



Delis, I., Ince, R. A. A., Sajda, P. and Wang, Q. (2022) Neural encoding of active multi-sensing enhances perceptual decision-making via a synergistic cross-modal interaction. *Journal of Neuroscience*, 42(11), pp. 2344-2355.

(doi: [10.1523/JNEUROSCI.0861-21.2022](https://doi.org/10.1523/JNEUROSCI.0861-21.2022))

This is the Author Accepted Manuscript.

There may be differences between this version and the published version. You are advised to consult the publisher's version if you wish to cite from it.

<http://eprints.gla.ac.uk/262391/>

Deposited on: 7 January 2022

The Journal of Neuroscience

<https://jneurosci.msubmit.net>

JN-RM-0861-21R1

Neural encoding of active multi-sensing enhances perceptual decision-making via a synergistic cross-modal interaction

Ioannis Delis, University of Leeds  
Robin Ince, University of Glasgow  
Paul Sajda, Columbia Univ  
Qi Wang, Columbia University

Commercial Interest:

1 Neural encoding of active multi-sensing enhances perceptual decision-making  
2 via a synergistic cross-modal interaction

3 Ioannis Delis<sup>1\*</sup>, Robin A.A. Ince<sup>2</sup>, Paul Sajda<sup>3,4</sup>, Qi Wang<sup>3</sup>

4

5 <sup>1</sup>School of Biomedical Sciences, University of Leeds, Leeds, LS2 9JT, UK

6 <sup>2</sup>School of Psychology and Neuroscience, University of Glasgow, G12 8QQ, UK

7 <sup>3</sup>Department of Biomedical Engineering, Columbia University, New York, NY,  
8 10027, USA

9 <sup>4</sup>Data Science Institute, Columbia University, New York, NY, 10027, USA

10

11 \*Please address correspondence to [i.delis@leeds.ac.uk](mailto:i.delis@leeds.ac.uk)

12

13 **Abbreviated title:** Neural mechanisms of active multisensory decisions

14

15 **Competing Interest Statement:** The authors declare no competing financial  
16 interests.

17

### 18 **Acknowledgments**

19

20 This work was supported by the the European Commission (H2020-MSCA-IF-  
21 2018/845884, “NeuCoDe” to I.D.), the Physiological Society (2018 Research  
22 Grant Scheme to I.D.), the National Institutes of Health (R01-MH085092 to P.S.),  
23 the U.S. Army Research Laboratory (W911NF-10-2-0022 to P.S.), the Wellcome  
24 Trust ([214120/Z/18/Z] to R.A.A.I.) and the UK Economic and Social Research  
25 Council (ES/L012995/1 to P.S.), and a NARSAD Young Investigator award to  
26 Q.W.

27

28 No of pages: 32

29 No of figures: 4

30 Abstract: 250 words

31 Significance statement: 120 words

32 Discussion: 1331 words

33

34 **Abstract**

35 Most perceptual decisions rely on the active acquisition of evidence from the  
36 environment involving stimulation from multiple senses. However, our  
37 understanding of the neural mechanisms underlying this process is limited.  
38 Crucially, it remains elusive how different sensory representations interact in the  
39 formation of perceptual decisions. To answer these questions, we employed an  
40 active sensing paradigm coupled with neuroimaging, multivariate analysis and  
41 computational modeling to probe how the human brain processes multisensory  
42 information to make perceptual judgments. Participants of both sexes actively  
43 sensed to discriminate two texture stimuli using visual (V) or haptic (H)  
44 information or the two sensory cues together (VH). Crucially, information  
45 acquisition was under the participants' control, who could choose where to  
46 sample information from and for how long on each trial. To understand the neural  
47 underpinnings of this process, we first characterized where and when active  
48 sensory experience (movement patterns) is encoded in human brain activity  
49 (electroencephalography - EEG) in the three sensory conditions. Then, to offer a  
50 neurocomputational account of active multisensory decision formation, we used  
51 these neural representations of active sensing to inform a drift diffusion model of  
52 decision-making behavior. This revealed a multisensory enhancement of the  
53 neural representation of active sensing which led to faster and more accurate  
54 multisensory decisions. We then dissected the interactions between the V, H and  
55 VH representations using a novel information-theoretic methodology. Ultimately,  
56 we identified a synergistic neural interaction between the two unisensory (V, H)  
57 representations over contralateral somatosensory and motor locations that  
58 predicted multisensory (VH) decision-making performance.

59

60  
61  
62  
63  
64  
65  
66  
67  
68  
69  
70  
71  
72  
73  
74  
75  
76  
77  
78  
79  
80  
81  
82  
83  
84  
85  
86  
87  
88

**Significance Statement**

In real-world settings, perceptual decisions are made during active behaviors, such as crossing the road on a rainy night, and include information from different senses (e.g. car lights, slippery ground). Critically, it remains largely unknown how sensory evidence is combined and translated into perceptual decisions in such active scenarios. Here we address this knowledge gap. First, we show that the simultaneous exploration of information across senses (multi-sensing) enhances the neural encoding of active sensing movements. Second, the neural representation of active sensing modulates the evidence available for decision and, importantly, multi-sensing yields faster evidence accumulation. Finally, we identify a crossmodal interaction in the human brain that correlates with multisensory performance, constituting a putative neural mechanism for forging active multisensory perception.

## 89 **Introduction**

90

91 In our daily lives, we make judgments based on noisy or incomplete  
92 information that we gather from our environment (Heekeren et al., 2004;  
93 Juavinett et al., 2018; Najafi and Churchland, 2018), usually including stimuli  
94 from multiple senses (Angelaki et al., 2009; Chandrasekaran, 2017). The  
95 acquired sensory information crucially depends on our actions - what we see,  
96 hear and touch is influenced by our movements - a process known as active  
97 sensing (Schroeder et al., 2010; Yang et al., 2016b). For example, imagine  
98 attempting to cross the road on a rainy night. You need to interact with the  
99 environment, i.e. turn your head and move your eyes, and process the incoming  
100 stimuli (e.g. car lights, slippery ground) to decide whether and when it is safe to  
101 do so. If you feel the road is slippery, you may need to monitor your steps and at  
102 the same time you may have to walk faster or step back if a car is approaching.

103 This example indicates that in real-world settings most perceptual  
104 decisions are made during active behaviors (Musall et al., 2019). The quality of  
105 the acquired evidence is driven by such active behaviors, which, in turn, affect  
106 the efficiency of the perceptual decisions that we make as a result of this active  
107 sensing process (Yang et al., 2016a; Gottlieb and Oudeyer, 2018). A first crucial  
108 element of fast and accurate perceptual decisions is the combination of evidence  
109 from different sensory streams (e.g. sight and touch) to form a unified percept  
110 and reduce uncertainty about the stimulus (Ernst and Banks, 2002). However,  
111 while there is extensive evidence that the integration of information from different  
112 sensory modalities improves perceptual choice accuracy (Lewis and Noppeney,  
113 2010; Raposo et al., 2012) and response time (Drugowitsch et al., 2014),  
114 multisensory information processing has not been studied in an active scenario,  
115 where human participants are allowed to implement their own strategy for  
116 gathering evidence - as is the case in real life settings.

117 Here we addressed this gap in the literature aiming to uncover the neural  
118 mechanisms underlying the formation of perceptual decisions via the active

119 acquisition and processing of multisensory information. To achieve this, we  
120 capitalised on our previous work probing the neural correlates of active tactile  
121 decisions (Delis et al., 2018) and extended it to a multisensory setting that  
122 includes visual and haptic information presented simultaneously or separately.  
123 We hypothesised that the neural encoding of active sensory experience would be  
124 enhanced when multisensory information was available and that this neural  
125 multisensory gain would lead to improvements in decision-making performance.

126 An important aspect of our study is that the participants had full control of  
127 the evolution and duration of each trial. In other words, they could choose how  
128 much information to sample, where to sample this information from and for how  
129 long. Thus, we first aimed to characterise cortical coupling to continuous active  
130 sensing and then combined this with a popular sequential-sampling model of  
131 decision-making, the drift diffusion model (DDM) (Ratcliff and McKoon, 2008), to  
132 understand how the identified representations of active sensing behaviors  
133 influence decisions in the human brain. Here, to bridge the gap between active  
134 evidence acquisition and decision formation, we used the neural correlates of  
135 active (multi-)sensing to constrain the DDM.

136 Finally, to quantify cross-modal interactions in the brain, we applied a  
137 novel information-theoretic framework named Partial Information Decomposition  
138 (PID) (Williams and Beer, 2010; Timme et al., 2014; Ince, 2017). PID quantifies  
139 the contribution of a) each sensory modality and b) cross-modal representational  
140 interactions (“redundant” or “synergistic”) to the multisensory neural  
141 representation (Park et al., 2018). Redundancy measures the similarity of the  
142 neural representation of the two modalities, while synergy indicates a better  
143 prediction of the neural response from both modalities simultaneously. Ultimately,  
144 this approach revealed the interactions between representations of different  
145 sensing modalities in the brain and shed light onto their role in decision-making  
146 behavior.

147  
148

## 149 **Materials and Methods**

150

151 *Experimental design and paradigm.* Fourteen healthy right-handed participants  
152 (8 female, aged  $24\pm 2$  years) performed a two-alternative forced choice (2AFC)  
153 discrimination task during which they had to compare the amplitudes of two  
154 sinusoidal stimuli of the same frequency. All experimental procedures have been  
155 reviewed and approved by the Institutional Review Board (IRB) at Columbia  
156 University.

157 To generate visual and tactile stimuli that can be actively sensed, we  
158 employed a haptic device called a Pantograph (Campion et al., 2005), which can  
159 be controlled to generate the sensation of exploring real surfaces (Fig. 1A). The  
160 Pantograph is a 2-dimensional force-feedback device, that is, a) it produces a 2D  
161 tactile output and b) it simultaneously measures 2D information about the finger  
162 position and applied force. Here we used its first property to generate stimulation  
163 and the second property to record the kinematics of the movements performed  
164 by the participants while they actively explored the presented stimuli. In  
165 particular, we split the workspace of the Pantograph (of dimensions 110 mm x 60  
166 mm) into two subspaces (left - L and right - R, 55 mm x 60mm each) and  
167 generated continuous sinusoidal stimuli of different amplitudes (but same  
168 wavelength of 10 mm) in the two subspaces (Fig. 1B). Then, we instructed the  
169 participants to discriminate the amplitude of the two subspaces as quickly and as  
170 accurately as possible a) using only visual (V) information, b) using only haptic  
171 (H) information and c) combining the two sensory cues (VH). Crucially for our  
172 investigation here, participants were free to choose how to explore this virtual  
173 texture, i.e., where and how fast to move their fingers and how long to explore  
174 each one of the two sides for before making their perceptual choice. Participants  
175 placed their right index finger on the interface plate of the Pantograph (see Fig.  
176 1A) and moved it freely to explore the textures of both subspaces (Fig. 1C)  
177 before reporting their choice (i.e., which amplitude is higher) by pressing one of  
178 two buttons on a keyboard (left or right arrow) using their left hand.



