict mean results for all participants. Error bars represent  
 748 the standard error of the mean. (e) Correlation between the accuracy of responses (discrimination) and  
 749 RMSE (reproduction) (robust skipped Spearman correlation,  $r = -0.62$ , 95% CI between  $-0.78$  and  $-$   
 750  $0.33$ ,  $p < .001$ ; CI stands for Confidence interval). (f) Correlation between the mean of "longer"  
 751 (discrimination) and mean bias (difference between reproduced and reference interval) ( $r = -0.42$ , 95%  
 752 CI between  $-0.67$  and  $-0.06$ ,  $p = 0.02$ ). In (e) and (f), circles depict individual values and the line  
 753 represents the correlation between values.

754  
 755 Fig 2. **Task decoding during S1.** (a) Task decoding accuracy above chance level (zero is chance  
 756 level) throughout the first 750 ms from S1 onset (all valid trials). Bold horizontal lines indicate values  
 757 significantly greater than zero ( $p < .05$ ) from the permutation analysis. (b) Univariate F-values in 125 ms  
 758 steps from 0 ms to 750 ms from stimulus onset. Differences between tasks were accentuated in frontal  
 759 sensors at late periods. (c) Grand averages of the signal for the different tasks at frontal (Fp1, AF7,  
 760 Fp2, AF8, F5, F3, F1, Fz, F2, F4, F6, AF4, AF3), central (FC3, FC1, FC2, FC4, C4, C2, Cz, C1, C3,  
 761 CP3, CP1, CPz, CP2, CP4), and posterior channels (P8, P6, P4, P2, Pz, P1, P3, P5, P7, PO10, PO8,  
 762 PO4, POz, PO3, PO7, PO9, O1, Oz, O2). The shaded areas represent the standard error of the mean.

763  
 764 Fig 3. **Task decoding in the last 100 ms of the reference stimulus.** (a) Decoding accuracy above  
 765 chance level (zero is chance level). The yellow circle depicts the mean accuracy for all participants and  
 766 the smaller grey circles individual accuracies (b) Univariate F-values for task differences during the  
 767 period. (c) Mean amplitude of the signal for the different tasks at frontal, central, and posterior channels  
 768 (using the same channels as in Fig. 2). The light-coloured circles depict each participant's values,  
 769 whereas dark-coloured circles depict mean results for all subjects. Error bars represent the standard  
 770 error of the mean. To visualize activity of all intervals from S1 onset to 600ms after S1 offset, see  
 771 Extended Data Figure 3-1.

772  
 773 Fig 4. **Time-interval decoding in the last 100 ms of the reference stimulus.** (a) Decoding accuracy  
 774 for the duration within and between discrimination and reproduction tasks. The yellow and dark purple  
 775 circles depict the mean accuracies for all participants, and the grey or light purple smaller circles  
 776 represent individual accuracies (b) Univariate F-values for interval differences during the period. (c)  
 777 Mean signal amplitude for the different intervals and tasks at frontal, central, and posterior channels  
 778 (using the same channels as in Figures 2 and 3). For (a) and (c), the light-coloured circles depict each  
 779 participant's values, whereas the dark-coloured circles depict mean results for all participants. Error  
 780 bars represent the standard error of the mean.

781  
 782 Fig 5. **Task decoding after S1 offset.** (a) Task decoding accuracy above chance level (zero is chance  
 783 level) after S1 offset. Bold horizontal lines indicate values significantly greater than zero ( $p < .05$ ) from  
 784 the permutation analysis. (b) Univariate F-values in 125 ms windows from 0 to 600 ms from stimulus  
 785 offset. Task-related differences were more pronounced at central electrodes. (c) Grand averages of the  
 786 signal for the different tasks at frontal, central, and posterior electrodes. The shaded areas represent  
 787 the standard error of the mean.

