

# Evidence accumulation determines conscious access

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1 **A fundamental scientific question concerns the neuronal basis of perceptual**  
2 **consciousness, which encompasses the perceptual experience and reflexive monitoring**  
3 **associated with a sensory event. Although recent human studies identified individual**  
4 **neurons reflecting stimulus visibility, their functional role for perceptual consciousness**  
5 **remains unknown. Here, we provide neuronal and computational evidence indicating that**  
6 **perceptual and reflexive consciousness are governed by an all-or-none process**  
7 **involving accumulation of perceptual evidence. We recorded single-neuron activity in a**  
8 **participant with a microelectrode implant in the posterior parietal cortex, considered a**  
9 **substrate for evidence accumulation, while he detected vibrotactile stimuli around**  
10 **detection threshold and provided confidence estimates. We found that detected stimuli**  
11 **elicited firing rate patterns resembling evidence accumulation during decision-making,**  
12 **irrespective of response effectors. Similar neurons encoded the intensity of task-**  
13 **irrelevant stimuli, suggesting their role for consciousness per se, irrespective of report.**  
14 **We generalized these findings in healthy volunteers using electroencephalography and**  
15 **reproduced their behavioral and neural responses with a computational model. This**  
16 **model considered stimulus detection if accumulated evidence reached a bound, and**  
17 **confidence as the distance between maximal evidence and that bound. Applying this**  
18 **mechanism to our neuronal data, we were able to decode single-trial confidence ratings**  
19 **both for detected and undetected stimuli. Our results show that the specific gradual**  
20 **changes in neuronal dynamics during evidence accumulation govern perceptual**  
21 **consciousness and reflexive monitoring in humans.**

22 The processing of sensory signals by the human brain gives rise to two interrelated phenomena:  
23 perceptual consciousness, defined as the subjective experience associated with a sensory  
24 event (Chalmers, 1995; Nagel, 1974; Block 2011), and perceptual monitoring, defined as the  
25 capacity to introspect and reflect upon the subjective experience associated with a sensory  
26 event (Flavell, 1979; Koriat, 2006; Fleming, Dolan, and Frith 2012). The main strategy employed  
27 to study conscious processing consists in relating first-order subjective reports to neural activity  
28 to identify the minimal set of neuronal events and mechanisms sufficient for a specific conscious  
29 percept (i.e., neural correlates of consciousness or NCCs : Koch et al., 2016). To identify NCCs,  
30 most experimental paradigms have adopted a contrastive approach, whereby distinct  
31 phenomenal experiences induced by constant sensory stimulation are compared (Baars, 1998).  
32 One of the simplest contrasts is obtained when stimuli are presented at low intensity or  
33 embedded in noise so that only a certain proportion of them is detected (Dehaene et al., 2006).  
34 A comparison of neural activity elicited by detected and missed stimuli allows distinguishing the  
35 neural correlates of conscious vs. unconscious sensory processing, and therefore identifying  
36 NCCs given that specific confounds are ruled out (Aru et al., 2012). However, although rare  
37 investigations in humans have described single neurons in the temporal lobe encoding stimulus  
38 detection (Quiroga et al., 2008; Reber et al., 2017), the mechanistic role of neuronal activity for

39 perceptual consciousness remains unknown. One prominent theory of consciousness, the  
40 global neuronal workspace, proposes that a stimulus is consciously perceived when its  
41 corresponding neural activity is globally broadcasted across the cortex (Mashour, et al., 2020).  
42 This theory assumes that this global broadcast is triggered when an (unconscious) evidence  
43 accumulation process reaches a threshold (Dehaene et al., 2014; Dehaene, 2009; Shadlen  
44 2011), similar to the physiological processes underlying decision-making (Bollimunta & Ditterich,  
45 2012; Katz et al., 2016; Roitman & Shadlen, 2002; Zhou & Freedman, 2019). Although various  
46 neuroimaging studies have interpreted increases in neural activity elicited by detected stimuli  
47 (versus missed stimuli) as evidence accumulation (Salti et al., 2015; Tagliabue et al., 2019;  
48 Wyart & Tallon-Baudry, 2009), little empirical evidence supports an evidence accumulation  
49 account of perceptual consciousness, especially at the single neuron level.

50 Besides perceptual consciousness, the main strategy to study perceptual monitoring consists in  
51 assessing how second-order reports like confidence judgments co-vary with the accuracy of a  
52 given perceptual task (first-order reports; Fleming & Lau, 2014). As most studies investigating  
53 perceptual monitoring rely on first-order discrimination tasks with stimuli that are always  
54 detected, less is known regarding how the brain monitors the presence or absence of subjective  
55 experience (Li et al., 2014; Mazor et al., 2020). Moreover, the interdependencies between  
56 perceptual consciousness and monitoring remain to be described empirically: while some  
57 theories of consciousness argue that conscious access requires a higher order representation  
58 of a stimulus (Brown et al., 2019; Lau & Rosenthal, 2011), or necessarily comes with a sense of  
59 confidence (Shea & Frith, 2019), other theories argue that first-order representations may be  
60 sufficient (Lamme, 2010; Zeki, 2007). Like for perceptual consciousness, several models  
61 propose that evidence accumulation plays an important role for the formation of perceptual  
62 confidence (Kvam et al., 2015; Pereira et al., 2020; Pleskac & Busemeyer, 2010; van den Berg  
63 et al., 2016). Yet, to our knowledge the underlying neural mechanisms remain to be described.

64 Here, we sought to investigate the role of evidence accumulation in perceptual consciousness  
65 and perceptual monitoring by asking participants to detect weak vibrotactile stimuli and rate their  
66 confidence in having detected them. We reasoned that both detection and confidence underlie  
67 decision-making processes whereby participants accumulate perceptual evidence over time and  
68 gauge its level relative to decision criteria. We examined this possibility in a patient implanted  
69 with a microelectrode array in the posterior parietal cortex (PPC, Fig. 1A), considered as one of  
70 the functional hotspots of evidence accumulation in the non-human primate brain (Bollimunta &

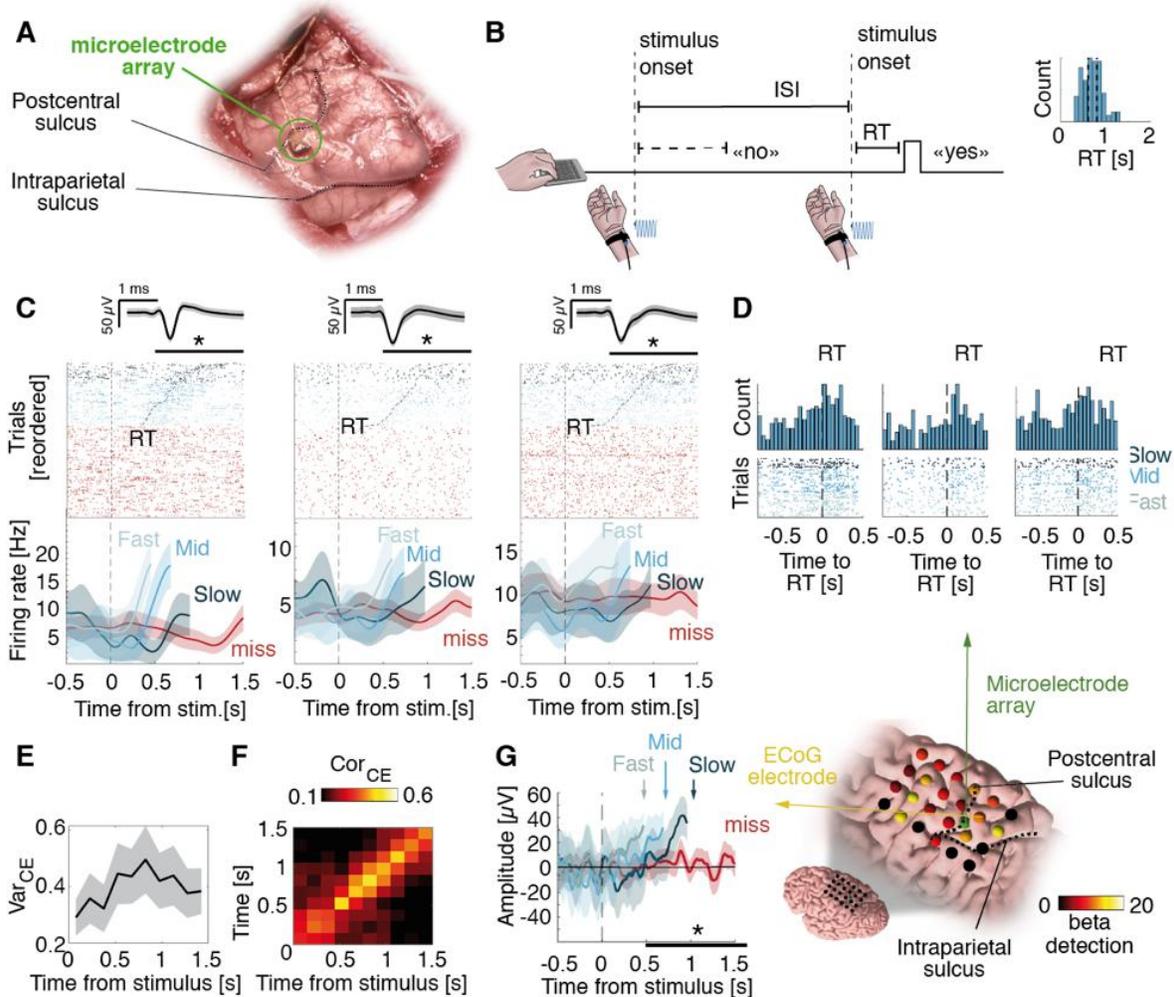
71 Ditterich, 2012; Gold & Shadlen, 2007; Katz et al., 2016; Roitman & Shadlen, 2002; Zhou &  
72 Freedman, 2019). We isolated 368 putative single neurons (Fig. S1) in three different  
73 experiments with immediate, delayed, and no-responses in order to characterize the neural  
74 correlates of detection and confidence at the single-neuron and population levels and link  
75 evidence accumulation in the PPC to perceptual consciousness irrespective of response  
76 effectors. These results were generalized in a fourth experiment involving a group of healthy  
77 volunteers in whom we recorded scalp electroencephalography, perceptual consciousness and  
78 monitoring responses while they detected the same vibrotactile stimuli. In a final step, we test  
79 and propose an evidence accumulation computational model that reproduced the behavioral  
80 and neural markers of both detection and confidence. Together, these results indicate that  
81 subjective reports of perceptual consciousness and monitoring involve a common mechanism of  
82 evidence accumulation orchestrated by the PPC.