179 Specifically, in the H condition, the Pantograph produced sinusoidal forces of  
180 different intensity between L and R. When the participants placed their index  
181 fingers on the plate (interface) of the Pantograph, these forces at the interface  
182 had the effect of causing fingertip deformations and thus tactile sensations that  
183 resembled exploring real surfaces. Thus, when moving their finger on the  
184 Pantograph, participants had the sensation of touching a rough surface (with  
185 different amplitudes between L and R – see Fig.1B middle panel). In the V  
186 condition, stimuli matching the tactile stimuli were presented on a screen of the  
187 same dimensions. More precisely, amplitudes of the sinusoidal virtual texture in  
188 H were translated into contrast levels of sinusoidal gratings in V, i.e. the  
189 participants were seeing black and white stripes of different intensity/contrast  
190 between L and R. Presentation of visual stimuli was generated using  
191 Psychtoolbox and visual contrast varied between 0.5 and 1.5 around the default  
192 contrast value. The visual angle was  $12^{\circ} \pm 6^{\circ}$ . Stimulus presentation was  
193 controlled by a real-time hardware system (Matlab XPCTarget) to minimize  
194 asynchrony which was  $<1\text{ms}$ . Importantly, to match the sense of touch, only the  
195 part of the workspace corresponding to the participant's finger location was  
196 revealed on the screen (i.e. a moving dot following the participant's finger - see  
197 Fig. 1B left panel). Thus, in the V condition, grayscale visual textures (of different  
198 contrast between L and R) were shown wherever the participants moved their  
199 fingers while no forces were applied to the participants' fingers (i.e. no H  
200 stimulation). Hence, in both sensory domains, participants could only sense the  
201 presented stimulus via active exploration, i.e. finger movements on the x-axis.  
202 Accordingly, in the VH condition, both the visual and haptic textures were  
203 congruently presented and sensed by the participants using finger movements  
204 (Fig. 1B right panel). Overall, participants had to decide whether L or R had  
205 higher amplitude based on their haptic (in H trials), visual (in V trials) or visuo-  
206 haptic (in VH trials) perception of this virtual surface. Participants reported that  
207 they perceived the V and H signals as one stimulus in the VH condition.

208 The amplitude difference between L and R (representing the difficulty of the task)  
209 varied from trial to trial. On each trial, participants compared between the  
210 reference amplitude 1 (presented either on the left or right subspace) and one of  
211 six other amplitude levels (0.5, 0.75, 0.9, 1.1, 1.25, 1.5). Each trial was initiated  
212 by the participant. Trial onset was considered the time point at which horizontal  
213 finger velocity exceeded 0. Trial duration was determined by the participant and  
214 lasted for the whole period during which the participant made exploratory  
215 movements to sense the surface. The trial ended when the participant pressed  
216 the < or > key on the keyboard with their left hand to indicate their L or R choice.  
217 Each participant performed 20 trials for each amplitude level and for each  
218 sensory condition (V, H, VH), resulting  $K = 20$  trials x 6 amplitudes x 3 conditions  
219 = 360 trials in total. One participant showed poor behavioral performance  
220 (accuracy was not significantly different from chance level) and another  
221 participant's EEG recordings were significantly contaminated with eye movement  
222 artifacts, thus data from these two participants were removed from any  
223 subsequent analyses. We report results from the remaining  $N = 12$  participants.  
224 We also discarded trials in which participants did not respond within 10secs from  
225 trial onset or their RTs were shorter than 0.3 seconds. This resulted in the  
226 rejection of 4.9% of the trials.

227 *Data recording and pre-processing.* During performance of the task, we  
228 measured a) the choice accuracy and response time (RT) of participants'  
229 responses, b) movement kinematics (x, y coordinates of finger position recorded  
230 by the Pantograph) at a sampling frequency of 1000Hz and c) EEG signals at  
231 2048 sampling frequency using a Biosemi EEG system (ActiveTwo AD-box, 64  
232 Ag-AgCl active electrodes, 10-10 montage).

233 To compare accuracies and RTs across sensory conditions, we used two-way  
234 ANOVAs with factors condition and stimulus difference followed by Bonferroni-  
235 corrected post-hoc t-tests. We also fit psychometric curves to the accuracy data

236 of each participant using a cumulative Gaussian distribution and computed the  
237 point of subjective equality (PSE) and slope of the curve at the PSE.

238 Single-trial movement velocity waveforms were computed using the derivatives  
239 of the recorded position. EEG recordings were preprocessed using EEGLab  
240 (Delorme and Makeig, 2004) as follows. EEG signals were first down-sampled to  
241 1000Hz to match movement kinematics and dynamics. Then, they were  
242 bandpass filtered to 1-50Hz using a Hamming windowed FIR filter. To isolate the  
243 purely neural component of the EEG data, we used the following procedure: we  
244 first reduced the dimensionality of the EEG data by reconstituting the data using  
245 only the top 32 principal components derived from Principal Component Analysis  
246 (PCA). Although we record from 64 channels, we expect our recordings to span a  
247 considerably lower-dimensional space (as a result of correlations, crosstalk and  
248 common sources), thus to enhance the ability of ICA to identify truly independent  
249 components, we reduce the data dimensions to half using PCA. Thereafter, an  
250 Independent Component Analysis (ICA) decomposition of the data was  
251 performed using the Infomax algorithm (Bell and Sejnowski, 1995). We then used  
252 an ICA-based artifact removal algorithm called MARA (Winkler et al., 2011) to  
253 remove ICs attributed to blinks, horizontal eye movements (HEOG), muscular  
254 activity (EMG), and any loose or highly noisy electrodes. MARA assigned each  
255 IC a probability of being an artifact; we removed components with probabilities  
256 above 0.5.

257 *Decoding finger kinematics from EEG signals.* To assess the neural encoding of the  
258 participants' active sensory experience in the three sensory conditions, we used a  
259 multivariate linear regression analysis introduced in (Di Liberto et al., 2015) and shown  
260 in Equation 1 below. As in our previous work (Delis et al., 2018), we hypothesized that  
261 the sensorimotor strategy employed by the participant can be represented by the  
262 velocity profiles of the participant's exploratory movements which capture changes of  
263 movement direction as well as speed changes. Thus, as kinematic feature representing  
264 the active sensing behavior, we used 1-d finger velocity on the x-axis (capturing L-R  
265 finger movements) but also finger position (on the x-axis) yielded qualitatively very

266 similar results. Finger movement in the y-axis (which did not provide any sensory  
 267 information) did not show any significant correlation with the EEG signals and was not  
 268 considered further. We thus performed a multivariate ridge regression (Crosse et  
 269 al., 2016) predicting the 1-d finger velocity (on the x-axis) from the EEG data.  
 270 Specifically, our decoding analysis aimed to reconstruct the movement velocity  
 271 from a linear combination of the EEG recordings with time lags ranging between  
 272 [-200ms, 400ms] with respect to the instantaneous velocity values. Specifically,  
 273 we aimed to decode the velocity profile  $s(t)$  of the participants' scanning  
 274 movements from the simultaneously recorded EEG signals  $m(i, t)$ , as  
 275 follows:

$$\hat{s}(t) \cong \sum_{\tau} \sum_i g(\tau, i) m(t + \tau, i) \quad (1)$$

276 where  $\hat{s}(t)$  is the reconstructed finger velocity and  $g(i, \tau)$  is a filter that integrates  
 277 information spatially across EEG channels  $i$  and temporally across time lags  $\tau$  to  
 278 decode the velocity profile from the EEG recordings. Here we used  $\tau \in$   
 279  $[-200ms, 400ms]$ , i.e. we examined the EEG information about the finger velocity  
 280 at time  $t$  from  $t - 200ms$  (200ms earlier) up to  $t + 400ms$  (400ms later). Varying  
 281 these lags did not improve reconstruction performance and yielded qualitatively  
 282 similar results with the main effects always in the  $[-200ms, 400ms]$  temporal  
 283 window, so we used this window for all our further analyses. To learn the  
 284 decoding filters and compute the velocity approximation accuracy ( $r^2$ ) between  
 285 the original and the reconstructed velocity profiles, we used the multivariate  
 286 temporal response function (mTRF) Matlab Toolbox implementing regularised  
 287 linear (ridge) regression (Crosse et al., 2016). In all our filter estimations, we  
 288 used a cross-validation procedure. We first randomly split our data into two sets,  
 289 a training set (80% of the trials) to learn the filters and a test set (the remaining  
 290 20% of the trials) to apply the filters to and compute the reported  $r^2$  values. In the  
 291 training set, we performed 5-fold cross-validation to identify the optimal value of  
 292 the ridge parameter  $\lambda$  (varying  $\lambda = 2^0, \dots, 2^{20}$ ) that maximizes  $r^2$  between the

293 estimated and the measured velocity. These investigations revealed that values  
294 of  $\lambda$  between  $2^0$  and  $2^4$  yielded almost identical  $r^2$  across all models, thus we  
295 used  $\lambda = 2^2$  for all models for consistency.

296 Since the weights of the decoding filters are not interpretable in terms of the  
297 neural origins of the underlying processes (Haufe et al., 2014), we transformed  
298 them into encoding filters  $f(\tau, i)$  using the “forward model” formalism (Parra et  
299 al., 2002; Haufe et al., 2014), as follows:

$$f(\tau, i) = \frac{m(t, i)^T m(t, i) g(i, \tau)}{\hat{s}(t)^T \hat{s}(t)} \quad (2)$$

300 We then plotted the weights of the forward models  $f(\tau, i)$  at specific time lags  $\tau$   
301 as scalp maps to visualise the relationship between sensorimotor behavior and  
302 neural activity in each one of the three sensory conditions (V, H, VH). *Statistical*  
303 *analysis of EEG-behavior couplings*. To determine statistical significance of the  
304 learned EEG-velocity mappings, we randomized the phase spectrum of the EEG  
305 signals, which disrupted the temporal relationship between the EEG activity and  
306 the kinematics while preserving the autocorrelation structure of the signals  
307 (Theiler et al., 1992). We generated 1000 phase-randomized surrogates of the  
308 EEG data and computed correlations with the kinematics to define the null  
309 distribution from which we estimated p-values. This phase-randomization  
310 procedure maintains the magnitude spectrum of the EEG signals, thus  
311 conserving their autocorrelation structure, which is a fundamental feature of the  
312 original signals when the significance of cross-correlation is assessed. Hence,  
313 using this procedure, the obtained surrogates that define the null distribution are  
314 a more plausible comparison (resulting in a stricter statistical test) than randomly  
315 shuffled surrogates.

316 *Informed modeling of decision-making performance*. Having characterised  
317 the cortical coupling to the sensorimotor strategies in the three sensory  
318 conditions, we then probed the relationship between the identified EEG-velocity

319 couplings and decision-making performance. To provide this missing link  
320 between active sensing and decision formation, we implemented a Hierarchical  
321 Drift Diffusion Model (HDDM), a well-known cognitive model of decision-making  
322 behaviour, and informed it with the results of our previous decoding analysis.

323 We fit the participants' decision-making performance, i.e. accuracy and  
324 response time (RT), with a hierarchical drift diffusion model (HDDM) (Wabersich  
325 and Vandekerckhove, 2014) which assumes a stochastic accumulation of  
326 sensory evidence over time, toward one of two decision boundaries  
327 corresponding to correct and incorrect choices (Ratcliff and McKoon, 2008). The  
328 model returns estimates of internal components of processing such as the rate of  
329 evidence accumulation (drift rate), the distance between decision boundaries  
330 controlling the amount of evidence required for a decision (decision boundary), a  
331 possible bias towards one of the two choices (starting point) and the duration of  
332 non-decision processes (non-decision time), which include stimulus encoding  
333 and response production. As per common practice, we assumed that stimulus  
334 differences affected the drift rate (Palmer et al., 2005).