788  
 789 Fig 6. **Time-interval decoding after S1 offset** (a) Decoding accuracy above chance level in the  
 790 segment after S1 offset. Bold horizontal lines indicate values significantly greater than zero ( $p < .05$ ) from  
 791 the permutation analysis. (b) Average univariate F-values in 100 ms from 0 to 600 ms from stimulus  
 792 offset. Differences related to duration were more pronounced at posterior electrodes at early periods  
 793 (200 to 300 ms) and frontal at late periods (300 to 500 ms). (c) Grand signal averages for the different  
 794 durations and tasks at frontal, central, and posterior electrodes (same channel separation as in Figures  
 795 2-5). The shaded areas represent the standard error of the mean.

796  
 797 Fig 7. **Task decoding after S1 offset on pseudo-trials isolating differences between shortest and**  
 798 **longest references.** (a) Decoding accuracy above chance level in the segment after S1 offset. Bold

799 horizontal lines indicate values significantly greater than zero ( $p < .05$ ) from the permutation analysis. (b)  
800 and (c) Mean differences from the longest to the shortest interval in discrimination and reproduction  
801 tasks, respectively, in moments where accuracy was significantly above chance (from 378 ms to 414  
802 ms). (d) Mean difference between (b) and (c) topographies. To visualize the subtracted activity in each  
803 condition, see Extended Data Figure 7-1.

804

805 **Fig 8. Summary of Effects.** Schematic representation of the observed effects. We found task  
806 differences in brain activity on S1 onset, at the end of S1 and S1 offset. We found differences in brain  