## 83 Results

### 84 Experiment 1: immediate-response task

85 In *Experiment 1*, the participant was asked to detect vibrotactile stimuli applied to the right wrist  
86 (contralateral to the PPC implant) with an intensity around detection threshold. Responses were  
87 provided by a keypress with the left hand, immediately after perceiving a stimulus. A trial was  
88 considered a hit when the participant responded within 2 s following stimulus onset (41.20% of  
89 trials; mean response time (RT) and 95% confidence interval:  $0.71 \pm 0.02$ s), otherwise, it was  
90 considered a miss (58.80% of trials Fig. 1B). The participant rarely responded “yes” in the  
91 absence of stimuli (0.36%; false-alarms), indicative of conservative behavior. We found 94/186  
92 detection-selective neurons (50.54%;  $p = 0.001$ , Poisson GLM with permutation test across  
93 neurons) with spike counts explained by detection (yes/no responses) between 0.5 to 1.5 s after  
94 the stimulus onset. Some neurons were characterized by a hallmark of evidence accumulation  
95 where increases in firing rates preceded detection reports depending on their response times  
96 (Bollimunta & Ditterich, 2012; Katz et al., 2016; Roitman & Shadlen, 2002; Zhou & Freedman,  
97 2019): the cumulative sum of spikes following stimulus onset correlated with the corresponding  
98 RT in 67/94 detection-selective neurons (71.28%;  $p = 0.001$ ; Fig. 1C) with some neurons  
99 showing gradually increasing spike counts prior to the keypress (Fig. 1D). To further support  
100 that increased spike counts represent an evidence accumulation process, we verified that the  
101 proportion of variance not attributed to the point process increased after stimulus onset (Fig. 1E)  
102 and that the corresponding covariance decayed with increasing time lag (Fig. 1F), in line with

103 what is expected for a diffusion process (Churchland et al., 2011). Finally, we replicated the  
 104 increase in firing rate with electrocorticography (ECoG) by showing that the strongest effect of  
 105 detection was localized in the PPC and pre-central gyrus (Fig. 1G). To summarize, we  
 106 uncovered individual neurons in the human PPC with firing rates ramping up prior to detection  
 107 reports, consistent with evidence accumulation.



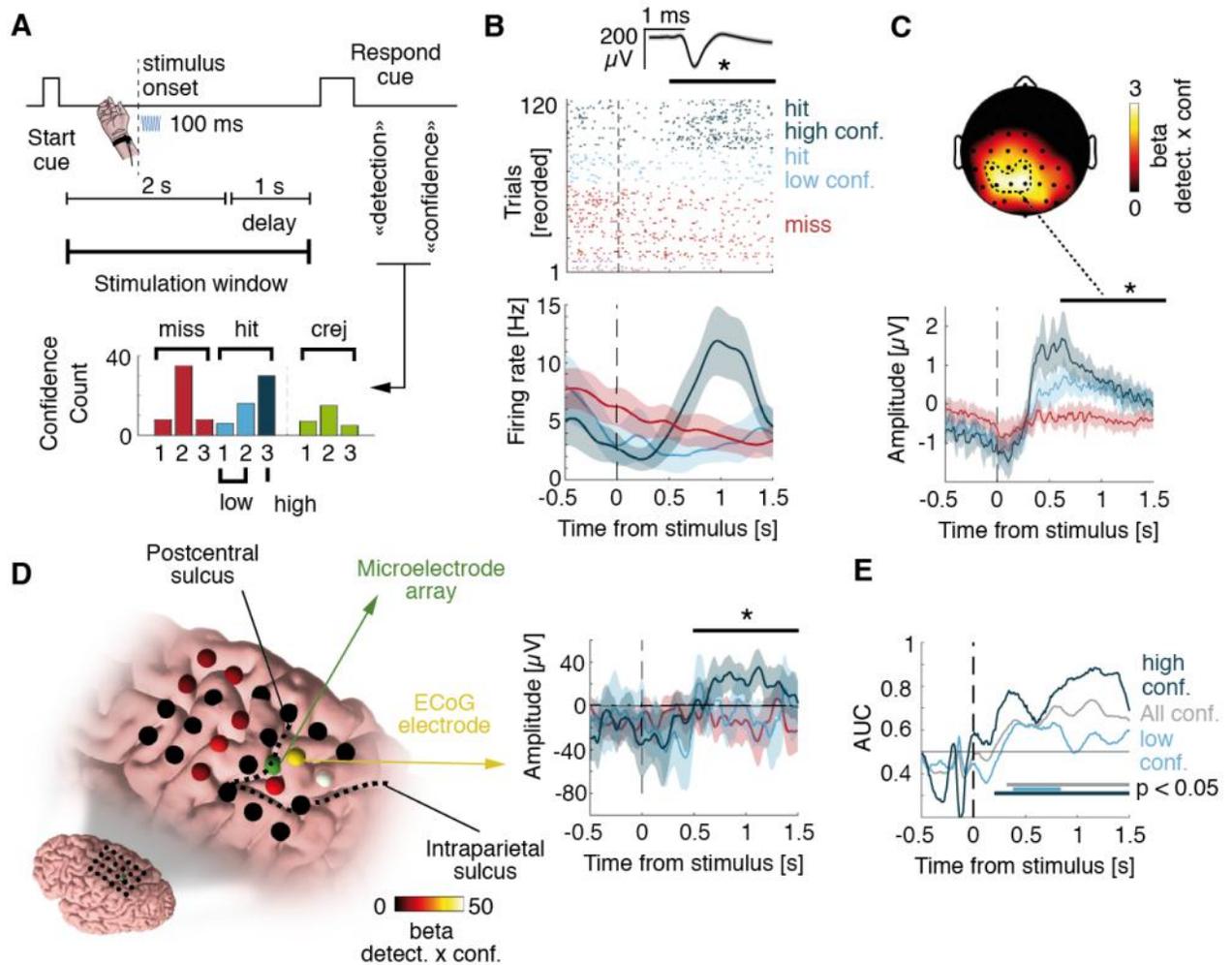
108 *Fig.1. Neuronal correlates of detection in an immediate-response task (Experiment 1). (A) Intraoperative photo of the*  
 109 *microelectrode array posterior to the postcentral sulcus and dorsal to the intraparietal sulcus. (B) The participant*  
 110 *pressed a key as soon as he felt a stimulus (dashed vertical lines). In this example, the first stimulus is a miss (i.e. no*  
 111 *key press within 2s following stimulus onset) and the second stimulus is a hit. ISI: inter-stimulus interval. Inset: RT*  
 112 *distribution. (C) Example selective neurons with a latency effect for RT. Top: raster plot time-locked to stimulus onset*  
 113 *with spike waveform and shaded standard deviation above. Hits were reordered according to RT (black dashed trace).*  
 114 *Bottom: average firing rate for three tertiles of RT (blue) and for misses (red). Statistics were performed on*  
 115 *continuous data. (D) Top: RT-aligned spike count histograms for neurons in C (50 ms bins). Bottom: corresponding*  
 116 *raster plots. (E) VarCE increases during the putative decision process for detection- and RT-selective neurons*  
 117 *(N=47). Shaded areas represent 95%-confidence intervals (95%-CI) across selective neurons. (F) Corresponding*  
 118 *analysis of covariance representing CorCE as heat maps, averaged across detection- and RT-selective neurons*  
 119 *(N=47). (G) Left: Average ECoG response, aligned to stimulus onset from one electrode posterior to the*  
 120 *microelectrode array for three tertiles of RT. Right: ECoG grid with beta coefficients for detection. Non-significant*  
 121 *electrodes are in black. All shaded areas represent 95%-CI and black horizontal bars represent the analysis window*  
 122 *for statistics.*