335 In short, the model iteratively adjusts the above parameters to maximize  
336 the summed log likelihood of the predicted mean response time (RT) and  
337 accuracy. The DDM parameters were estimated in a hierarchical Bayesian  
338 framework, in which prior distributions of the model parameters were updated on  
339 the basis of the likelihood of the data given the model, to yield posterior  
340 distributions (Wiecki et al., 2013; Wabersich and Vandekerckhove, 2014). The  
341 use of Bayesian analysis, and specifically the hierarchical drift diffusion model  
342 has several benefits relative to traditional DDM analysis. First, this framework  
343 supports the use of other variables as regressors of the model parameters to  
344 assess relations of the model parameters with other physiological or behavioral  
345 data (Frank et al., 2015; Turner et al., 2015; Nunez et al., 2017). This regression  
346 model, which is included in HDDM, allows estimation of trial-by-trial influences of  
347 a covariate (e.g. a brain measure) onto DDM parameters. In other words, trial-by-

348 trial fluctuations of the estimated HDDM parameters can be approximated as a  
349 linear combination of other trial-by-trial measures of cognitive function (Wiecki et  
350 al., 2013; Forstmann et al., 2016). This property of the HDDM enabled us to  
351 establish the link between the results of the EEG-velocity coupling analysis and  
352 the decision parameters of the model, by using the EEG-velocity couplings as  
353 predictors of the HDDM parameters, as explained below (also see Eq. 3 for an  
354 example of such a linear regression of the drift rate parameter). Second, the  
355 model estimates posterior distributions of the main parameters (instead of  
356 deterministic values), which directly convey the uncertainty associated with  
357 parameter estimates (Kruschke, 2010). Third, as a result of the above, the  
358 hierarchical structure of the model allows estimation of the HDDM parameters  
359 across participants and conditions, thus yielding distributions at different levels of  
360 the model hierarchy (e.g. the population level and the participant level  
361 respectively). In this way, the HDDM capitalizes on the statistical power offered  
362 by pooling data across participants (population-level parameters) but at the same  
363 time accounts for differences across participants (represented by the variance of  
364 the population-level distribution and the individual participant-level estimates).  
365 Fourth, the Bayesian hierarchical framework has been shown to be especially  
366 effective when the number of observations is low (Ratcliff and Childers, 2015).

367 To implement the hierarchical DDM, we used the JAGS Wiener module  
368 (Wabersich and Vandekerckhove, 2014) in JAGS (Plummer, 2003), via the  
369 Matjags interface in Matlab to estimate posterior distributions. For each trial, the  
370 likelihood of accuracy and RT was assessed by providing the Wiener first-  
371 passage time (WFPT) distribution with the four model parameters (boundary  
372 separation, starting point, non-decision time, and drift rate). Capitalizing on the  
373 advantages of HDDM, we ran the model pooling data across all participants and  
374 conditions and estimated both population-level and participant-level distributions.  
375 Parameters were drawn from uniformly distributed priors and were estimated with  
376 non-informative mean and standard deviation group priors. As per standard  
377 practice for accuracy-coded data, the starting point was set as the midpoint

378 between the two decision boundaries as participants could not develop a bias  
379 towards correct or incorrect choices.. For each model, we ran 3 separate Markov  
380 chains with 5500 samples of the posterior parameters each; the first 500 were  
381 discarded (as “burn-in”) and the rest were subsampled (“thinned”) by a factor of  
382 50 following the conventional approach to MCMC sampling whereby initial  
383 samples are likely to be unreliable due to the selection of a random starting point  
384 and neighboring samples are likely to be highly correlated (Wabersich and  
385 Vandekerckhove, 2014). The remaining samples constituted the probability  
386 distributions of each estimated parameter. To ensure convergence of the chains,  
387 we computed the Gelman-Rubin  $R^2$  statistic (which compares within-chain and  
388 between-chain variance) and verified that all group-level parameters had an  $R^2$   
389 close to 1 and always lower than 1.01.

390 Here, to obtain a mechanistic account of the effect of EEG-velocity  
391 coupling on decision-making behaviour, we incorporated the single-trial  
392 measures of these couplings ( $r^2$  values defined above) into the HDDM  
393 parameter estimation (Fig. 3B). Specifically, as part of the model fitting within the  
394 HDDM framework, we used the single-trial velocity reconstruction accuracies  $r^2$   
395 as regressors of the decision parameters to assess the relationship between trial-  
396 to-trial variations in EEG-velocity couplings and each model parameter.  
397 Furthermore, to characterise the effect of active sensing movements on decision  
398 formation, we also incorporated movement parameters in the HDDM framework.  
399 Specifically, we computed the following movement parameters: a) the average  
400 finger velocity ( $v_m$ ) on each trial, b) the number of crossings ( $n_{cr}$ ) between L and  
401 R which is an indicator of the time it took participants to switch between the two  
402 stimuli and c) the time participants spent exploring one of the two stimuli (here  
403 we arbitrarily selected the low-amplitude stimulus on each trial,  $t_{low}$ ) as an  
404 indicator of exploration time. To understand how these movement parameters  
405 affect the decision-making process and specifically whether they relate to a)  
406 sensory processing and movement planning/execution (i.e. non-decision



407 processes) and/or b) evidence accumulation (i.e. decision processes) and/or c)  
 408 the speed-accuracy trade-off adopted by the participants, we used these  
 409 parameters as regressors for non-decision time, drift rate and decision boundary,  
 410 as follows:

411

$$\tau = \beta_0 + \beta_1 * r^2 + \beta_v * v_m + \beta_{sw} * n_{cr} + \beta_{exp} * t_{low} \quad (3)$$

$$\delta = \gamma_0 + \gamma_1 * r^2 * s + \gamma_v * v_m + \gamma_{sw} * n_{cr} + \gamma_{exp} * t_{low} \quad (4)$$

$$\alpha = \theta_0 + \vartheta_1 * r^2 + \vartheta_v * v_m + \vartheta_{sw} * n_{cr} + \vartheta_{exp} * t_{low} \quad (5)$$

412 where  $\tau, \delta, \alpha$  represent the single-trial non-decision time, drift rate and decision  
 413 boundary respectively., Velocity reconstruction accuracy  $r^2$ , mean finger velocity  
 414  $v_m$ , number of crossings  $n_{cr}$  and time spent exploring the lower amplitude  
 415 stimulus  $t_{low}$  are the single-trial predictor variables with regression coefficients  
 416  $\beta_i, \gamma_i, \delta_i$  respectively and  $s = 0.1, 0.25, 0.5$  is the stimulus difference on each trial  
 417  $k = 1, \dots, K$  of each participant  $n = 1, \dots, N$ . As per common practice, we modelled  
 418 a linear relationship between drift rates and stimulus differences reflecting the  
 419 dependence of the speed of information integration on the amount of evidence  
 420 available (Palmer et al., 2005; Ratcliff and McKoon, 2008).

421 By using the above regression approach we were able to test the influence of  
 422 the above EEG and movement parameters on each of the HDDM parameters.  
 423 Thus, we tested different models in which the single-trial values of the above  
 424 parameters were used as predictors for all combinations of the HDDM  
 425 parameters (drift rate, non-decision time and decision boundary). To select the  
 426 best-fitting model, we used the Deviance Information Criterion (DIC), a measure  
 427 widely used for fit assessment and comparison of hierarchical models  
 428 (Spiegelhalter et al., 2002). DIC selects the model that achieves the best trade-  
 429 off between goodness-of-fit and model complexity. Lower DIC values favor  
 430 models with the highest likelihood and least degrees of freedom.

431 *Statistical analysis of modeling results.* Posterior probability densities of each  
432 regression coefficient were estimated using the sampling procedure described  
433 above. Significantly positive (negative) effects were determined when >95% of  
434 the posterior density was higher (lower) than 0. To take into account the  
435 hierarchical structure of the model which estimated both population-level  
436 distributions and participant-level distributions of the parameters, all statistical  
437 tests at the population level were performed by contrasting the group-level  
438 distributions (not the individual participant means) across sensory conditions.  
439 This hierarchical statistical testing has been shown to reduce biases and actually  
440 yield conservative effect sizes (Boehm et al., 2018).

441

442 *Partial Information Decomposition.* We then aimed to uncover whether the visual  
443 (V) and haptic (H) neural representations of active sensing contained the same  
444 information (redundancy) that is present in the multisensory (VH) representation  
445 or to what extent their contributions are distinct (unique information) or  
446 complementary (synergy). To achieve this, we used the Partial Information  
447 Decomposition (PID) (Williams and Beer, 2010; Timme et al., 2014) applied to  
448 the predictions of the finger velocity encoding models learned in the different  
449 experimental conditions. PID provides an information theoretic approach to  
450 compare the outputs of different predictive models that goes beyond simply  
451 comparing accuracy to determine whether the different models share or convey  
452 unique predictive information content (Daube et al., 2019b). PID extends the  
453 concept of co-information (McGill, 1954), which is defined as follows:

$$454 \quad I(VH;V;H) = I(VH;V) + I(VH;H) - I(VH;[V,H]) \quad (6)$$

455 where  $I(X;Y)$  denotes the mutual information (MI) between variables X and Y.  
456 MI is a nonparametric measure of dependence between two variables which has  
457 the unique property that its effect size is additive (Shannon, 1948). Hence, co-  
458 information (also called interaction information when defined with opposite sign)

459 quantifies the difference between the sum of the MI when each modality is  
460 considered alone and the MI when the two modalities are observed together  
461 (Park et al., 2018).

462 Positive values of this difference indicate that some information about the  
463 predictions of the multisensory VH model is shared between the predictions  
464 obtained from the models trained in the unisensory V and H conditions. I.e. there  
465 are common or redundant representations of finger velocity in both V and H  
466 conditions. Negative values of the interaction information indicate a super-  
467 additive or synergistic interaction between the predictions of the V and H models,  
468 i.e. the two models provide more information about the multisensory (VH)  
469 prediction when observed together than would be expected from observing each  
470 individually. However, interaction information measures the net difference  
471 between synergy and redundancy in the system, thus it is possible to have zero  
472 interaction information, even in the presence of redundant and synergistic  
473 interactions that cancel out in the net value (Williams and Beer, 2010; Ince,  
474 2017). This occurs because classic Shannon quantities cannot separate  
475 redundant and synergistic contributions, which has led to a growing field  
476 developing Partial Information Decomposition measures to address this  
477 shortcoming.

478 To give a simple example of such a case, let us consider 3 variables, each  
479 consisting of two bits (i.e. binary (0/1) variables with  $p(0)=p(1)=0.5$ ). Let also  
480 assume that the first bit is shared between all 3 variables and the second bit  
481 follows the XOR distribution across the three variables. In this case, there is clear  
482 redundancy and synergistic structure, but co-information / interaction information  
483 is zero (Griffith and Koch, 2014).

484 More precisely, PID addresses this methodological problem by decomposing MI  
485 into unique redundant and synergistic components, as follows:

$$486 \quad I(VH;V;H) = I_{uni}(VH;V) + I_{uni}(VH;H) + I_{red}(VH;V,H) + I_{syn}(VH;V,H) \quad (7)$$

487 where  $I_{uni}(VH;V)$  is the part of the VH model predictions that can be explained  
488 only from the V model predictions,  $I_{uni}(VH;H)$  is the part of the VH model  
489 predictions that can be explained only from the H model predictions,  
490  $I_{red}(VH;V,H)$  is the part of the VH model predictions that is common (redundant)  
491 to both the V and H model predictions and  $I_{syn}(VH;V,H)$  is the extra (synergistic)  
492 information about the VH model predictions that arises when both V and H  
493 predictions are considered together. PID decomposes the joint mutual  
494 information between two predictor signals (here the EEG activity predicted from  
495 an encoding model trained in the unisensory V, H conditions) and a target signal  
496 (here the EEG activity predicted from an encoding model trained in the  
497 multisensory VH condition) into four terms: redundancy, the unique information in  
498 each predictor, and synergy. Redundancy quantifies the information in the target  
499 signal that is shared between the two predictor signals. Synergy quantifies  
500 improvement in prediction of the target when both predictors are observed  
501 together and represents information about the target signal which cannot be  
502 obtained from the individual predictors separately.