807 activity across intervals at the end of S1 and S1 offset. Similar differences were both within and between  
808 tasks. Task-dependent differences in temporal intervals were found only after S1 offset.

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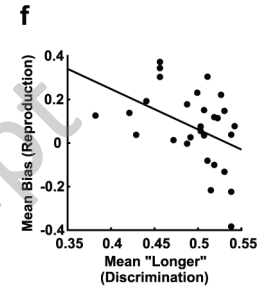
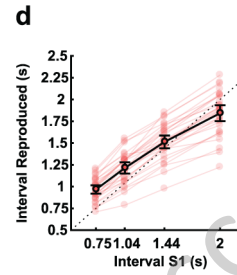
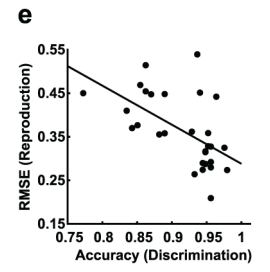
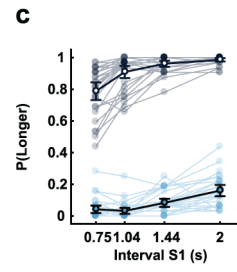
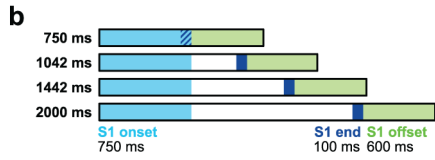
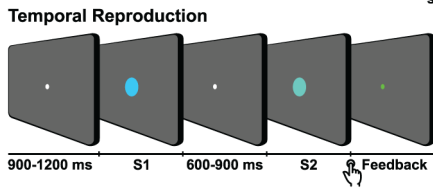
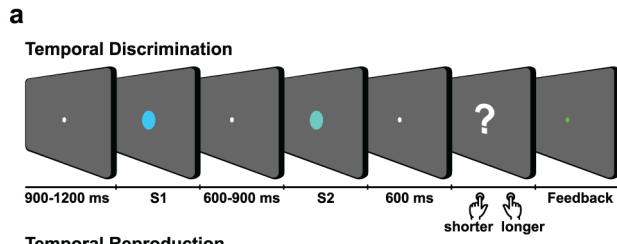