## 123 **Experiment 2: delayed-response task**

124 Next, we tested whether neuronal responses relate to conscious perception irrespective of  
125 motor actions by imposing a delay between stimulus onset and reports. We also assessed  
126 whether the strength of these neuronal representations co-vary with reported confidence  
127 (Rutishauser et al., 2015, 2018). In Experiment 2, we asked the participant to report vocally the  
128 detection of the stimuli with a minimal delay of 1 s after stimulus onset (Fig. 2A, upper panel).  
129 To assess the role of evidence accumulation for conscious monitoring, we also asked the  
130 participant to vocally report his confidence (high, medium, low) in his response. Similar to  
131 Experiment 1, 50.5% of stimuli were detected (hits) (20% trials had no stimuli, of which 5% were  
132 false-alarms, confirming his conservative strategy). When a stimulus was presented, confidence  
133 was higher following hits ( $2.46 \pm 0.10$ ) than misses ( $2.00 \pm 0.08$ ;  $X^2 = 20.09$ ,  $p = 4.3 \cdot 10^{-5}$ ),  
134 indicative of accurate detection monitoring processes (Fig. 2A, lower panel).

135 We ran a factorial analysis to identify neurons encoding detection and/or confidence. We found  
136 17/86 neurons showing an interaction between detection and confidence (19.77%,  $p = 0.002$ ,  
137 permutation test) driven by an increased firing rate for hits with high confidence (Fig. 2B). Only  
138 one neuron showed only a main effect of detection ( $1.16\%$ ,  $p = 0.57$ ) and two a main effect of  
139 confidence ( $2.33\%$ ,  $p = 0.88$ ). A similar interaction between detection and confidence was found  
140 in ECoG electrodes surrounding the microelectrode array (Fig. 2D) and in  
141 electroencephalography (EEG) signals from 18 healthy volunteers recruited from Experiment 4  
142 (Fig. 2C), consistent with previous EEG studies (Herding et al., 2019; Tagliabue et al., 2019). To  
143 characterize how neuronal population activity relates to detection and confidence, we trained  
144 decoders on the firing rate of all neurons and evaluated them out-of-sample. We decoded hits  
145 from misses better than chance for both high confidence (Fig. 2E; max. area under the curve  
146 (AUC): 0.88, 1.16s after stimulus onset) and low confidence (max. AUC: 0.63 accuracy at 0.77  
147 s). This indicates that although low confidence hits and misses were indistinguishable based on  
148 individual neurons they could be discriminated at the population-level, which confirms that our  
149 results were not driven by high-confidence trials only. Finally, the output of the best decoder (at  
150 1.13 s) correlated with confidence for hits ( $R = 0.59$ ;  $p < 0.001$ , permutation test) but not for  
151 misses ( $R = 0.16$ ;  $p = 0.13$ ), confirming that the neuronal signal driving detection also explains  
152 confidence for detected stimuli. Together, results from Experiments 1 and 2 show that PPC  
153 neurons exhibit evidence accumulation behavior and encode detection and confidence reports  
154 irrespective of motor actions and report effector (i.e., keypress in Experiment 1, voice in  
155 Experiment 2). Of note, the latency of the evidence accumulation process we uncovered in

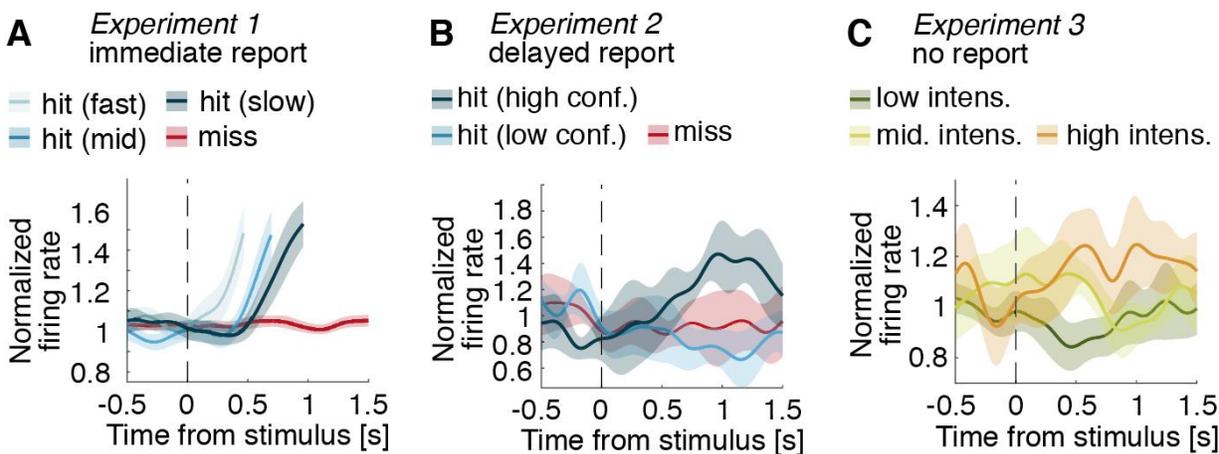
156 Experiment 2 is qualitatively compatible with the distribution of RTs measured in Experiment 1,  
 157 which suggests that conscious access occurs with a delay of up to 1 s following weak  
 158 vibrotactile stimulation.



159 *Fig.2. Neuronal correlates of detection and confidence in a delayed-response task (Experiment 2).* (A) Top:  
 160 *Vibrotactile stimuli were applied during a 2s window following an auditory cue. After 1s delay, the participant was*  
 161 *prompted to give detection and confidence reports. Bottom: Distribution of confidence. For display purposes hereafter,*  
 162 *signals corresponding to confidence values of 1 and 2 were merged into low-confidence, while confidence values of 3*  
 163 *were considered as high-confidence. Statistics were done on the three levels.* (B) *Example selective neuron. Top:*  
 164 *Raster plot time-locked to stimulus onset with spike waveform with shaded standard deviation above. Bottom:*  
 165 *Corresponding firing rates.* (C) *EEG data showing a topographic map of beta coefficient for the interaction between*  
 166 *detection and confidence for hits (dashed trace). The EEG amplitude time-locked to stimulus onset and averaged*  
 167 *over 18 healthy controls is shown below.* (D) *Left: ECoG grid with beta coefficients for detection x confidence. Non-*  
 168 *significant electrodes are in black. Right: Average ECoG amplitudes, aligned to stimulus onset from the electrode*  
 169 *next to the microelectrode array* (E) *Decoding performance for different confidence levels. Horizontal lines show*  
 170 *times of significant performance (permutation tests). All shaded areas represent 95%-CI and black horizontal bars*  
 171 *represent the analysis window for statistics.*

### 172 Experiment 3: no-report paradigm

173 To distinguish neuronal activity associated with subjective experience from activity associated  
174 with subjective report (Aru et al., 2012; Pitts et al., 2014; Tsuchiya et al., 2015), in *Experiment 3*  
175 we let the participant mind-wander while he was exposed to stimuli ranging between 0.5 to 5  
176 times the perceptual-threshold intensity. We reasoned that neuronal activity would still encode  
177 the intensity even for task-irrelevant stimuli if evidence accumulation determines conscious  
178 perception beyond mere reports. While no behavioral task was enforced, we found that the  
179 activity of 14/96 neurons increased with increasing stimulus intensity (14.58%,  $p = 0.008$ ; Fig.  
180 3C), similar to hits in Experiments 1-2 (Fig. 3A, B). The fact that stimulus intensity was  
181 represented at the single-neuron level although the participant was not engaged in the task  
182 argues against the possibility that our previous results in Experiments 1-2 reflected task activity  
183 rather than perceptual processing leading to conscious access (Aru et al., 2012; Pitts et al.,  
184 2014; Tsuchiya et al., 2015).