503 To perform PID here, we used a recent implementation based on common  
504 change in surprisal for Gaussian variables (Ince, 2017) which has been shown to  
505 be effective when applied to neuroimaging data (Park et al., 2018; Daube et al.,  
506 2019a).

507 To implement the above approach on our data, we used the recordings of the VH  
508 condition where the two unisensory representations of active sensory experience  
509 could be directly compared with the multisensory representation. We took the  
510 velocity-encoding models obtained in each condition (V, H, VH) and applied them  
511 to the VH data (see Eq. 3) to obtain the V, H and VH predictions of each EEG  
512 sensor activity for all VH trials. Since the unisensory models (V, H) were fit in the  
513 corresponding unisensory condition, they could only have learned a unisensory  
514 representation, whereas the VH model learned a multisensory representation of

515 active sensing velocity. Thus, we applied PID for each participant separately to  
516 predict the VH model predictions from the two unisensory V and H model  
517 predictions, which enabled us to quantify the cross-modal interactions between  
518 the two unisensory representations across all EEG sensors.

519 *Statistical analysis of PID results.* We performed this decomposition  
520 independently for each EEG channel and obtained scalp maps for the four PID  
521 terms (redundant information, unique information of A, unique information of V,  
522 synergistic information) for each participant. To avoid over-fitting, we  
523 implemented a 5-fold cross-validation procedure. We randomly split the VH data  
524 into 5 subsets used 4 of them to learn the VH, V and H models and the held-out  
525 set to perform the PID on. We repeated this process 5 times to obtain PID values  
526 for all the VH data. To assess statistical significance of the obtained values, we  
527 performed a permutation test. Specifically, we shuffled the target signal, i.e. the  
528 VH model of active sensing, 1000 times while keeping the two predictor signals  
529 (V and H models respectively) unchanged and applied PID to predict the VH  
530 model surrogate data. Output values of the original PID decomposition were  
531 considered significant if they exceeded the 99-th percentile of the distribution of  
532 the surrogate data. Multiple comparisons were corrected for using FDR  
533 (Genovese et al., 2002).

534  
535  
536  
537  
538  
539  
540  
541  
542  
543  
544

## 545 **Results**

546

547 We collected behavioral and EEG data while 14 participants actively  
548 interrogated a 2-dimensional texture stimulus that differed in its amplitude in one  
549 dimension (left - L vs right – R). Participants used visual information (V), haptic  
550 information (H) or both types of sensory information simultaneously (VH) to make  
551 a 2-alternative forced perceptual choice (2AFC), i.e., report (via a key press) as  
552 quickly and as accurately as possible on which side (L or R) the texture stimulus  
553 had higher amplitude (Fig. 1B). To sample information from both sides,  
554 participants performed finger movements scanning the workspace of the  
555 Pantograph before reaching a decision (Fig. 1C).

556 In the H condition, the Pantograph (see Materials and Methods for more  
557 details on the device used to generate the stimuli) was programmed to produce  
558 sinusoidal forces, which yielded the sensation of exploring a rough texture  
559 surface (with different amplitudes between L and R (when participants moved  
560 their index finger on the workspace of the Pantograph (see Fig.1B middle panel).  
561 In the visual domain, participants were moving their fingers to reveal greyscale  
562 stripes of different intensity/contrast between L and R (see Fig. 1B left panel). In  
563 the VH condition, both the visual and haptic textures were congruently presented  
564 wherever the participants moved their fingers (Fig. 1B right panel). Overall,  
565 participants had to decide whether L or R had higher amplitude based on their  
566 haptic (in H trials), visual (in V trials) or visuo-haptic (in VH trials) perception of  
567 this virtual surface.

568

### 569 *Multisensory gain in behavioral performance*

570 Multisensory stimulation resulted in significantly higher discrimination  
571 accuracy (91.5%±2.1% in VH vs 85.8%±2.2% in V and 86.3%±2.2% in H, two-  
572 way ANOVA with factors condition and stimulus difference,  $F(2,99)=5.64$ ,  
573  $p<0.005$ , see also slopes in the corresponding psychometric curves in Fig. 1D,

574  $PSE_v = 0.034 \pm 0.013, PSE_h = -0.001 \pm 0.009, PSE_{vh} = -0.019 \pm 0.007, slope_v =$   
575  $2.397 \pm 0.2964, slope_h = 1.826 \pm 0.147, slope_{vh} = 3.001 \pm 0.2514$ ) compared to  
576 the unisensory conditions (post-hoc t-tests, Bonferroni corrected,  $p=0.009$  for V-  
577 VH and  $p=0.019$  for H-VH). Response times also reduced in VH ( $4.11 \pm 0.30s$  vs  
578  $4.41 \pm 0.31s$  in V and  $4.25 \pm 0.29s$  in H, two-way ANOVA with factors condition and  
579 stimulus difference,  $F(2,99)=3.19, p=0.045$ , see also corresponding cumulative  
580 distribution functions in the three conditions, Fig. 1E). This result was significant  
581 at the population level for VH vs V differences (post-hoc t-test,  $p=0.021$ ,  
582 Bonferroni corrected) but not VH vs H differences (post-hoc t-test,  $p=0.066$ ,  
583 Bonferroni corrected) in response times. As expected, we also found a main  
584 effect of stimulus differences, with accuracy increasing ( $F(2) = 91.82, p < 0.0001$ )  
585 and reaction times decreasing ( $F(2) = 4.56, p < 0.02$ ) with larger stimulus  
586 differences, respectively. There was no interaction between the sensory  
587 condition and stimulus difference on either measure (accuracy:  $F(4) = 0.66, p =$   
588  $0.62$ ; reaction times:  $F(4) = 0.05, p = 0.99$ ). Taken together, these results indicate  
589 that multisensory information increased decision-making performance.

590

### 591 *Reconstruction of active sensing velocity from EEG recordings*

592 We then aimed to establish a relationship between brain activity and the  
593 active sensory experience of the participants in each one of the three sensory  
594 conditions. To this end, we performed a multivariate ridge regression (Crosse et  
595 al., 2016) between the EEG data and the 1-d finger velocity data (on the x-axis)  
596 to quantify neural encoding of sensorimotor behavior.

597 This analysis yielded the optimal linear combination of EEG channel  
598 activations with time lags ranging between  $[-200ms, 400ms]$  that approximated  
599 the measured movement velocities. We found that reconstruction accuracy  
600  $r^2$  was above chance level in all sensory conditions (all  $p-values < 0.01$ , Fig. 2B).  
601 To obtain interpretable topographies of the neural activity underlying these EEG-  
602 velocity couplings, we inverted the obtained velocity-decoding (backward)

603 models into velocity-encoding (forward) models (Parra et al., 2005; Haufe et al.,  
604 2014). This revealed that centro-frontal locations (with positive weights) and  
605 occipital locations (with negative weights) contributed most to velocity  
606 reconstruction in the three sensory conditions with time lags ranging from 20 to  
607 160 ms - see Fig. 2A showing the scalp topographies of the forward models and  
608 Fig. 2C-D showing the corresponding temporal response functions (averaged  
609 across frontal and occipital channels respectively) in the three sensory  
610 conditions.

611

612

### 613 *Impact of active multi-sensing on the quality of perceptual evidence*

614 To characterise the relationship between the identified EEG-velocity  
615 couplings and decision-making performance,, we employed a Hierarchical Drift  
616 Diffusion Model (HDDM). In brief, the HDDM decomposes task performance (i.e.  
617 accuracy and RT), into internal components of processing representing the rate  
618 of evidence integration (drift rate,  $\delta$ ), the amount of evidence required to make a  
619 choice (decision boundary separation,  $\alpha$ ), and the duration of other processes,  
620 such as stimulus encoding and response production (non-decision time,  $\tau$ ).  
621 Ultimately, by comparing the obtained values of all three core HDDM parameters  
622 across the V, H and VH trials, we could associate any behavioral differences  
623 resulting from the deployment of multisensory information (more accurate and  
624 faster perceptual choices as in Fig. 1) to the constituent internal process reflected  
625 by each model parameter.

626 Here, to obtain a mechanistic account of the formation of perceptual  
627 decisions via the active sampling of (multi-)sensory information, we incorporated  
628 the single-trial measures of brain-sensing- couplings ( $r^2$  values) into the HDDM  
629 parameter estimation (Fig. 3B). Specifically, we applied the obtained decoding  
630 filters to the single-trial EEG data and computed velocity reconstruction  
631 accuracies for each trial of each sensory condition (using a nested cross-



632 validation process, see Materials and Methods for more details). Then, as part of  
633 the HDDM fitting process, we integrated these single-trial  $r^2$  values in the  
634 HDDM framework by using them as regressors of the three core HDDM  
635 parameters (drift rate, non-decision time and decision boundary – see Materials  
636 and Methods). The corresponding regression coefficients were estimated  
637 together with the HDDM parameters thus enabling the assessment of the  
638 relationship between trial-to-trial variations in EEG-velocity couplings and each  
639 model parameter. We also used as regressors three movement parameters  
640 (average velocity  $v_m$ , number of crossings between L and R  $n_{cr}$  and time spent  
641 on the lower amplitude stimulus  $t_{low}$ ) which served to dissociate the effect of the  
642 exploratory movements (captured by these parameters) on decision formation  
643 from the effect of the neural encoding of these active sensing movements  
644 (captured by  $r^2$ ).

645 We found that the best-fitting model (achieving the best complexity-  
646 approximation trade-off as evaluated by the Deviance Information Criterion, Fig.  
647 3A) was the one using  $r^2$  as regressor of the drift rate only and  $n_{cr}$ ,  $t_{low}$  as  
648 regressors of non-decision time only ( Figure 3B shows a graphical illustration of  
649 the best-fitting model and Fig. 3C shows the model fitting of the accuracy and RT  
650 data where bars represent actual data and lines represent model fits). The  
651 means and confidence intervals of the estimated values of the three core HDDM  
652 parameters are reported in Table 1. Crucially for our investigation here, the EEG-  
653 velocity couplings  $r^2$  were predictive of drift rates in single trials (regression  
654 coefficients  $\beta_1$  were larger than zero for all three sensory conditions,  
655  $Prob(\gamma_1(V) > 0) > 0.97, Prob(\gamma_1(H) > 0) > 0.99, Prob(\gamma_1(VH) > 0) > 0.999$ ; Fig.  
656 3D). Furthermore, the contribution of  $r^2$  to drift rate was higher in VH trials  
657 compared to V and H trials ( $Prob(\gamma_1(VH) > \gamma_1(V)) > 0.95$  and  $Prob(\gamma_1(VH) >$   
658  $\gamma_1(H)) > 0.99$ ; Fig. 3D) indicating a multisensory enhancement of evidence  
659 accumulation rates via an increased weighting of the EEG-velocity couplings in  
660 the VH condition.

661 We then examined whether this multisensory gain could explain the  
662 observed improvements in behavioral performance when multisensory  
663 information is available. Indeed, this enhanced contribution of  $r^2$  to drift rate was  
664 predictive of multisensory improvements in behavioral performance. Specifically,  
665 cross-participant differences in  $\beta_1$ 's across conditions correlated with the reported  
666 increases in accuracy ( $r = 0.58$ ,  $p = 0.049$  for VH vs V and  $r = 0.75$ ,  $p = 0.005$   
667 for VH vs H; Fig. 3F), suggesting that differences in accuracies across  
668 participants were accounted for by the contributions of EEG-velocity couplings to  
669 evidence accumulation. Thus, participants with greater drift rate amplification  
670 achieved stronger enhancements in their behavioral performance as a result of  
671 multisensory information available.