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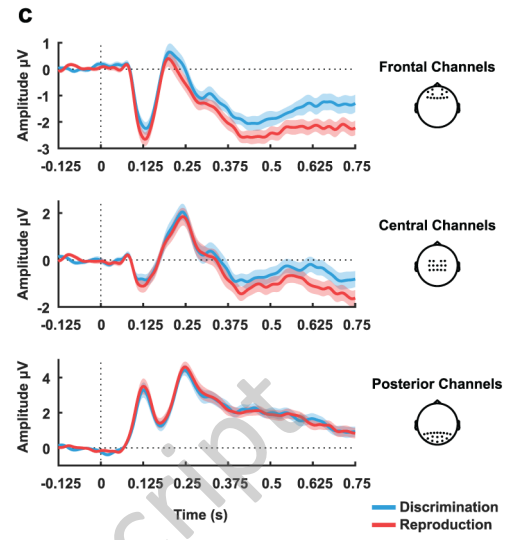
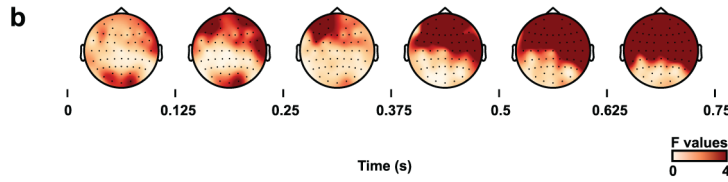
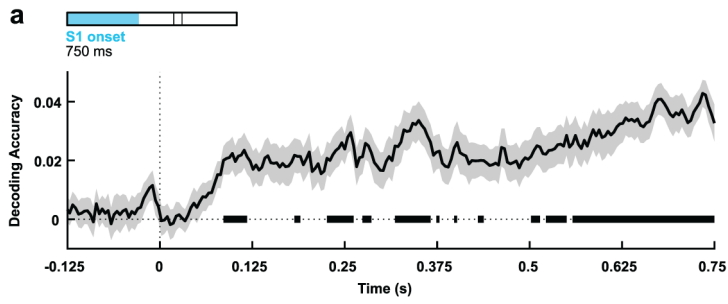
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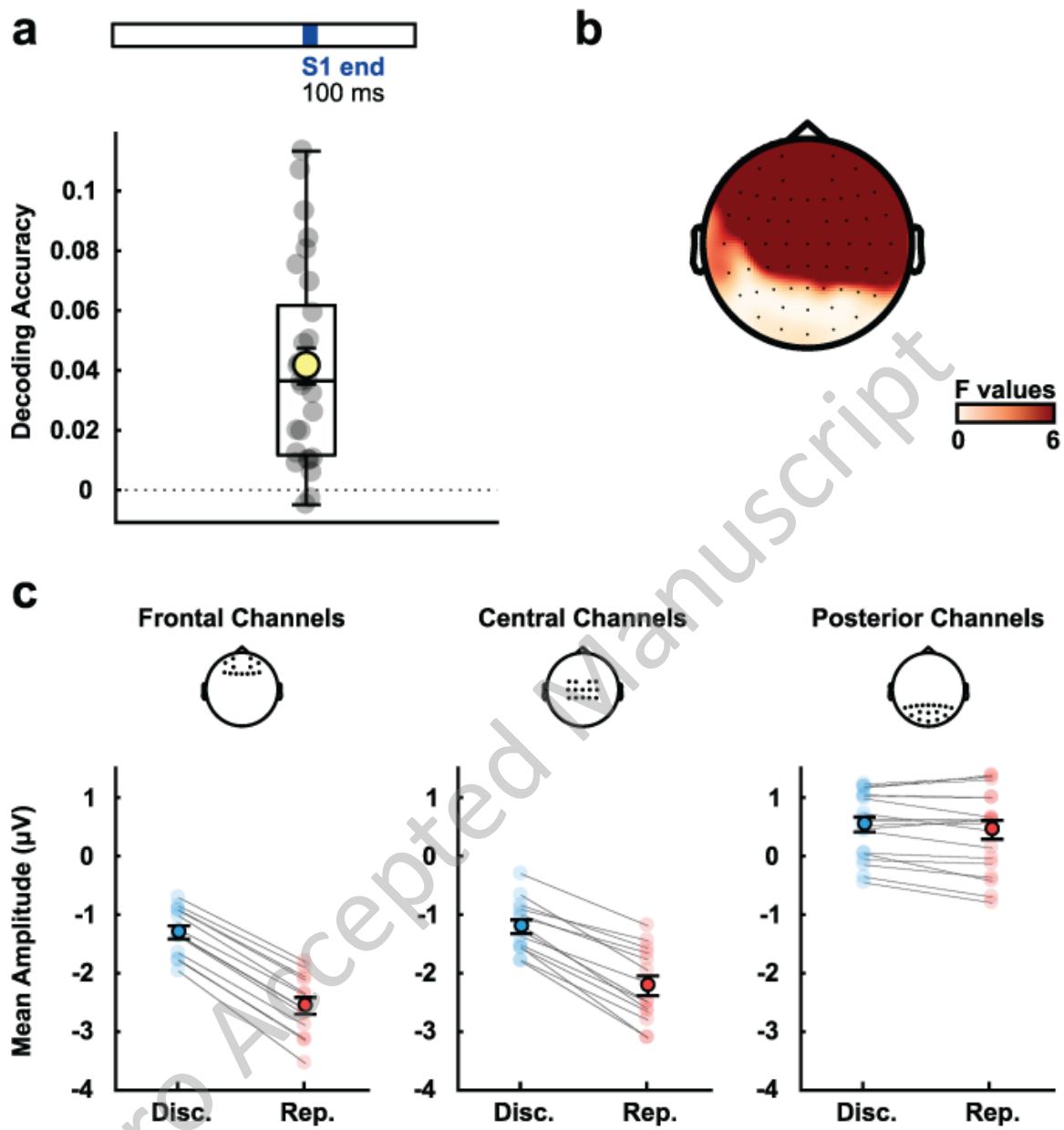
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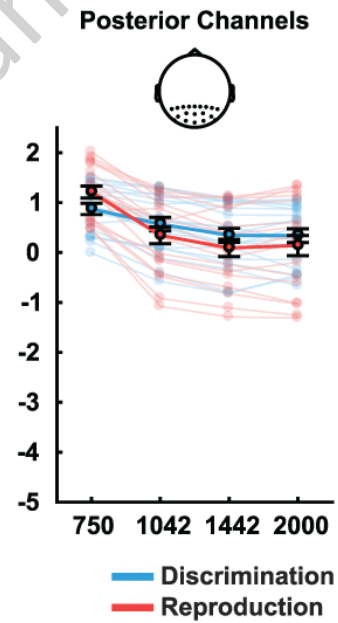
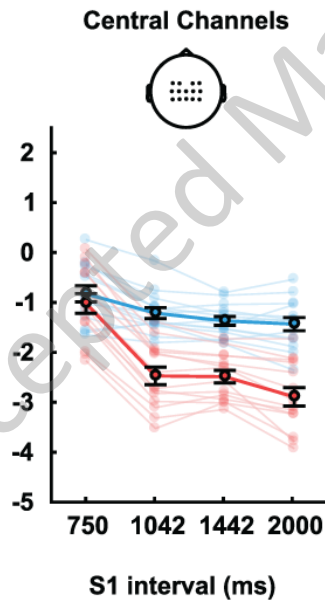
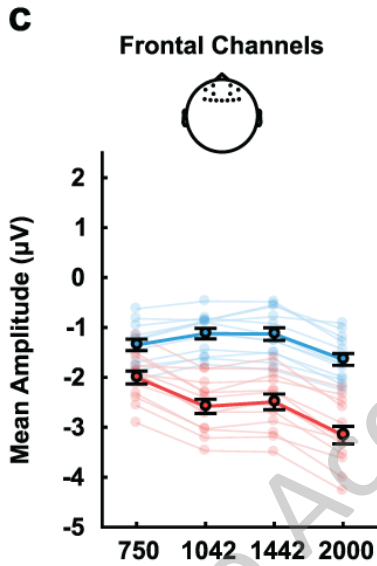
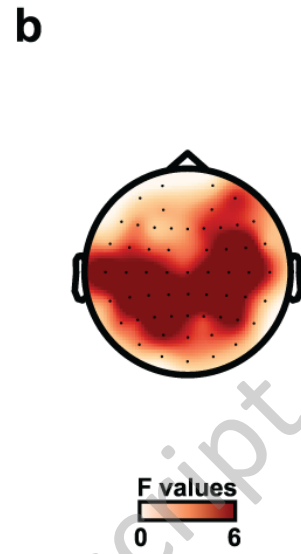
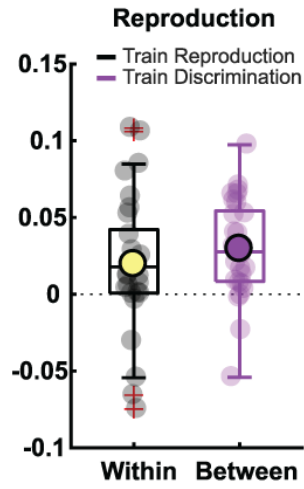