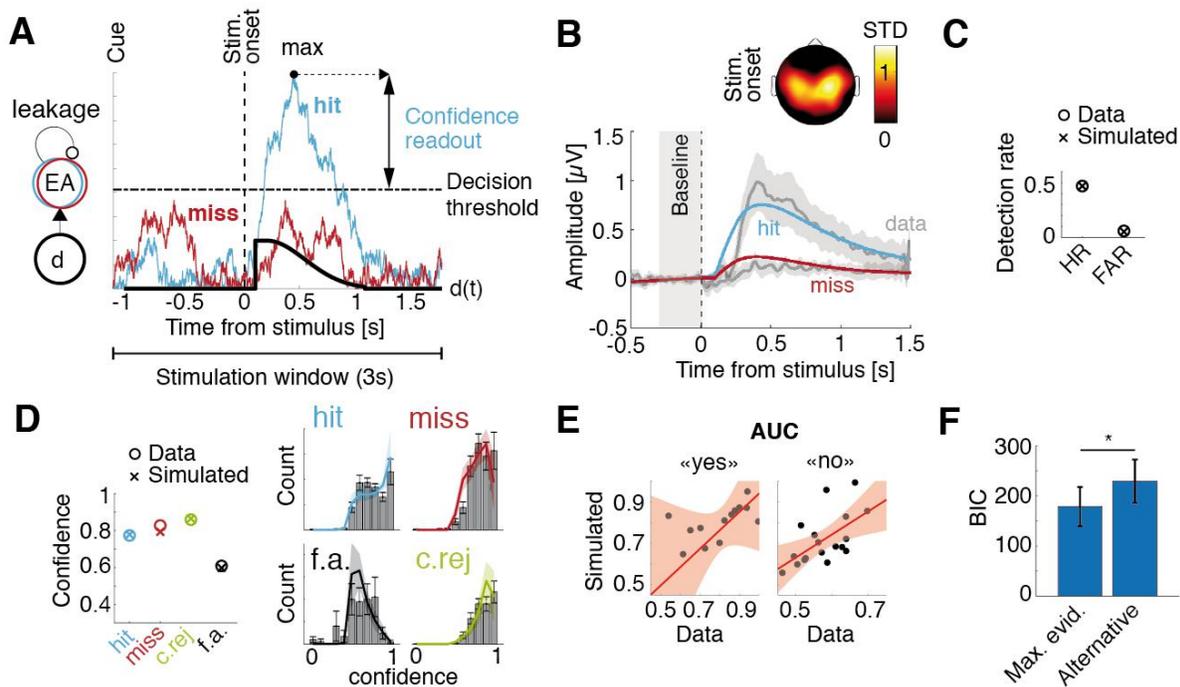
185 **Fig. 3.** Average firing rates of responsive neurons. Firing rates were normalized using a 0.3 s pre-stimulus baseline.  
186 (A) Normalized firing rate for three bins of RT (hits; blue) and for misses (red), averaged across detection-selective  
187 and RT-selective neurons with higher firing rates for hits ( $N=47$ ). In Experiment 1, the participant answered with a  
188 keypress for hits. (B) Normalized firing rate for high and low confidence for hits (blue) and for misses (red), averaged  
189 across all detection- and confidence- selective neurons with higher firing rates for hits ( $N=10$ ). In Experiment 2, the  
190 participant waited at least one second before reporting detection and confidence vocally. (C) Normalized firing rate for  
191 three bins of stimulus intensity, averaged across intensity-selective neurons ( $N=14$ ). In Experiment 3, the participant  
192 provided no detection or confidence report and was let to mind wander.

#### 193 **Experiment 4: computational model of detection and confidence**

194 Informed by these human single-neuron data from Experiments 1-3, we sought to generalize  
195 our decisional account of perceptual consciousness by identifying evidence accumulation  
196 mechanisms underlying detection and confidence in EEG data (18 healthy volunteers, task  
197 similar to Experiment 2). Participants behaved similarly to the aforementioned patient, with a  
198 balanced number of hits and misses (Supplementary results) and EEG responses also showed  
199 an interaction effect between detection and confidence (Fig. 2C). We developed an evidence  
200 accumulation model to fit the behavioral and EEG data, assuming that participants attempted to  
201 detect the stimulus by continuously accumulating evidence during a 3s stimulation window (from  
202 trial onset until the response cue). To model the time uncertainty in our task (participants did not  
203 know when a stimulus could be applied), we assumed that participants started accumulating  
204 evidence before the stimulus onset (Devine et al., 2019). This was modelled as a null drift rate  
205 across time except for a short-lasting boost triggered by the stimulus. A stimulus was perceived  
206 if the simulated evidence accumulation (EA) process reached a bound (Kang et al., 2017) at any  
207 time during the stimulus window (Fig. 4A), compatible with all-or-none views of conscious  
208 access (Dehaene et al., 2014).

209 Confidence was read out from the distance between accumulated evidence and the decision  
210 threshold (Pereira et al., 2020; Pleskac & Busemeyer, 2010). Importantly, we sampled  
211 confidence when evidence reached a maximum across the stimulation window, which allowed  
212 implementing a confidence readout for misses and correct rejections, for which no decision  
213 threshold is crossed. To fit the model parameters to the data, we considered the shape of the  
214 electrophysiological signature for hits and misses as a neural correlate of evidence  
215 accumulation (O'Connell et al., 2012; Philiastides et al., 2014; Tagliabue et al., 2019), defined  
216 by the weighted average of all EEG electrodes that maximally discriminated hits from misses.  
217 We first fitted the parameters of a detection model to these electrophysiological responses (Fig.  
218 4B, S2) as well as to hit and false alarm rates (Fig. 4B, inset; Fig. S3). We then fitted two  
219 additional parameters for confidence bias and sensitivity to observed confidence distributions.  
220 The resulting model fitted the confidence ratings well (average R across participants  $0.83 \pm 0.03$   
221 for hits,  $0.85 \pm 0.03$  for misses,  $0.81 \pm 0.04$  for correct rejections and  $0.45 \pm 0.09$  for false alarms;  
222 Fig. 4C, S4), suggesting that evidence accumulation is a plausible mechanism underlying  
223 perceptual consciousness and its electrophysiological correlates. The data and the model were  
224 still consistent when stratifying per confidence level. Metacognitive sensitivity predicted by our  
225 model and observed in the data were correlated for both “yes” responses ( $R=0.60$ ,  $p=0.001$ ,

226 permutation test) and “no” responses ( $R=0.61$ ,  $p=0.009$ ; Fig. 4E), showing that our model also  
 227 successfully predicted metacognitive performance. Finally, an alternative model assuming that  
 228 confidence for detected stimuli is sampled at a fixed latency after crossing the decision  
 229 threshold and confidence for undetected stimuli is sampled from a random distribution led to a  
 230 worse fit of the data ( $BIC = 229.31 \pm 43.19$  compared to  $BIC = 178.82 \pm 38.86$  for the maximal  
 231 evidence model;  $z = -2.33$ ,  $p = 0.020$ ; Fig. 4F). This difference in goodness of fit was also  
 232 observable in the correspondence between observed and simulated averaged confidence for  
 233 hits ( $R = 0.81 \pm 0.03$  for the maximal evidence model compared to  $R = 0.63 \pm 0.09$  for the  
 234 alternative model;  $z = 2.29$ ;  $p = 0.022$ ).



235 **Fig. 4. Computational model based on evidence accumulation.** (A) Time-varying drift rate ( $d$ ; thick black trace) had a  
 236 short-lasting boost after a non-decision time following stimulus onset (dashed vertical line). Example evidence  
 237 accumulation for one trial (EA; cyan trace for a hit, red trace for a miss) rises sharply after the drift boost and is  
 238 attracted back to zero due to leakage. A stimulus is considered as perceived (hit) if EA reaches a decision threshold  
 239 (horizontal line), and as non-perceived (miss) if not. The maximum of accumulated evidence with respect to the  
 240 decision threshold is used as a confidence readout. (B) Model fit of the pEA locked on stimulus onset for hits (cyan  
 241 trace) and misses (red trace). The corresponding observed EEG data is shown in grey. Average scalp topography of  
 242 pEA weights is shown above. (C) Hit rate (HR) and false alarm rate (FAR). Datapoints are represented as ‘o’ and  
 243 model simulations as ‘x’. (D) Left: Average confidence for hits (cyan), misses (red), correct rejections (green) and  
 244 false alarms (black). Right: Model fits of the confidence distributions. Histograms show confidence distributions with  
 245 95%-CI whiskers. Colored traces show model simulations. All shaded areas represent 95%-CI. (E) Area under the  
 246 curve (AUC) correlation between observed data (horizontal axis) and simulated data (vertical axis) for “yes”  
 247 responses (hits and false alarms; left) and “no” responses (correct rejections and misses; right). Regression line  
 248 is shown in red with shaded areas representing 95%-CI. (F) Model comparison in terms of Bayesian information  
 249 criterion (BIC) between the maximal evidence model and the alternative model. Whiskers represent 95%-CI and  
 250 asterisk indicates statistical significance ( $p < 0.05$ ).