672 We also found that both switching time between the two stimuli as  
673 captured by  $n_{cr}$  and exploration time spent on one of the two stimuli as captured  
674 by  $t_{low}$  were predictive of non-decision time ( $Prob(\beta_{sw} > 0) > 0.999$ ,  $Prob(\beta_{exp} >$   
675  $0) > 0.999$  for all V,H,VH; Fig. 3G-H) in single trials indicating that non-decision  
676 processes (i.e. related to sensory processing and movement planning/execution)  
677 are dependent on switching and exploration times. There was a positive cross-  
678 participant correlation ( $r = 0.695$ ,  $p = 0.0121$ ) between  $\beta_{exp}$  and RT (averaged  
679 across trials and sensory conditions) suggesting that participants with larger  
680 contributions of exploration time to their non-decision times took longer to  
681 respond (Fig 3I). However, we found no reliable difference in the corresponding  
682 regression coefficients ( $\beta_{sw}, \beta_{exp}$ ) between the three sensory conditions  
683 ( $Prob(\beta_{sw}(VH) > \beta_{sw}(V)) = 0.632$ ,  $Prob(\beta_{sw}(VH) > \beta_{sw}(H)) = 0.843$ ,  
684  $Prob(\beta_{exp}(VH) > \beta_{exp}(V)) = 0.107$ ,  $Prob(\beta_{exp}(VH) > \beta_{exp}(H)) = 0.210$ ; Fig.  
685 3G-H). There was also no difference in the decision boundaries in the three  
686 sensory conditions ( $Prob(\alpha(VH) > \alpha(V)) = 0.731$ ,  $Prob(\alpha(VH) > \alpha(H)) > 0.804$ ;  
687 Fig. 3E). These results indicate that neither the switching and exploration times

688 nor the amount of evidence required to make a decision were dependent on the  
689 sensory condition.

690

### 691 *Quantifying multisensory interactions*

692 Having established that the neural encoding of the behavioral kinematics  
693 is related to the multisensory gain in decision evidence, we then aimed to assess  
694 how the neural representations of the two unisensory stimuli (V, H) interact to  
695 form a multisensory representation. To this end, we employed Partial Information  
696 Decomposition, which enables the quantification of cross-modal representational  
697 interactions in the human brain (see Methods for details). Specifically, the PID  
698 information theoretic framework quantifies the degree to which a) each  
699 unisensory (V,H) representation contributes uniquely to the encoding of active  
700 sensing behavior (unique V or H information), b) the two unisensory (V,H)  
701 representations share information about active sensing (redundancy) and c) the  
702 two unisensory (V,H) representations convey more information when observed  
703 simultaneously (synergy). Here, we used PID to predict the forward (velocity-  
704 encoding) VH model (target signal) from the two unisensory forward models V  
705 and H (predictor signals). The decomposition revealed that the V model provided  
706 unique information in right parieto-temporal locations whereas the H model  
707 contributed uniquely in left prefrontal and parieto-occipital locations (Fig. 4A, all  
708  $p$ -values<0.01, FDR corrected). Crucially, we also found multisensory  
709 interactions in the form of a) redundant effects in left prefrontal and parieto-  
710 occipital electrodes and b) synergistic effects over left centro-parietal scalp (Fig.  
711 4A, all  $ps$ <0.01, FDR corrected). Here, a redundant interaction means that the  
712 representation of velocity is common to both the V and H modalities (Ince et al.,  
713 2017; Park et al., 2018). A synergistic interaction means a better prediction of  
714 the modelled multisensory response can be made when considering both the V  
715 and the H representations together (rather than independently). That is,

716 knowledge of the simultaneous combination of the EEG signal predicted by V  
717 and H models gives more information about the VH EEG signal.

718

719 *Multisensory accuracy scales with synergistic interactions*

720 Next we investigated the behavioral relevance of the identified cross-  
721 modal interactions. In particular, we asked whether the identified synergistic  
722 representation of the two modalities was predictive of behavioral performance  
723 across participants. Indeed, we found a significant positive correlation (Pearson's  
724  $R = 0.75$  and  $0.72$ , all  $p < 0.01$ ) between synergy in both significant channels  
725 (CP3 and C5) and accuracy in VH, suggesting that participants with more  
726 synergistic representations at left centro-parietal electrodes achieved better  
727 multisensory performance (Fig. 4B). This result suggests that synergy in  
728 contralateral centro-parietal EEG signals modulates multisensory decision-  
729 making behavior. Due to small sample size we cannot be sure this finding will  
730 generalise, but nonetheless report it as an interesting exploratory finding.

731

732

733

734

735

736

737

738

739

740

741

## 742 **Discussion**

743

744 In this work, we coupled neural decoding of continuous sensorimotor behavior  
745 with modeling of decision-making performance and a quantitative assessment of  
746 crossmodal neural interactions to understand how the human brain forms  
747 perceptual decisions via the active acquisition of multisensory evidence. We  
748 showed that the neural encoding of active sensing modulates the decision

749 evidence regardless of the sensing modality. We further demonstrated that the  
750 simultaneous sensing of different modalities enhances this neural coupling and  
751 this enhancement drives the dynamics of active multisensory decisions. We  
752 finally dissected the neural information conveyed by cross-modal interactions and  
753 identified a potential neural mechanism supporting multisensory decisions.

754 Recent research on active sensing uncovered the strategies implemented by  
755 humans to sample sensory information (Yang et al., 2016b). Here we  
756 investigated this active sensing approach in a decision-making task using a  
757 computational approach which decodes the neural activity that encodes  
758 movement kinematics. Crucially, we made a first step in broadening this line of  
759 research to a) include sensory information from multiple modalities and b) reveal  
760 its neural underpinnings. These two developments enabled us to uncover the  
761 different sensory representations of active sampling behavior in the human brain.

762 To achieve this, we implemented an informed cognitive modeling approach that  
763 linked the neural correlates and the movement characteristics of active sensing  
764 behavior with the cognitive processes involved in decision-making. Specifically,  
765 we asked if decision-making depends on the neural representations of active  
766 (multi-)sensing. To answer this question, we used a single-trial measure of the  
767 neural encoding of active sensing behavior as predictor of decision-making  
768 performance and found that, indeed, trial-to-trial fluctuations of the neural  
769 representations of active sensing are predictive of the rate of evidence  
770 accumulation for all three sensory conditions (V, H, VH). Crucially, we showed  
771 that the multisensory (VH) representation of active sensing was a stronger  
772 predictor of drift rate (Figure 3D) thus offering a neural link between active multi-  
773 sensing and perceptual decision-making. We also split the motion profile into its  
774 two main components, i.e. a) switching between the two alternative stimuli and b)  
775 exploration within one particular stimulus and demonstrated that both  
776 components were predictive of the duration of non-decision processes (Figure  
777 3G-H), thus simply reflecting the time spent for movement planning and

778 execution and the consequent acquisition and encoding of sensory information.  
779 These novel findings were only made possible by the use of an active multi-  
780 sensing paradigm in a decision-making task and the joint cognitive modeling of  
781 behavioral, neural and sensorimotor signals.

782 We then capitalized on the identified neural representations of active (multi-  
783 sensing), to dissect cross-modal interactions in the human brain. To this end, we  
784 employed PID, a recently developed rigorous methodology for the quantification  
785 of information conveyed uniquely or jointly by different neural representations  
786 (Williams and Beer, 2010; Timme et al., 2014; Ince, 2017). PID further  
787 distinguishes between two types of interactions between the neural  
788 representations of the two sensory modalities (V, H). A synergistic interaction  
789 indicates that a better prediction of the multisensory neural response can be  
790 made when the predicted values of the unimodal forward models for V and H are  
791 considered jointly rather than independently. Our results suggest that this  
792 synergistic interaction of the two neural representations correlates with  
793 multisensory behavioural performance (Figure 4B). Instead, a redundant  
794 interaction indicates that the two unimodal models provide the same information  
795 about the multisensory condition, thus the multisensory response there is  
796 common to both modalities (Park et al., 2018; Daube et al., 2019a). This  
797 suggests that the underlying neural signals reflect a modality-invariant  
798 representation.

799 As a result of this analysis, we were able to identify neural signals representing  
800 these two types of interactions. Specifically, we found that EEG channels in  
801 (parieto-)occipital and prefrontal areas carried redundant representations of the  
802 two sensory streams, perhaps reflecting supramodal coding mechanisms of  
803 active sensing (Figure 4A, redundancy). This finding is in line with previous  
804 research assigning a multimodal role to occipital cortex (Lacey et al., 2007;  
805 Murray et al., 2016) and suggesting that multisensory enhancements originate  
806 from the sensory cortices (Kayser and Logothetis, 2007; Lakatos et al., 2007;

807 Lewis and Noppeney, 2010). Specifically, recent research involved the visual  
808 cortex in audio-visual interactions (Mishra et al., 2007; Cao et al., 2019; Rohe et  
809 al., 2019) as well as tactile perception and visuo-haptic interactions (Lucan et al.,  
810 2010; Sathian, 2016; Gaglianese et al., 2020). In agreement with the above, here  
811 we also found unique H information in parieto-occipital electrodes. Concerning  
812 the prefrontal cortex (PFC), recent evidence assigned to it a modality-general  
813 role in arbitrating between segregation or fusion of sensory evidence from  
814 different modalities (Cao et al., 2019). Thus, the involvement of the PFC in the  
815 regulation of adaptive multisensory behaviors in general (Koechlin and  
816 Summerfield, 2007; Donoso et al., 2014; Tomov et al., 2018) and perceptual  
817 decisions in particular (Heekeren et al., 2006; Philiastides et al., 2011; Rahnev et  
818 al., 2016; Sterzer, 2016) makes it a likely contributor to the formation of the most  
819 appropriate sensory representation that drives decision-making behavior. In other  
820 words, the PFC may support a mechanism gauging candidate (multisensory or  
821 unisensory) representations for selecting among multiple strategies to solve the  
822 task at hand (Calvert, 2001; Hein et al., 2007; Noppeney et al., 2010; Cao et al.,  
823 2019). Our active multi-sensing task requires participants to continuously weigh  
824 different sensing strategies and refine their scanning patterns to maximize  
825 information gain. Hence, the PFC may capitalise on multisensory information  
826 (when of benefit) to support such flexible behavior striking a balance between  
827 sampling more evidence and committing to a choice.

828 The above findings are consistent with our previous study focusing on the tactile  
829 modality, which attributed a sensory processing function to occipital cortex  
830 (specifically localized to the lateral occipital complex) and a decision formation  
831 function to right prefrontal cortex (middle frontal gyrus) (Delis et al., 2018). Taken  
832 together with the current results, our findings suggest these two brain areas may  
833 play a crossmodal role in supporting active perception and decision-making.  
834 Overall, our work adds to the existing literature on multi-sensory interactions by  
835 quantifying how sensory representations interact to encode active sensing  
836 behaviors.

837 More importantly, here we revealed a novel functional role for contralateral  
838 centro-parietal signals in active visuo-haptic decisions. We found that brain  
839 signals over left centro-parietal scalp locations showed stronger encoding of  
840 active sensing when the two sensory streams were available (Figure 4A,  
841 synergy), thus possibly representing a neural mechanism of multisensory  
842 integration. In line with the ongoing debate on the multisensory nature of primary  
843 sensory cortices (Ghazanfar and Schroeder, 2006; Liang et al., 2013), cross-  
844 modal visuo-haptic interactions leading to enhanced neural representations have  
845 been found in the primary somatosensory cortex (S1) (Zhou and Fuster, 2000;  
846 Dionne et al., 2010). Here we further characterised these interactions as carrying  
847 super-additive/synergistic representations of the active multi-sensory experience  
848 and demonstrated that they are related to the accuracy of active multisensory  
849 judgments.