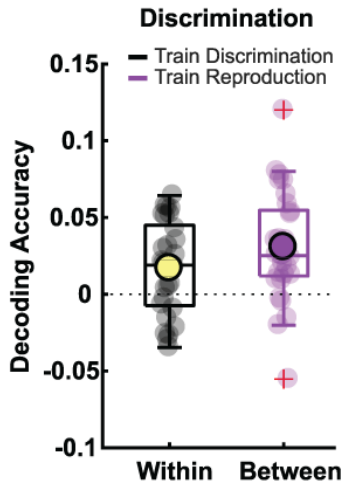
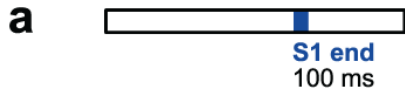


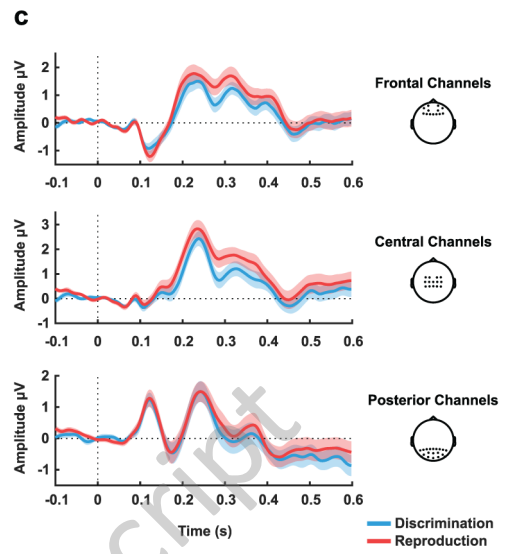
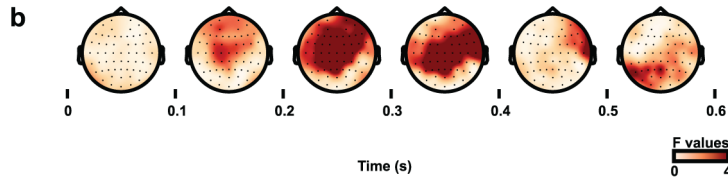
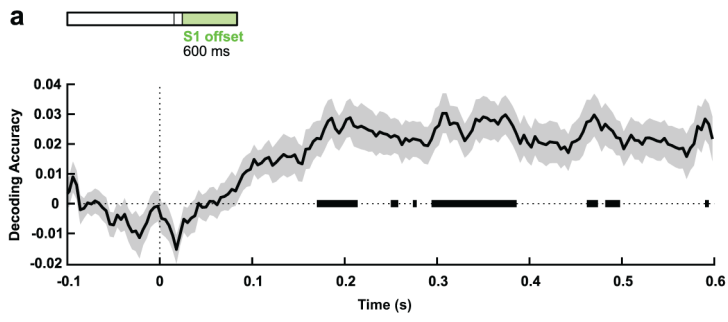
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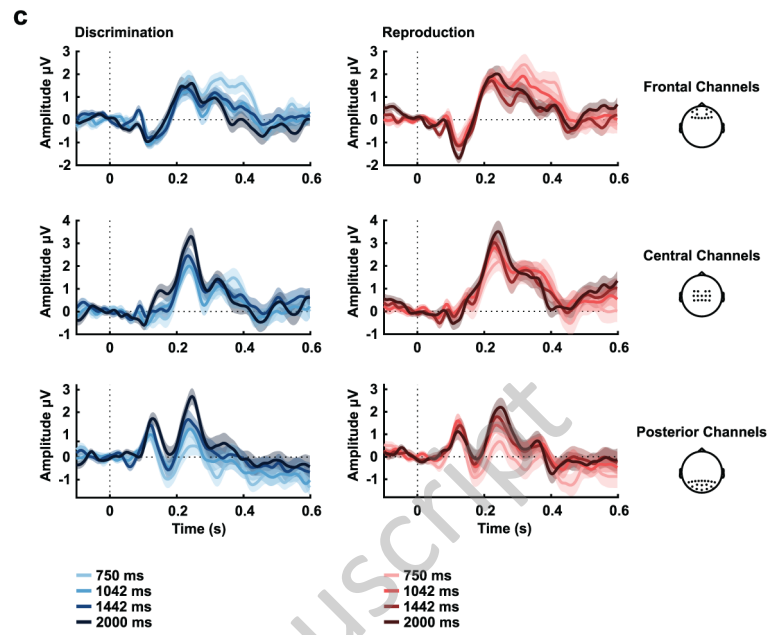
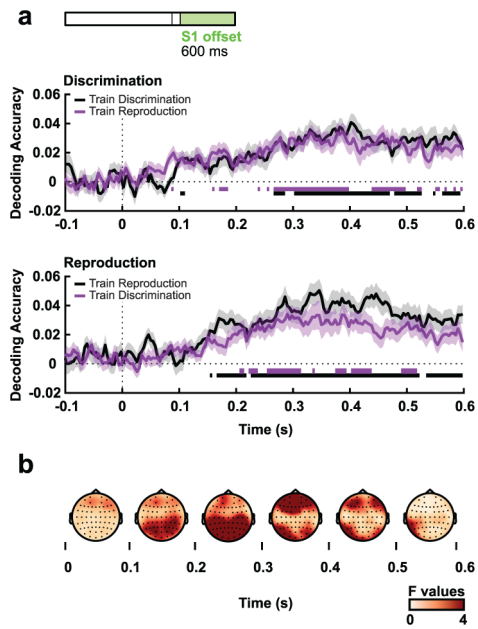
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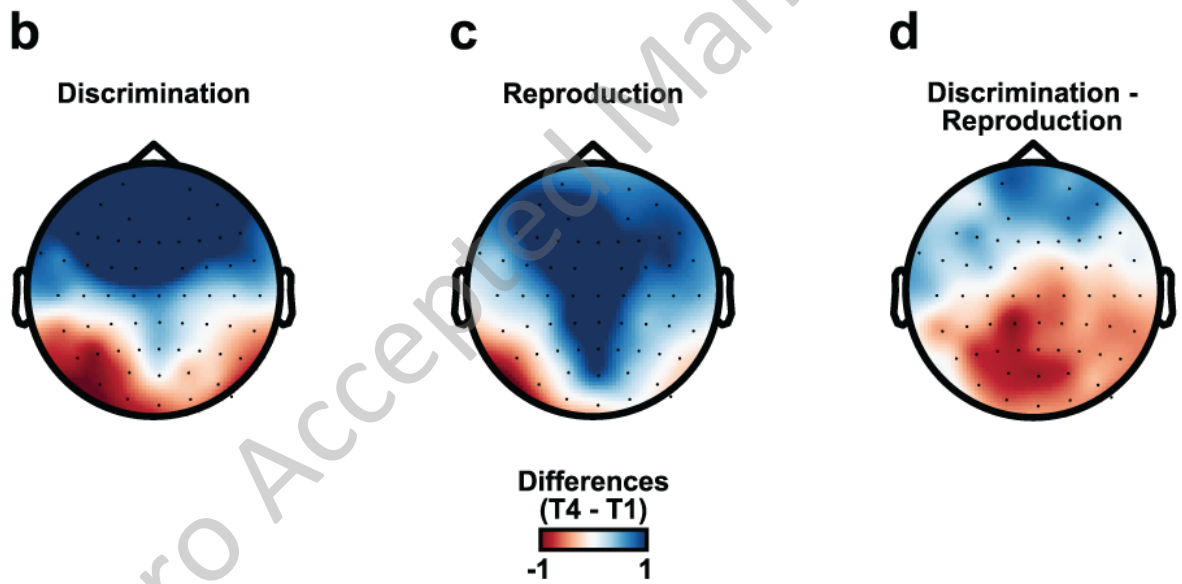
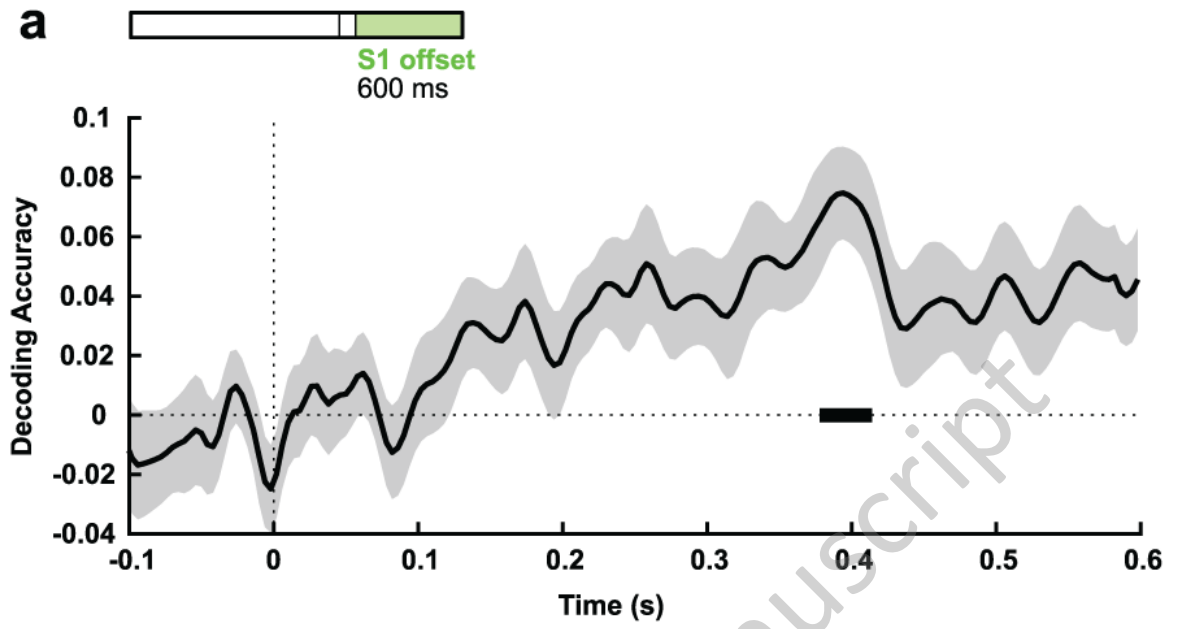




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**Summary of Effects**