251 Informed by our modelling results in healthy participants, we set out to verify whether we could  
252 decode confidence for misses from single-neuron data in Experiment 2 using a decoder defining  
253 confidence as the maximum of accumulated evidence. We took the best decoder for hits and  
254 misses (trained on stimulus-locked data) and applied it out-of-sample across the stimulation  
255 window (i.e. cue-locked). We decoded confidence for hits ( $R = 0.49$ ,  $p = 0.001$ , permutation test)  
256 and confidence for misses ( $R = -0.31$ ,  $p = 0.015$ ), which the aforementioned stimulus-locked  
257 decoder could not achieve. The time corresponding to the decoded maximal evidence  
258 correlated with stimulus onset for hits ( $R = 0.37$ ,  $p = 0.001$ ) but not for misses ( $R = 0.03$ ,  $p =$   
259  $0.58$ ), suggesting that evidence for confidence in misses was not sampled synchronously with  
260 the stimulus, thereby verifying the plausibility of the maximal evidence decoder on our patient's  
261 single-neuron data.

## 262 Discussion

263 We propose a mechanism of evidence accumulation to explain the behavioral and neural  
264 markers of perceptual consciousness and monitoring. We show that tactile detection relates to  
265 an increase of the firing rate of single neurons in the posterior parietal cortex of a human  
266 participant, as well as an increased scalp EEG response recorded in a group of healthy  
267 participants. In both cases, the amplitude of the corresponding neural response was dependent  
268 on the confidence in hits. This increase in neural response as well as in the detection reports  
269 were well described by a computational model indicating that a plausible mechanism underlying  
270 the building of confidence in both the presence and absence of a stimulus is for the brain to take  
271 the maximal evidence accumulated over time.

### 272 *Encoding of detection by individual neurons in the posterior parietal cortex*

273 We had the opportunity to collect data from individual neurons in the human PPC, at the  
274 junction between the postcentral and intraparietal sulcus in the superior parietal lobule. The  
275 PPC has been associated with a multitude of functions linking perception to planning and action  
276 (Andersen & Cui, 2009) and receives multisensory inputs including those from the primary  
277 somatosensory cortex (Pearson & Powell, 1985). In Experiment 1, we found individual neurons  
278 in the PPC with higher firing rates following detected stimuli. We argue that these neurons are  
279 responsible for evidence accumulation based on the following three findings. Firstly, in  
280 Experiment 1 we found neurons whose increase in firing rate for hits was synchronized to

281 response times (Gold & Shadlen, 2007). Secondly, in Experiment 1 the variance of the  
282 corresponding spike rates increased after stimulus onset (Churchland et al., 2011). Thirdly, in  
283 Experiment 3, we observed an increase in the firing rates for increasing intensities of (task-  
284 irrelevant) stimuli (Gold & Shadlen, 2007). Based on these three hallmarks of evidence  
285 accumulation, we argue that our results consist in the first single-neuron account of perceptual  
286 evidence accumulation in a human subject capable of subjective reports. Indeed, although  
287 electrophysiological correlates of evidence accumulation have been found in various regions of  
288 non-human primate brains, including the frontal cortex or subcortical structures (Ding & Gold,  
289 2010; Hanks et al., 2015; Odegaard et al., 2018), the arguably most common region studied in  
290 relation with neural accumulation of perceptual evidence is the lateral intraparietal (LIP) area of  
291 the PPC (Bollimunta & Ditterich, 2012; Katz et al., 2016; Roitman & Shadlen, 2002; Zhou &  
292 Freedman, 2019). However, whether perceptual evidence accumulation neurons such as those  
293 reported in non-human primate studies could support conscious reports is unclear, as subjective  
294 experience cannot be measured explicitly in non-human species, and because such neurons  
295 were – to our knowledge – not reported in humans yet.

#### 296 *Encoding of confidence by individual neurons in the posterior parietal cortex*

297 In Experiment 2, we asked the participant again to detect stimuli and found neurons similar to  
298 those in Experiment 1 with higher firing rates after stimuli reported as perceived. The finding of  
299 detection-selective neurons when responses were provided by key press (Experiment 1) or  
300 orally (Experiment 2) suggests that the mechanism of evidence accumulation we propose is  
301 response-invariant. Importantly, we asked the participant to report the confidence he had in his  
302 responses, and found that the change in firing rates for detected stimuli was modulated by  
303 confidence, showing that confidence relates to the strength of single neuron's responses to  
304 detected stimuli. This mechanistic overlap, which – to our knowledge – was not yet shown in  
305 humans capable of reporting subjective confidence was confirmed at the neuronal population  
306 level: multivariate decoders trained to discriminate hits vs. misses allowed us to decode  
307 confidence for hits when time-locking to the stimulus onset and for both hits and misses when  
308 locking on the onset of maximal evidence.

#### 309 *Computational modelling and replication at the scalp level*

310 Because microelectrode implants in parietal regions are extremely rare in humans, we sought to  
311 generalize our findings by recording behavioral and neural data in a group of healthy volunteers  
312 in Experiment 4. Behavioral results revealed highly similar patterns between the two samples,

313 indicating that detection and confidence reports in Experiments 1-2 were not impacted by the  
314 clinical condition. Experiment 4 also allowed us to generalize our single-neuron findings at a  
315 larger scale based on EEG recordings. EEG data showed a similar dependence of detection-  
316 related activity on confidence for hits, similar to previous work in the visual domain using a  
317 different awareness scale (Tagliabue et al., 2019) and a discrimination task (Boldt & Yeung,  
318 2015; Gherman & Philiastides, 2015). Of note, both neural responses recorded at the  
319 intracranial (single-neuron, EcoG; Experiment 1-3) and scalp levels (Experiment 4) were  
320 observed at a rather late latency following stimulus onset (>200 ms), suggesting that these  
321 responses were not related to early somatosensory perceptual processes. We then reasoned  
322 that since similar increases in neural activity are assumed to reflect accumulation of evidence  
323 (O'Connell et al., 2012, 2018; Tagliabue et al., 2019), an evidence accumulation model should  
324 predict both behavioral results (hit rate, false-alarm rate and confidence for hits, misses, correct  
325 rejections and false-alarms) and corresponding neural responses. Using neural data to fit the  
326 model instead of response times allowed us to fit a leakage parameter (Yu et al., 2015) and to  
327 compensate for the fact that, in a detection task, response times are unavailable for undetected  
328 stimuli. The model derives confidence as the distance between the maximal evidence  
329 accumulated over time and the decision bound. This flexible readout provides a major  
330 advantage when computing confidence in the absence of stimulus detection (i.e. misses) as well  
331 as in the absence of a stimulus (i.e. correct rejections and false-alarms), which cannot be  
332 achieved with models using decision-locked confidence readouts in discrimination tasks  
333 (Pereira et al., 2020; Pleskac & Busemeyer, 2010; van den Berg et al., 2016). An alternative  
334 model with a fixed-timing readout and a random confidence for unperceived stimuli performed  
335 significantly worse. Our modelling results corroborate our electrophysiological results across  
336 Experiments 1-4 and are consistent with decision-making models of confidence applied to  
337 animal data, postulating a shared encoding of evidence for decision and confidence (Kiani &  
338 Shadlen, 2009), possibly enriched by post-decisional evidence (Fleming et al., 2018; Pleskac &  
339 Busemeyer, 2010; van den Berg et al., 2016). Moreover, a recent study comparing models  
340 based on signal detection theory showed that the model that best fit observed data involves a  
341 second-order "metacognitive" noise to the decisional evidence (Maniscalco & Lau, 2016). Our  
342 model implicitly implements this metacognitive noise through the influence of first-order  
343 parameters such as leakage on post-decisional evidence readouts. Indeed, in participant with  
344 strong leakage, accumulated evidence rises and decays fast, leading to low metacognitive noise.  
345 On the contrary, in participants with little leakage, once no more informative evidence is  
346 accumulated, the level of evidence accumulation tends to oscillate around the reached

347 maximum, leading to higher metacognitive noise. A-posteriori analyses showed that the leakage  
348 parameter correlated with metacognitive sensitivity (Supplementary information). Our model  
349 thus provides a simple mechanism supporting metacognition, including subliminal stimuli,  
350 explains neural responses and was verified at the single neuron and EEG level, as we were  
351 able to decode confidence ratings above chance using this procedure.