850 It is also worth noting that our results do not rule out the possibility that  
851 other brain areas – not directly related to active sensing - may contribute to  
852 regulating the speed and accuracy of active multisensory decisions. In fact,  
853 recent research breakthroughs have explained the development of multisensory  
854 representations from different sensory streams in the human brain (Aller and  
855 Noppeney, 2019; Cao et al., 2019; Rohe et al., 2019). Furthermore, recent  
856 studies have started to investigate how the interactions between sensory  
857 representations shape decision formation (Bizley et al., 2016; Franzen et al.,  
858 2020; Mercier and Cappe, 2020).

859 Our primary aim here was to provide the missing link between the active  
860 acquisition of multisensory evidence and its transformation to choice. Overall, our  
861 findings validated the hypotheses that a) active sensing guides decision  
862 formation via evidence sampling and accumulation and b) multisensory  
863 information spurs perceptual decisions by enhancing the neural encoding of  
864 active behaviors. Our information-theoretic analysis also revealed the neural  
865 substrates of multisensory interactions in the human brain that support active  
866 multisensory perception. Ultimately, we identified and characterised a set of



867 human brain signals that underpin multisensory judgements by subserving an  
868 enhancement of the neural encoding of active perception when multisensory  
869 information is available.

870  
871  
872  
873  
874  
875  
876  
877  
878  
879  
880  
881  
882  
883  
884  
885  
886  
887  
888  
889  
890  
891  
892  
893  
894  
895  
896  
897  
898 **References**  
899

900 Aller M, Noppeney U (2019) To integrate or not to integrate: Temporal dynamics of hierarchical  
901 Bayesian causal inference. *PLoS Biol* 17:e3000210.  
902 Angelaki DE, Gu Y, DeAngelis GC (2009) Multisensory integration: psychophysics,  
903 neurophysiology, and computation. *Curr Opin Neurobiol* 19:452-458.  
904 Bell AJ, Sejnowski TJ (1995) An information-maximization approach to blind separation and blind  
905 deconvolution. *Neural Comput* 7:1129-1159.  
906 Bizley JK, Jones GP, Town SM (2016) Where are multisensory signals combined for perceptual  
907 decision-making? *Curr Opin Neurobiol* 40:31-37.

908 Boehm U, Marsman M, Matzke D, Wagenmakers EJ (2018) On the importance of avoiding  
909 shortcuts in applying cognitive models to hierarchical data. *Behav Res Methods*  
910 50:1614-1631.

911 Calvert GA (2001) Crossmodal processing in the human brain: insights from functional  
912 neuroimaging studies. *Cereb Cortex* 11:1110-1123.

913 Campion G, Wang Q, Hayward V (2005) The Pantograph Mk-II: A haptic instrument. 2005  
914 IEEE/Rsj International Conference on Intelligent Robots and Systems, Vols 1-4:723-728.

915 Cao Y, Summerfield C, Park H, Giordano BL, Kayser C (2019) Causal Inference in the Multisensory  
916 Brain. *Neuron* 102:1076-1087 e1078.

917 Chandrasekaran C (2017) Computational principles and models of multisensory integration. *Curr*  
918 *Opin Neurobiol* 43:25-34.

919 Crosse MJ, Di Liberto GM, Bednar A, Lalor EC (2016) The Multivariate Temporal Response  
920 Function (mTRF) Toolbox: A MATLAB Toolbox for Relating Neural Signals to Continuous  
921 Stimuli. *Frontiers in Human Neuroscience* 10.

922 Daube C, Ince RAA, Gross J (2019a) Simple Acoustic Features Can Explain Phoneme-Based  
923 Predictions of Cortical Responses to Speech. *Curr Biol* 29:1924-1937 e1929.

924 Daube C, Giordano BL, Ince RAA, Gross J (2019b) Quantitatively Comparing Predictive Models  
925 with the Partial Information Decomposition. In: 2019 Conference on Cognitive  
926 Computational Neuroscience. Berlin, Germany.

927 Delis I, Dmochowski JP, Sajda P, Wang Q (2018) Correlation of neural activity with behavioral  
928 kinematics reveals distinct sensory encoding and evidence accumulation processes  
929 during active tactile sensing. *Neuroimage* 175:12-21.

930 Delorme A, Makeig S (2004) EEGLAB: an open source toolbox for analysis of single-trial EEG  
931 dynamics including independent component analysis. *Journal of Neuroscience Methods*  
932 134:9-21.

933 Di Liberto GM, O'Sullivan JA, Lalor EC (2015) Low-Frequency Cortical Entrainment to Speech  
934 Reflects Phoneme-Level Processing. *Current Biology* 25:2457-2465.

935 Dionne JK, Meehan SK, Legon W, Staines WR (2010) Crossmodal influences in somatosensory  
936 cortex: Interaction of vision and touch. *Hum Brain Mapp* 31:14-25.

937 Donoso M, Collins AG, Koechlin E (2014) Human cognition. *Foundations of human reasoning in*  
938 *the prefrontal cortex. Science* 344:1481-1486.

939 Drugowitsch J, DeAngelis GC, Klier EM, Angelaki DE, Pouget A (2014) Optimal multisensory  
940 decision-making in a reaction-time task. *Elife* 3.

941 Ernst MO, Banks MS (2002) Humans integrate visual and haptic information in a statistically  
942 optimal fashion. *Nature* 415:429-433.

943 Forstmann BU, Ratcliff R, Wagenmakers EJ (2016) Sequential Sampling Models in Cognitive  
944 Neuroscience: Advantages, Applications, and Extensions. *Annu Rev Psychol* 67:641-666.

945 Frank MJ, Gagne C, Nyhus E, Masters S, Wiecki TV, Cavanagh JF, Badre D (2015) fMRI and EEG  
946 predictors of dynamic decision parameters during human reinforcement learning. *J*  
947 *Neurosci* 35:485-494.

948 Franzen L, Delis I, De Sousa G, Kayser C, Philiastides MG (2020) Auditory information enhances  
949 post-sensory visual evidence during rapid multisensory decision-making. *Nat Commun*  
950 11:5440.

951 Gaglianese A, Branco MP, Groen IIA, Benson NC, Vansteensel MJ, Murray MM, Petridou N,  
952 Ramsey NF (2020) Electrocorticography Evidence of Tactile Responses in Visual Cortices.  
953 *Brain Topogr* 33:559-570.

954 Genovese CR, Lazar NA, Nichols T (2002) Thresholding of statistical maps in functional  
955 neuroimaging using the false discovery rate. *Neuroimage* 15:870-878.

956 Ghazanfar AA, Schroeder CE (2006) Is neocortex essentially multisensory? *Trends Cogn Sci*  
957 10:278-285.

958 Gottlieb J, Oudeyer PY (2018) Towards a neuroscience of active sampling and curiosity. *Nat Rev*  
959 *Neurosci* 19:758-770.

960 Griffith V, Koch C (2014) Quantifying Synergistic Mutual Information. In: *Guided Self-*  
961 *Organization: Inception. Emergence, Complexity and Computation* (M. P, ed). Berlin,  
962 Heidelberg: Springer.

963 Haufe S, Meinecke F, Gorgen K, Dahne S, Haynes JD, Blankertz B, Biessmann F (2014) On the  
964 interpretation of weight vectors of linear models in multivariate neuroimaging.  
965 *Neuroimage* 87:96-110.

966 Heekeren HR, Marrett S, Bandettini PA, Ungerleider LG (2004) A general mechanism for  
967 perceptual decision-making in the human brain. *Nature* 431:859-862.

968 Heekeren HR, Marrett S, Ruff DA, Bandettini PA, Ungerleider LG (2006) Involvement of human  
969 left dorsolateral prefrontal cortex in perceptual decision making is independent of  
970 response modality. *Proceedings of the National Academy of Sciences of the United*  
971 *States of America* 103:10023-10028.

972 Hein G, Doehrmann O, Muller NG, Kaiser J, Muckli L, Naumer MJ (2007) Object familiarity and  
973 semantic congruency modulate responses in cortical audiovisual integration areas. *J*  
974 *Neurosci* 27:7881-7887.

975 Ince RA, Giordano BL, Kayser C, Rousset GA, Gross J, Schyns PG (2017) A statistical framework  
976 for neuroimaging data analysis based on mutual information estimated via a gaussian  
977 copula. *Hum Brain Mapp* 38:1541-1573.

978 Ince RAA (2017) Measuring multivariate redundant information with pointwise common change  
979 in surprisal. *Entropy* 19:318.

980 Juavinett AL, Erlich JC, Churchland AK (2018) Decision-making behaviors: weighing ethology,  
981 complexity, and sensorimotor compatibility. *Curr Opin Neurobiol* 49:42-50.

982 Kayser C, Logothetis NK (2007) Do early sensory cortices integrate cross-modal information?  
983 *Brain Struct Funct* 212:121-132.

984 Koechlin E, Summerfield C (2007) An information theoretical approach to prefrontal executive  
985 function. *Trends Cogn Sci* 11:229-235.

986 Kruschke JK (2010) What to believe: Bayesian methods for data analysis. *Trends in Cognitive*  
987 *Sciences* 14:293-300.

988 Lacey S, Campbell C, Sathian K (2007) Vision and touch: multiple or multisensory representations  
989 of objects? *Perception* 36:1513-1521.

990 Lakatos P, Chen CM, O'Connell MN, Mills A, Schroeder CE (2007) Neuronal oscillations and  
991 multisensory interaction in primary auditory cortex. *Neuron* 53:279-292.

992 Lewis R, Noppeney U (2010) Audiovisual synchrony improves motion discrimination via  
993 enhanced connectivity between early visual and auditory areas. *J Neurosci* 30:12329-  
994 12339.

995 Liang M, Mouraux A, Hu L, Iannetti GD (2013) Primary sensory cortices contain distinguishable  
996 spatial patterns of activity for each sense. *Nat Commun* 4:1979.

997 Lucan JN, Foxe JJ, Gomez-Ramirez M, Sathian K, Molholm S (2010) Tactile shape discrimination  
998 recruits human lateral occipital complex during early perceptual processing. *Hum Brain*  
999 *Mapp* 31:1813-1821.

1000 McGill WJ (1954) Multivariate information transmission. *Psychometrika*:97-11.

1001 Mercier MR, Cappe C (2020) The interplay between multisensory integration and perceptual  
1002 decision making. *Neuroimage* 222:116970.

1003 Mishra J, Martinez A, Sejnowski TJ, Hillyard SA (2007) Early cross-modal interactions in auditory  
1004 and visual cortex underlie a sound-induced visual illusion. *J Neurosci* 27:4120-4131.

1005 Murray MM, Thelen A, Thut G, Romei V, Martuzzi R, Matusz PJ (2016) The multisensory  
1006 function of the human primary visual cortex. *Neuropsychologia* 83:161-169.

1007 Musall S, Urai AE, Sussillo D, Churchland AK (2019) Harnessing behavioral diversity to  
1008 understand neural computations for cognition. *Curr Opin Neurobiol* 58:229-238.

1009 Najafi F, Churchland AK (2018) Perceptual Decision-Making: A Field in the Midst of a  
1010 Transformation. *Neuron* 100:453-462.

1011 Noppeney U, Ostwald D, Werner S (2010) Perceptual decisions formed by accumulation of  
1012 audiovisual evidence in prefrontal cortex. *J Neurosci* 30:7434-7446.

1013 Nunez MD, Vandekerckhove J, Srinivasan R (2017) How attention influences perceptual decision  
1014 making: Single-trial EEG correlates of drift-diffusion model parameters. *Journal of*  
1015 *Mathematical Psychology* 76:117-130.

1016 Palmer J, Huk AC, Shadlen MN (2005) The effect of stimulus strength on the speed and accuracy  
1017 of a perceptual decision. *J Vis* 5:376-404.

1018 Park H, Ince RAA, Schyns PG, Thut G, Gross J (2018) Representational interactions during  
1019 audiovisual speech entrainment: Redundancy in left posterior superior temporal gyrus  
1020 and synergy in left motor cortex. *PLoS Biol* 16:e2006558.

1021 Parra L, Alvino C, Tang A, Pearlmutter B, Yeung N, Osman A, Sajda P (2002) Linear spatial  
1022 integration for single-trial detection in encephalography. *Neuroimage* 17:223-230.

1023 Parra LC, Spence CD, Gerson AD, Sajda P (2005) Recipes for the linear analysis of EEG.  
1024 *Neuroimage* 28:326-341.

1025 Philiastides MG, Auksztulewicz R, Heekeren HR, Blankenburg F (2011) Causal role of dorsolateral  
1026 prefrontal cortex in human perceptual decision making. *Curr Biol* 21:980-983.

1027 Plummer M (2003) JAGS: A program for analysis of Bayesian graphical models using Gibbs  
1028 sampling In: 3rd International Workshop on Distributed Statistical Computing.

1029 Rahnev D, Nee DE, Riddle J, Larson AS, D'Esposito M (2016) Causal evidence for frontal cortex  
1030 organization for perceptual decision making. *Proc Natl Acad Sci U S A* 113:6059-6064.

1031 Raposo D, Sheppard JP, Schrater PR, Churchland AK (2012) Multisensory decision-making in rats  
1032 and humans. *J Neurosci* 32:3726-3735.

1033 Ratcliff R, McKoon G (2008) The diffusion decision model: Theory and data for two-choice  
1034 decision tasks. *Neural Computation* 20:873-922.

1035 Ratcliff R, Childers R (2015) Individual Differences and Fitting Methods for the Two-Choice  
1036 Diffusion Model of Decision Making. *Decision (Wash D C)* 2015.

1037 Rohe T, Ehlis AC, Noppeney U (2019) The neural dynamics of hierarchical Bayesian causal  
1038 inference in multisensory perception. *Nat Commun* 10:1907.

1039 Sathian K (2016) Analysis of haptic information in the cerebral cortex. *J Neurophysiol* 116:1795-  
1040 1806.

1041 Schroeder CE, Wilson DA, Radman T, Scharfman H, Lakatos P (2010) Dynamics of Active Sensing  
1042 and perceptual selection. *Curr Opin Neurobiol* 20:172-176.

1043 Shannon CE (1948) A mathematical theory of communication. *Bell Syst Tech J* 27:379-423 &  
1044 623-656.

1045 Spiegelhalter DJ, Best NG, Carlin BR, van der Linde A (2002) Bayesian measures of model  
1046 complexity and fit. *Journal of the Royal Statistical Society Series B-Statistical*  
1047 *Methodology* 64:583-616.

1048 Sterzer P (2016) Moving forward in perceptual decision making. *Proc Natl Acad Sci U S A*  
1049 113:5771-5773.

1050 Theiler J, Eubank S, Longtin A, Galdrikian B, Farmer JD (1992) Testing for Nonlinearity in Time-  
1051 Series - the Method of Surrogate Data. *Physica D* 58:77-94.

1052 Timme N, Alford W, Flecker B, Beggs JM (2014) Synergy, redundancy, and multivariate  
1053 information measures: an experimentalist's perspective. *J Comput Neurosci* 36:119-140.

1054 Tomov MS, Dorfman HM, Gershman SJ (2018) Neural Computations Underlying Causal Structure  
1055 Learning. *J Neurosci* 38:7143-7157.

1056 Turner BM, van Maanen L, Forstmann BU (2015) Informing Cognitive Abstractions Through  
1057 Neuroimaging: The Neural Drift Diffusion Model. *Psychological Review* 122:312-336.

1058 Wabersich D, Vandekerckhove J (2014) Extending JAGS: A tutorial on adding custom  
1059 distributions to JAGS (with a diffusion model example). *Behavior Research Methods*  
1060 46:15-28.

1061 Wiecki TV, Sofer I, Frank MJ (2013) HDDM: Hierarchical Bayesian estimation of the Drift-  
1062 Diffusion Model in Python. *Front Neuroinform* 7:14.

1063 Williams PL, Beer RD (2010) Nonnegative Decomposition of Multivariate Information.  
1064 arXiv:10042515v1.

1065 Winkler I, Haufe S, Tangermann M (2011) Automatic classification of artifactual ICA-components  
1066 for artifact removal in EEG signals. *Behav Brain Funct* 7:30.

1067 Yang SC, Lengyel M, Wolpert DM (2016a) Active sensing in the categorization of visual patterns.  
1068 *Elife* 5.

1069 Yang SCH, Wolpert DM, Lengyel M (2016b) Theoretical perspectives on active sensing. *Current*  
1070 *Opinion in Behavioral Sciences* 11:100-108.

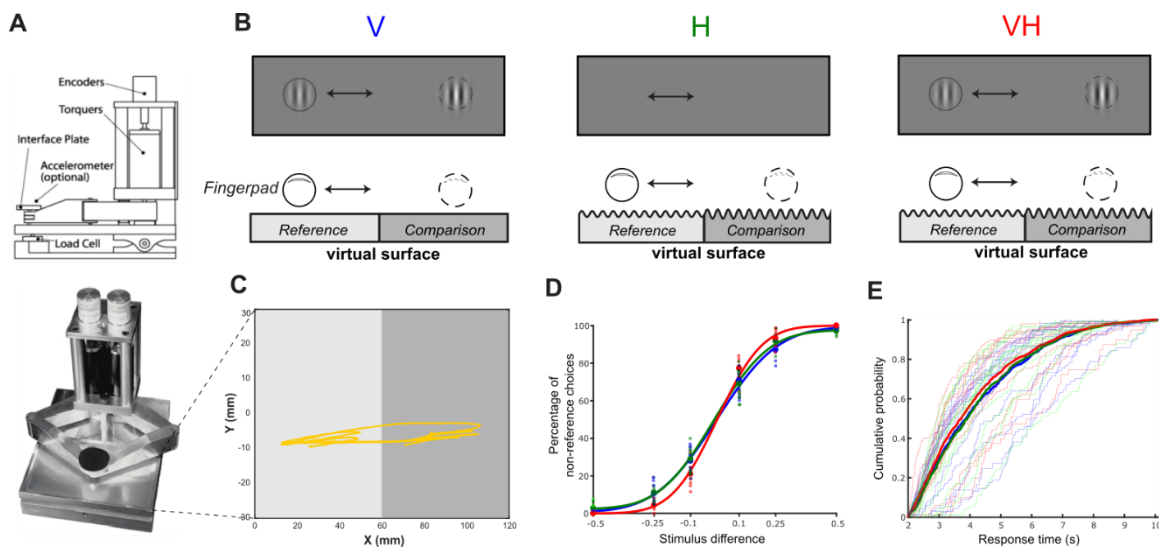
1071 Zhou YD, Fuster JM (2000) Visuo-tactile cross-modal associations in cortical somatosensory cells.  
1072 *Proc Natl Acad Sci U S A* 97:9777-9782.

1073

1074

1075  
1076

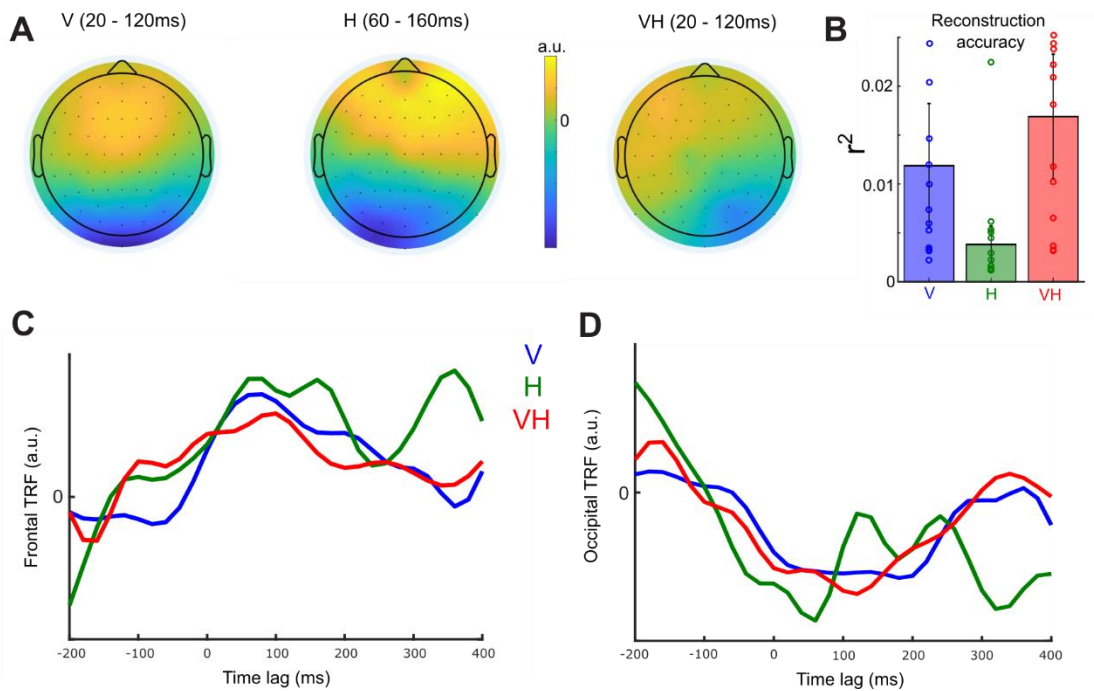
## Figures and Tables



1077

1078 **Figure 1. Experimental design and behavioral results.** A. The Pantograph is a  
1079 haptic device used to render virtual surfaces that can be actively sensed. Top:  
1080 the parts of the Pantograph shown from a lateral view. Participants placed their  
1081 index finger on the interface plate. Bottom: The Pantograph device used in this  
1082 experiment. B. The stimulus in the three sensory conditions. We programmed the  
1083 Pantograph to generate a virtual grating texture. The workspace was split into  
1084 two subspaces (left - L and right - R) that differed in the amplitude of the virtual  
1085 surface that the participants actively sensed. One of the two sides (randomly  
1086 assigned) had the reference amplitude (equal to 1) and the other had the  
1087 comparison amplitude that varied on each trial taking one of the values: 0.5,  
1088 0.75, 0.9, 1.1, 1.25, and 1.5. Participants performed the task using visual  
1089 information only (V), haptic information only (H) or the two sensory streams  
1090 together (VH). Amplitude of the stimulus in the haptic domain (H) was translated  
1091 as contrast in the visual domain (V). Crucially, to match the H condition, only a  
1092 moving dot following the participant's finger was revealed on the screen in V. C.  
1093 Index finger trajectory indicating the scanning pattern of the virtual texture in one  
1094 trial. On this trial, the participant actively sensed the left subspace first, then  
1095 moved to the right subspace and explored it before coming back to the left  
1096 subspace again and reporting their choice. D. Psychometric curves indicating the  
1097 percentage of non-reference choices for all three sensory conditions (V in blue, H  
1098 in green, VH in red) and for all stimulus differences. Large dots represent  
1099 average percentage of choices across participants and smaller dots represent  
1100 individual participant means. Data are fit using cumulative Gaussian functions. E.  
1101 Cumulative distributions (CDF) of response times for all three sensory conditions  
1102 V in blue, H in green, VH in red) across all trials of all participants. Thick lines  
1103 indicate CDFs across all participant data and thin lines indicate individual  
1104 participant CDFs for each sensory condition.