### 352 *Implications for perceptual consciousness*

353 Our results posit that stimulus detectability involves the accumulation of sampled evidence  
354 towards a decision bound, as previously discussed for discrimination tasks (Kang et al., 2017).  
355 Of note, the use of a detection task is compatible with a contrastive study of consciousness  
356 (Baars, 1998), as opposed to two-alternative forced choice discrimination tasks for which  
357 confidence ratings are well characterized, but which do not offer a direct contrast between  
358 perceived and unperceived stimuli. The view of conscious access as an all-or-none process  
359 involving a decision bound is compatible with the ignition mechanism put forward by the global  
360 workspace theory of consciousness (Mashour et al., 2020), according to which sufficiently  
361 activated encapsulated networks may coalesce into a single network responsible for  
362 broadcasting neural signals throughout the brain and thereby making them accessible to  
363 conscious reports. One could speculate that the triggering of an ignition is governed by  
364 bounded-evidence accumulation similar to the one operated by neuronal populations in the  
365 posterior parietal cortex. Recently, the use of classical contrastive approaches to delineate the  
366 neural correlates of consciousness has been criticized, on the basis that it may be confounding  
367 the cognitive and neural mechanisms associated with phenomenal experience per se, and  
368 those associated with reporting phenomenal experience (Aru et al., 2012). Some authors have  
369 proposed the use of “no-report paradigms”, in which perceptual experience is not inferred from  
370 participants’ responses, but from neural or peripheral signals while participants are passively  
371 exposed to stimuli (Frassle et al., 2014; Tsuchiya et al., 2015; but see Block, 2019; Phillips &  
372 Morales, 2020). Importantly, we found a population of neurons encoding perceptual evidence  
373 through a putative evidence accumulation process in Experiment 3, in which the participant was  
374 passively exposed to the stimuli similar to such no-report paradigms. Although these effects  
375 were weaker than the ones found in Experiment 1-2, they indicate that evidence accumulation  
376 operated by a neuronal population in the posterior parietal cortex is involved in conscious  
377 perception, even when the stimuli are task-irrelevant. In addition, the mechanistic overlap  
378 between detection and confidence we report cannot be due to similar motor responses  
379 associated with detection and confidence reports in Experiment 2, as those were collected

380 separately, seconds after the end of the stimulation window on which our analysis was based in  
381 the delayed detection task.

382 To conclude, our results posit that both detection and confidence for near-threshold stimuli  
383 involve the accumulation of evidence towards a criterion orchestrated by the PPC. We argue  
384 that this neuronal mechanism involving a decision bound may serve as a trigger for the neural  
385 ignition underlying conscious access (Moutard et al., 2015; van Vugt et al., 2018) and explains  
386 how contents remaining inaccessible to consciousness may still be subject to self-monitoring  
387 (Mazor et al., 2020; Meuwese et al., 2014). Our behavioral, neural, and modeling results clarify  
388 how perceptual consciousness and reflexive self-monitoring are intertwined mechanistically.

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606 STAR METHODS

607 KEY RESSOURCE TABLE

REAGENT or RESSOURCE	SOURCE	IDENTIFIER
<b>Software and Algorithms</b>		
<b>MATLAB 2018a</b>	MathWorks	RRID:SCR_001622; <a href="http://www.mathworks.com/products/matlab/">http://www.mathworks.com/products/matlab/</a>
<b>Osort</b>		RRID:SCR_015869; <a href="http://www.rutishauserlab.org/osort">http://www.rutishauserlab.org/osort</a>
<b>EEGLAB 2019.1.0</b>		RRID:SCR_007292; <a href="http://sccn.ucsd.edu/eeglab/index.html">http://sccn.ucsd.edu/eeglab/index.html</a>
<b>iELVis</b>		RRID:SCR_016109; <a href="http://ielvis.pbworks.com/w/page/116347253/FrontPage">http://ielvis.pbworks.com/w/page/116347253/FrontPage</a>
<b>Psychophysics toolbox 3</b>		RRID:SCR_002881; <a href="http://psychtoolbox.org/">http://psychtoolbox.org/</a>
<b>Algorithm to fit an evidence accumulation model to behavioral and neural data</b>		Upon acceptance
<b>Other</b>		
<b>Neuroport recording system</b>	Blackrock Microsystems	<a href="https://www.blackrockmicro.com/">https://www.blackrockmicro.com/</a>
<b>Brain Quick LTM</b>	Micromed	<a href="http://www.micromed.eu/en-us/">http://www.micromed.eu/en-us/</a>
<b>WaveGuard EEG</b>	ANTNeuro	<a href="http://www.ant-neuro.com">http://www.ant-neuro.com</a>

608 CONTACT FOR REAGENT AND RESSOURCE SHARING

609 Further information and requests for ressources should be addressed directly to the Lead Contact,  
610 Nathan Faivre ([nathan.faivre@univ-grenoble-alpes.fr](mailto:nathan.faivre@univ-grenoble-alpes.fr))

611 EXPERIMENTAL MODEL AND SUBJECT DETAILS

612 In experiments 1–3, the participant was a 23-year-old right-handed man suffering from drug-resistant  
613 epilepsy due to a focal cortical dysplasia in the left central sulcus. As part of the clinical management of  
614 his condition, he received a 4x6 ECoG grid covering the left premotor, motor, sensory and posterior  
615 parietal cortices. He accepted to participate in a clinical trial on neuronal recordings during invasive  
616 epilepsy monitoring at the Geneva University Hospitals (IN-MAP; NCT02932839) and a Utah  
617 microelectrode array was additionally implanted in the left posterior parietal cortex. The patient provided

618 informed written consent and the study was approved by the Commission Cantonale d’Ethique de la  
619 Recherche de la République et Canton de Genève (2016-01856). Eighteen healthy participants (7  
620 females; age: 25.2 years, SD = 4.1) took part in Experiment 4 for a monetary compensation. Participants  
621 gave written informed consent prior to participating and all experimental procedures were approved by  
622 the Commission Cantonale d’Ethique de la Recherche de la République et Canton de Genève (2015-  
623 00092 15-273).

## 624 METHOD DETAILS

625 Experimental paradigms were written in Matlab (Mathworks) using the Psychophysics toolbox (Brainard,  
626 1997; Kleiner, n.d.; Pelli, 1997). In all experiments, stimuli were applied on the lateral palmar side of the  
627 right wrist using a MMC3 Haptuator vibrotactile device from TactileLabs Inc. (Montréal, Canada) driven by  
628 a 230 Hz sinusoid audio signal lasting 100 ms. Experiments started by a simple estimation of the  
629 individual detection threshold. The tactile stimulus was applied with decreasing intensity with steps  
630 corresponding to 2% of the initial intensity until the participant reported not feeling it anymore three times  
631 in a row. We then repeated the same procedure but with increasing intensity and until the participant  
632 reported feeling the vibration three times in a row. The perceptual threshold was estimated to be the  
633 average between the two thresholds found using this procedure. This approximation was then used as a  
634 seed value for an adaptive staircase during the main experiments (see below). Experiments 1-3 were  
635 performed on different days at the patient’s bedside.

### 636 **Experiment 1**

637 Stimuli were applied in a pseudo-random way with an inter-stimulus interval of two seconds plus an  
638 exponentially distributed time (mean: 2 s). The participant was provided with a keypad and asked to press  
639 a key every time he felt a stimulus. Answers provided during the two seconds following a stimulus were  
640 considered as hits. Only one keypress occurred out of this two second post-stimulus window.

### 641 **Experiment 2**

642 An auditory cue signaled the start of the two seconds stimulus window during which the stimulus could be  
643 applied at any time (uniform distribution) in 80% of trials (the remaining 20% served as catch trials,  
644 unbeknownst to the participant). Stimulus onset was followed by a one second delay to ensure that  
645 stimulus-locked activity was not contaminated by the detection response. After this delay, a second  
646 auditory cue probed the participant for his detection response (“yes” or “no”), followed by a three levels  
647 confidence rating (1: “unsure”, 2: “somewhat sure”, 3: “very sure”). Detection and confidence ratings were  
648 provided vocally and registered by the experimenter.

### 649 **Experiment 3**

650 Stimuli were applied in a pseudo-random way with an inter-stimulus interval of two seconds plus an  
651 exponentially distributed time (mean: 2 s) with a random amplitude sampled from 11 intensities ranging  
652 from zero to five times the participant's perceptual threshold. The participant was not given any  
653 instructions and was left free to mind-wander during the experiment.

### 654 **Experiment 4**

655 Participants sat in front of a computer screen. A white fixation cross appeared in the middle of the screen  
656 for 2 s. From the moment the fixation cross turned green, participants were told that a tactile stimulus  
657 could be applied at any moment during the next 2 s. During this period, stimulus onset was uniformly  
658 distributed in 80% of trials, the 20% remaining trials served as catch trials, as in Experiment 2. In all trials,  
659 1 second after the green cross disappeared, participants were prompted to answer with the keyboard  
660 whether they felt the stimulus or not. Following a 500 ms stimulus onset asynchrony, participants were  
661 asked to report the confidence in their first order response by moving a slider on a visual analog scale  
662 with marks at 0 (certainty that the first-order response was erroneous), 0.5 (unsure about the first-order  
663 response) and 1.0 (certainty that the first-order response was correct). Detection and confidence reports  
664 were provided with the left (non-stimulated) hand, using different keys. The total experiment included 500  
665 trials divided in 10 blocks, and lasted about 2 hours.

### 666 **Electrophysiological data acquisition**

667 A 96-channel silicon-based microelectrode array ("Utah array"; Blackrock Microsystems, Salt Lake City,  
668 USA) was implanted in the posterior parietal cortex, immediately posterior to the postcentral sulcus and  
669 the hand representation of sensorimotor cortex (Fig. 1A). The location was confirmed through post-hoc  
670 electrode localization (Fig. 1G), performed through a coregistration of a preoperative MRI structural T1  
671 scan and a postoperative CT scan using the iELVIS toolbox (Groppe et al., 2017). The data from each of  
672 the 96 channels was amplified and sampled at 30 KHz for offline analysis (NeuroPort system, Blackrock  
673 Microsystems LLC, Salt Lake City, USA). Additionally, a 24 electrode ECoG grid (Ad-Tech Medical)  
674 covered the left hemisphere from the premotor cortex to the superior parietal lobule (Fig.1G, 2D). The  
675 data was amplified and sampled at 2048 Hz (Brain Quick LTM, Micromed, Treviso, Italy). In Experiment 4,  
676 electroencephalographic data were acquired from 62 active electrodes (10-20 montage) using a  
677 WaveGuard EEG cap and amplifier (ANTNeuro, Hengelo, The Netherlands) and digitized at a sampling  
678 rate of 1024 Hz. Horizontal and vertical electrooculography (EOG) was derived using bipolar referenced  
679 electrodes placed around participants' eyes. The audio signal driving the vibrotactile actuator was  
680 recorded as an extra channel to precisely realign data to stimulus onset.

### 681 **QUANTIFICATION AND STATISTICAL ANALYSIS**

## 682 **Invasive electrophysiological data processing and univariate analysis**

683 The raw signal from the microelectrode array was bandpass filtered between 300 and 3000 Hz for spike  
684 sorting. Trials with epileptic activity or other artifacts were removed from further analysis following visual  
685 inspection of ECoG data. Spikes were extracted and sorted using the semi-automatic template matching  
686 'Osort' algorithm (Rutishauser et al., 2006). Standard quality metrics were computed for each putative  
687 single unit in order to assess their quality (Fig. S1). We computed the firing rate every 1ms with a 100 ms  
688 standard deviation Gaussian sliding window.

689 In Experiment 1, a neuron was considered detection-selective when a significant (two-sided test) effect of  
690 detection was found on the number of spikes during a time window between 0.5 and 1.5 seconds after  
691 stimulus onset using a generalized linear model (GLM) with a Poisson distribution (Fu et al., 2019;  
692 Rutishauser et al., 2018). For this, we fitted a model with one beta regressor:  $\#spikes \sim \beta_0 + \beta_1 * detection$   
693 (hit or miss). For the latency analysis, we computed the cumulative sum of spikes starting at stimulus  
694 onset and correlated (Spearman) it with RTs for every time step (1 ms) between 0 and 1.5 s after stimulus  
695 onset. A neuron was considered RT-selective if the correlation was significant within this time range after  
696 correcting for false-discovery rate (FDR). To ensure that there was no overfitting and that our results were  
697 not driven by outliers, we used a non-parametric permutation test to assess whether the number of  
698 selective neurons was significantly above chance; we repeatedly (N=1000) applied the same tests on  
699 shuffled data and counted the number of selective neurons. We defined the p-value as the proportion of  
700 times that the number of selective neurons for shuffled data was higher than the number of selective  
701 neurons found in the data (Fu et al., 2019; Kamiński et al., 2017; Rutishauser et al., 2018). When no  
702 selective neuron was found in the shuffled data, we set  $p = 1/N = 0.001$ . In Experiment 2, we also used a  
703 Poisson GLM to regress the number of spikes during a time window between 0.5 and 1.5 seconds after  
704 stimulus onset. We fitted a model with three beta regressors:  $\#spikes \sim \beta_0 + \beta_1 * detection +$   
705  $\beta_2 * confidence + \beta_3 * detection * confidence$ . We only interpreted main effects ( $\beta_1, \beta_2$ ) in the absence of  
706 interactions ( $\beta_3$ ). If  $\beta_3$  was significant (two-sided test), we considered the neuron as detection- and  
707 confidence-selective. If  $\beta_1$  was significant but  $\beta_3$  was not, we considered the neuron only detection-  
708 selective (idem for confidence-selective). We applied the same permutation test as for Experiment 1. In  
709 Experiment 3, we fitted a Poisson GLM with one beta regressors:  $\#spikes \sim \beta_0 + \beta_1 * intensity$  to find  
710 intensity-selective neurons showing an increased firing rate with increasing stimulus intensity and applied  
711 the same permutation test as for Experiment 1 and 2.

712 For ECoG analyses, we re-referenced the channels to a common average and applied a lowpass filter  
713 (Hamming window with a cutoff frequency of 40 Hz). Trials with epileptic activity or other artifacts were  
714 removed from further analysis following visual inspection. We used linear models (LM) for statistics using  
715 the same regressors as for spike counts (see above). For display purposes only, we additionally  
716 smoothed the data with a 200 ms Savitzky-Golay filter (Savitzky & Golay, 1964).

## 717 **Analysis of variance for Experiment 1**

718 To further relate our results to evidence accumulation, we analyzed some typical signatures of drift  
719 diffusion-like processes: the variance in the number of spikes during an epoch can be decomposed into i)  
720 the variance of the point process expected if the neuron had a constant firing rate across trials, and ii) the  
721 remaining variance of the conditional expectation (VarCE) which is due to the variability of the neuron's  
722 underlying firing rate across trials. If neuronal activity follows a diffusion process, then VarCE should  
723 increase with decision time. Similarly, the correlation between conditional expectations (CorCE) should be  
724 stronger between adjacent time windows and decrease with time lag between time windows (Churchland  
725 et al., 2011). We followed the approach in Churchland and colleagues. In brief, we relied on an upper  
726 bound estimate of VarCE, assuming that the point process variance is proportional to the spike count so:

$$727 \quad s^2 = Var_{CE} + \phi \bar{N},$$

728 with  $s^2$  the total variance and  $\bar{N}$  the average number of spikes for one 50 ms epoch. We used 10 non-  
729 overlapping epochs ranging from 0 to 1.5 s post-stimulus. The variance of the point process was  
730 computed as is a weighted average of the variance of the point process for hits and for misses. The  
731 constant  $\phi$  can be set based on some heuristics such as by considering that VarCE is zero when the ratio  
732 of variance and mean firing rate is minimal (e.g. at the beginning of the decision process). Due to the  
733 limited number of trials available in this study, we preferred this approach to more complex methods  
734 involving data fitting.

735 We computed CorCE by dividing the covariance of the number of spikes for different epochs by the  
736 square root of the product of the VarCE:

$$737 \quad Cor_{CE}^{ij} = Cov^{ij} / \sqrt{Var_{CE}^i * Var_{CE}^j},$$

738 with  $Cov^{ij}$  the covariance between epoch i and j and  $Var_{CE}^i$  the VarCE for epoch i. For all computations,  
739 we reduced  $\phi$  by 20% to have positive semi-definite covariance matrices.

## 740 **Multivariate decoding (Experiment 2)**

741 We fed single neurons firing rates sampled every 10 ms into linear discriminant decoders with a L2  
742 regularization factor of 0.8 (similar results were obtained with different regularization factors). These  
743 decoders separated the space of input features with a linear hyperplane that best discriminates hits and  
744 misses. The decoders predict a hit when the distance of a sample to the separating hyperplane is higher  
745 than zero and a miss otherwise. To avoid overfitting, we separated our data in 10 cross-validation folds so  
746 that for each fold we trained decoders on the 90% of the data and tested them on the 10% remaining (i.e.

747 out-of-sample). The distance to the separating hyperplane was also used to compute the area under the  
748 curve (AUC) for out-of-sample data at each time point. We used permutation tests to assess whether  
749 similar AUC could have been obtained by chance while correcting for multiple comparisons across time  
750 points. We selected contiguous clusters of time points when AUC was higher than 0.6 or lower than 0.4  
751 and then computed the proportion of similar or bigger clusters obtained with shuffled labels. For each  
752 permutation, we computed AUC clusters over the whole set of time points to keep the autocorrelation  
753 structure in the shuffled data.

754 Confidence was decoded at the time point corresponding to the highest AUC. Decoded confidence was  
755 defined as the absolute distance of a sample to the separating hyperplane. We assessed confidence  
756 decoding by correlating (Spearman) decoded confidence with observed confidence and assessing  
757 significance using permutation tests (one-sided, as we could reasonably expect positive correlations). As  
758 this procedure was carried out on out-of-sample data, our results were not affected by overfitting. Finally,  
759 for maximal evidence decoding, we used the same decoder to decode firing rates between 0.5 and 3 s  
760 post-cue. We excluded the first 0.5 s due to some neurons showing post-cue activity. We then took the  
761 maximum of the decoder over that time window, correlated it with confidence observed in the data and  
762 assessed significance using permutation tests (one-sided). Again, this procedure was carried out on out-  
763 of-sample data so our results cannot be affected by overfitting.

#### 764 **Scalp EEG data preprocessing (Experiment 4)**

765 All channels were high-pass filtered using a Hamming window with a cutoff frequency of 0.1 Hz. We  
766 defined an epoch as the 3 seconds of data centered around the event corresponding to the vibrotactile  
767 stimuli recorded using an auxiliary channel. EEG and EOG data were then lowpass filtered using a  
768 Hamming window with a cutoff frequency of 40 Hz and visually inspected to remove trials and channels  
769 containing artifacts. We computed the independent component analysis (ICA) (Makeig et al., 1996) on a  
770 copy of the EEG epochs that were highpass filtered at 1Hz. The number of independent components (ICs)  
771 computed corresponded to 99% of the variance, which resulted in  $14.78 \pm 1.27$  ICs per subject. We used  
772 SASICA (Chaumon et al., 2015) with default parameters to automatically select ICs for rejection and  
773 visually inspected all components scheduled for rejection before actually rejecting them. IC weights kept  
774 were then back-projected to the original EEG epochs. Any channel rejected prior to the ICA was  
775 reinterpolated using spherical interpolation ( $N = 0.67 \pm 0.23$ , max 3). Finally, we visually inspected all  
776 channels and rejected artifactual epochs. All pre-processing was done with the EEGLAB toolbox  
777 (Delorme & Makeig, 2004). The final dataset comprised  $464.17 \pm 13.73$  epochs per subject.

778 To assess which electrodes were detection- and/or confidence-selective, we used a linear mixed model to  
779 regress single-trial average EEG responses in the 0.5 to 1.5 time-window used for single-neuron analysis.  
780 For each electrode, we tried different random factors and kept the model with the lowest Bayesian

781 Information Criterion. P-values were Bonferroni corrected for multiple comparisons. To compute the  
782 electrophysiological correlate of evidence accumulation, we sought to find the best weighting of EEG  
783 electrodes in terms of discriminability between hits and misses. For this, we trained decoders of hits  
784 versus misses between -0.5 and 1.5 s from stimulus onset with 20 ms steps in a 10-fold cross-validation  
785 scheme. We repeated this procedure 10 times and searched for the time point with highest average  
786 discriminability. We then retrained one decoder using the EEG at this time point and used the weights of  
787 this decoder to construct one single value at every time point, representing a proxy to the amount of  
788 evidence for hits. We baselined this proxy signal using the 300 ms pre-stimulus.

### 789 **Ornstein-Uhlenbeck bounded accumulation model**

790 To test whether the observed electrophysiological correlate of conscious detection could index evidence  
791 accumulation, we used an Ornstein-Uhlenbeck process which consists of a drift diffusion model with a  
792 leakage parameter driving the accumulated evidence back to zero (Busemeyer & Townsend, 1993). The  
793 model consisted of an evidence accumulation process  $EA(t)$  integrating a time-varying drift rate  $d(t)$  with a  
794 leakage factor  $\lambda$  plus additive white noise  $W(t)$  with a fixed standard deviation of  $\sigma = 0.1$  (Eq. 1). The  
795 evidence accumulation process  $EA(t)$  was bounded by zero to be more biologically plausible (since firing  
796 rates are positive).

$$797 \quad EA(t + 1) = \max([1 - \lambda * dt] * EA(t) + d(t) + \sigma W(t), 0)$$

798 (1)

799 To model temporal uncertainty, the accumulation process started at the beginning of the stimulus window  
800 (Devine et al., 2019) with a drift of zero and ended 3 s later, as in our experimental paradigm. On stimulus  
801 onset, and after a non-decision time ( $ndt$ ), the drift rate  $d(t)$  rose to a level  $\gamma$  for 100 ms (stimulus duration)  
802 and then decayed exponentially with a factor  $k$  (Eq. 2). We used the same distribution of stimulus onsets  
803 as in the data (from 0 to 2 s after the cue). To model variability in the drift rate for a detection task (Ratcliff  
804 & Van Dongen, 2011),  $\gamma$  was sampled from a half-normal distribution with mean  $\gamma\_ \mu$  and standard  
805 deviation  $\gamma\_ \sigma$  (i.e. absolute value of a normal distribution). This allowed us to have variability in the drift  
806 rate while keeping it positive.

$$807 \quad d(t) f(x) = \begin{cases} 0 & \text{if } t < s + ndt \\ 1 & \text{if } (s + ndt) \leq t \leq (s + ndt + 0.1) \\ v(t) & \text{if } t > (s + ndt + 0.1), \quad v(t) = \gamma e^{[t-s-ndt-0.1/k]^2} \end{cases} \quad (2)$$

808 With  $s$  the onset of the stimulus. Stimuli were considered to be detected if the accumulated evidence  
809 reached a decision bound  $\theta$ .

810 Confidence  $c(t)$  was simulated as the accumulated evidence  $EA(t)$ , scaled by a factor  $\alpha$  and shifted by a  
811 factor  $\beta$  (confidence bias), inverted if the decision bound was not reached ( $\text{invert}(x) = 1 - x$ ) before being  
812 saturated to the 0 - 1 interval by a sigmoidal function (Pereira et al., 2020) (Eq. 3). The time at which  
813 confidence  $c(t)$  was read-out corresponded to the maximum of  $EA(t)$  over the 3s stimulation time window.  
814 Of note, we expressed the confidence readout in percentage of the decision bound. This scaling did not  
815 affect simulated confidence but normalized the readout across participants and helped restrain the grid  
816 search for good initial parameters.

$$817 \quad c(t) = \frac{e^{\alpha * EA(t) + \beta}}{e^{\alpha * EA(t) + \beta} + 1} \quad (3)$$

### 818 **Model fitting**

819 We used a two-stage fitting procedure: We first fitted the parameters of the decisional process to  
820 detection responses and to the pEA described above and then fitted a second set of parameters to  
821 predict confidence ratings.

822 In the first stage, we simulated (N=500) trials of  $EA(t)$  along with the corresponding detection responses.  
823 The objective function of the optimization procedure was based on the likelihood of the model with  
824 respect to the hit rate and false-alarm rate observed in the data and the shape of the average of pEA(t)  
825 for hits and misses. Since our model is agnostic to the scale of pEA(t) and  $EA(t)$ , we scaled them both by  
826 their average over time and realizations (trials or simulations). The log-likelihood thus corresponded to the  
827 normal probability of observing such a hit-rate and false-alarm rate and the normal probability of  
828 observing such an electrophysiological response for hits and misses. We used a Nelder-Mead simplex  
829 optimization with 756 different initial parameters sampling a broad range of values for  $\gamma_{\mu}$ ,  $\gamma_{\sigma}$ ,  $\lambda$  and  $k$ .  
830 For each such iteration, we first did a grid search on  $\text{ndt}$  and  $\theta$  to find plausible starting values. We kept  
831 the parameters corresponding to the model with the best likelihood. To ensure a good fit, we did a final  
832 fitting with N=10'000 simulated trials.

833 In the second stage, we also simulated (N=500) trials of  $EA(t)$  along with the corresponding detection  
834 responses and used these to simulate confidence ratings. We used a Kolmogorov-Smirnov test for the  
835 log-likelihood of confidence for hits, misses and correct rejections. We used a Nelder-Mead simplex  
836 optimization with 66 different initial parameters sampling a broad range of values for  $\alpha$  and  $\beta$ . We kept  
837 the parameters corresponding to the model with the best likelihood. To ensure a good fit, we did a final  
838 fitting with N=10'000 simulated trials.

### 839 **Metacognitive sensitivity**

840 We evaluated metacognitive sensitivity or how well confidence predicted task performance (Fleming &  
841 Lau, 2014). For this, we assessed the relation between confidence ratings and detection accuracy using

842 the area under the curve, computed independently for “yes” responses (hits and false alarms) and “no”  
843 responses (correct rejections and misses) (Mazor et al., 2020; Meuwese et al., 2014)

#### 844 **Alternative model**

845 We compared our maximal evidence model with an alternative model which assumed that confidence  
846 was readout at a fixed timing ( $t_{RO}$ ) post-decision for perceived stimuli. For unperceived stimuli (i.e. with  
847 no decision), this alternative model assumed that participants reported random confidence estimates,  
848 based on Gaussian noise with mean  $\Omega$  and unit standard deviation. As in the maximal evidence model,  
849 confidence corresponded to evidence scaled by a factor  $\alpha$  and shifted by a factor  $\beta$  (confidence bias)  
850 before being saturated to the 0 - 1 interval by a sigmoidal function. The model thus comprised four  
851 parameters:  $\alpha$ ,  $\beta$ ,  $t_{RO}$  and  $\Omega$  which were fitted with the same procedure as for the maximal evidence  
852 model, except that the grid search for optimal initial parameters was extended to include two initial values  
853 for  $t_{RO}$ : 0.25 and 0.5 s. We used the Bayesian Information Criterion to compare the two models.

#### 854 **DATA AND SOFTWARE AVAILABILITY**

855 Behavioral, electrocorticographic and electroencephalographic data with the corresponding analyses  
856 scripts will be made available upon publication. Single-neuron data are available upon request.