1105  
1106  
1107  
1108  
1109  
1110  
1111  
1112  
1113  
1114



1115  
1116  
1117  
1118  
1119  
1120  
1121  
1122  
1123  
1124  
1125  
1126  
1127  
1128  
1129  
1130  
1131  
1132

**Figure 2. Results of velocity reconstruction analysis using EEG signals.** A. Scalp topographies of the forward models representing neural encoding of instantaneous finger velocity for the three sensory conditions. The presented scalp maps show velocity-encoding EEG signals averaged over the following time windows: [20,120]ms lags between velocity and EEG for V and VH and [60,160]ms lags for H. B. Accuracy of the velocity reconstruction from the EEG signals measured using the squared correlation coefficient ( $r^2$ ) between the original and the approximated velocity profile in the three sensory conditions (V in blue, H in green, VH in red). Bars represent means across participants and errorbars represent standard errors (sem). Dots represent individual participant data. C-D. Temporal response functions (TRFs) of the velocity-encoding EEG activity in the three sensory conditions (V in blue, H in green, VH in red) averaged over frontal electrodes (in C) and over occipital electrodes (in D).

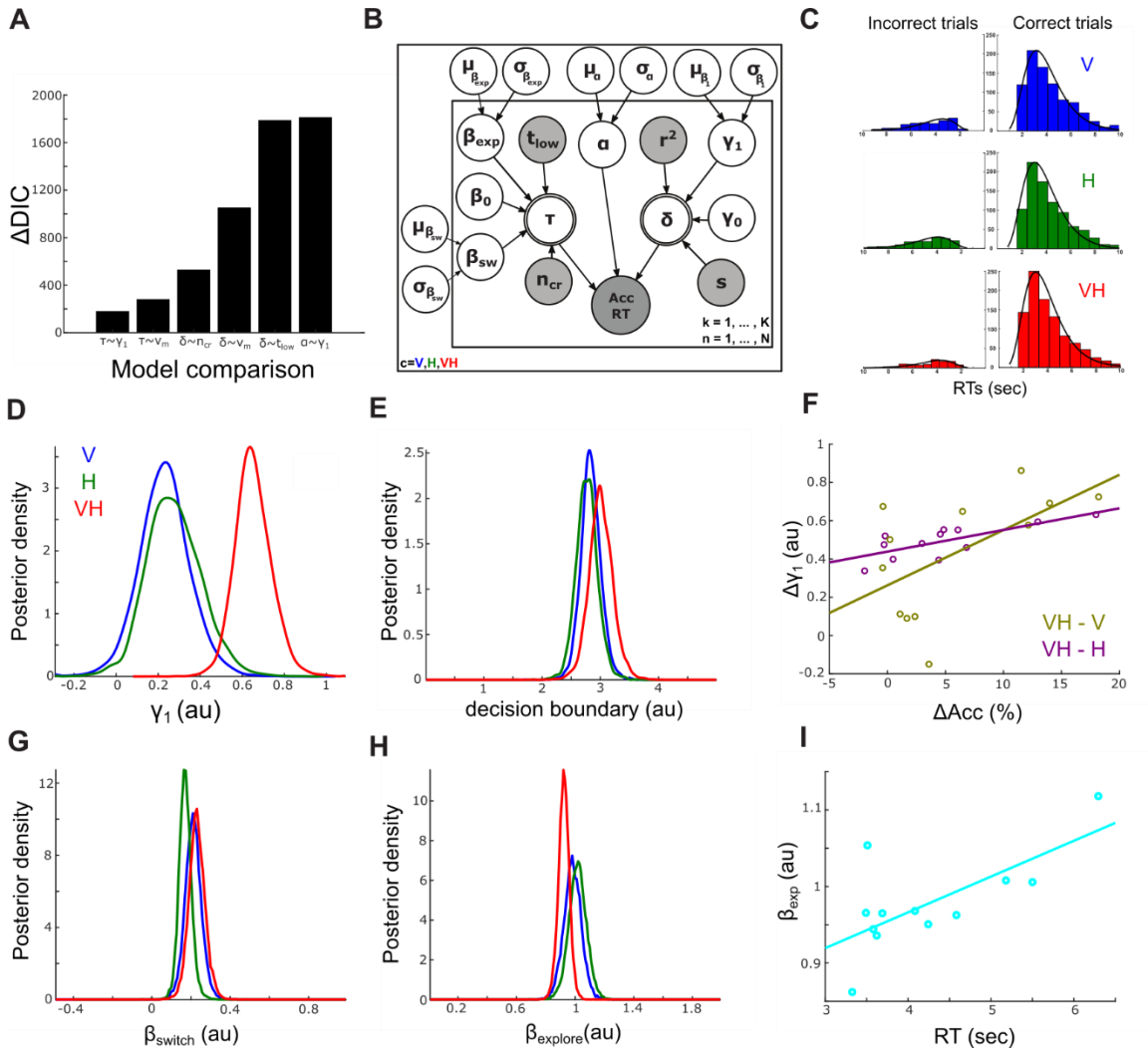
1133  
1134

**Table1: Estimated values of the three core HDDM parameters for the best-fitting model**

<b>Parameter</b>	<b>Mean</b>	<b>Confidence Interval (5%)</b>	<b>Confidence Interval (95%)</b>
Drift rate ( $\delta$ )	0.897	0.628	1.162
Non-decision time ( $\tau$ )	2.897	2.710	3.045
Decision boundary ( $\alpha$ )	2.853	2.501	3.256

1135  
1136  
1137  
1138  
1139  
1140  
1141  
1142  
1143  
1144



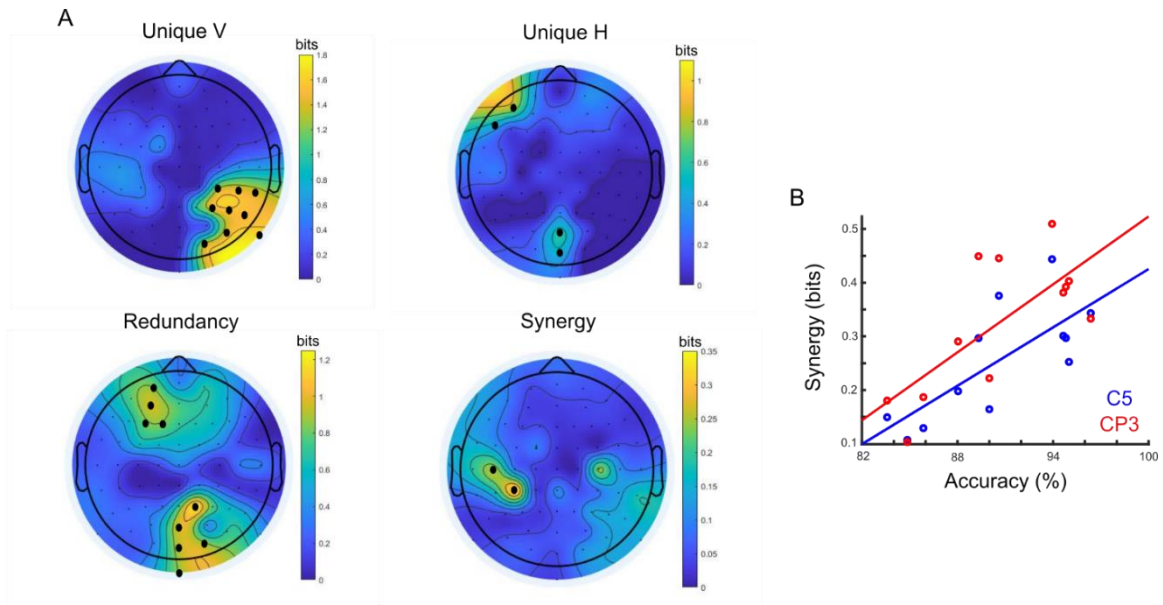


1146  
1147  
1148  
1149  
1150  
1151  
1152  
1153  
1154  
1155  
1156  
1157  
1158  
1159  
1160

**Figure 3. Informed modeling of decision-making behavior.** A. Comparison of the best-fitting model (with  $r^2$  as a regressor of drift rate  $\delta$  only and  $n_{cr}$ ,  $t_{low}$  as regressors of non-decision time  $\tau$  only) with alternate models using the Deviance Information Criterion (DIC). Positive  $\Delta DIC$  ( $DIC_{model} - DIC_{optimal}$ ) values for all six models indicate that the model of choice achieved a better trade-off between goodness-of-fit and number of free parameters. B. Graphical representation showing hierarchical estimation of HDDM parameters. Round nodes represent continuous random variables and double-bordered nodes represent variables defined in terms of other variables. Shaded nodes represent recorded or computed signals, i.e. single-trial behavioral data (accuracy, RT and stimulus differences  $s$ ), EEG-velocity couplings ( $r^2$ ) and kinematic parameters ( $n_{cr}$ ,  $t_{low}$ ). Parameters are modelled as Gaussian random variables with inferred means  $\mu$  and variances  $\sigma^2$ . Plates denote that multiple random variables share the same

1161 parents and children. The outer plate is over sensory conditions (V,H, VH) and  
1162 the inner plate is over all trials (K) and participants (N). C. Behavioral RT  
1163 distributions are shown as histograms for each sensory condition (V in blue, H in  
1164 green, VH in red) for correct (right) and incorrect (left) trials together with the  
1165 HDDM fits (black lines). Higher histogram values on the right indicate higher  
1166 proportion of correct choices. D. Posterior distributions of regression coefficients  
1167 ( $\gamma_1$ ) of the EEG-velocity couplings ( $r^2$ ), as predictors of the drift rate ( $\delta$ ) of the  
1168 HDDM shown in A. The three coloured curves indicate posterior distributions for  
1169 the three sensory conditions (blue – V, green – H, red – VH). E. Posterior  
1170 distributions of decision boundaries for the three sensory conditions (blue – V,  
1171 green – H, red – VH). F. Cross-participant correlation of differences in choice  
1172 accuracy ( $\Delta\text{Acc}$  - x-axis) and differences in  $\beta_1$  ( $\Delta\beta_1$  – y-axis) between the  
1173 multisensory (VH) and the two unisensory (V,H) conditions (VH-V in yellow, VH-  
1174 H in purple). G. Posterior distributions of regression coefficients ( $\beta_{sw}$ ) of the  
1175 number of crossings between L and R ( $n_{cr}$ ), as predictor of non-decision time ( $\tau$ )  
1176 of the HDDM shown in A. H. Posterior distributions of regression coefficients  
1177 ( $\beta_{exp}$ ) of the time spent on the low-amplitude stimulus ( $t_{low}$ ), as predictor of non-  
1178 decision time ( $\tau$ ) of the HDDM shown in A. I. Cross-participant correlation of  
1179 average response times across trials and sensory conditions (x-axis) and  $\beta_{exp}$  (y-  
1180 axis).

1181  
1182  
1183  
1184  
1185  
1186  
1187  
1188



1189 **Figure 4. Neural representations and cross-modal interactions.** A. Results of  
 1190 PID applied to predict the multisensory (VH) model of active sensing from the two  
 1191 unisensory (V and H) models. Dots on the scalp topographies indicate the EEG  
 1192 channels that provide significant ( $p < 0.01$ , FDR corrected) visual unique (top left),  
 1193 haptic unique (top right), redundant (bottom left) and synergistic (bottom right)  
 1194 neural information respectively. B. Across-subject correlation between synergy  
 1195 in the two significant EEG channels (CP3 in red and C5 in blue) and choice  
 1196 accuracy in the VH condition.  
 1197  
 1198

1199

1200 **Author Contributions:** Conceptualization: ID, PS, QW  
 1201 Methodology: ID, RAAI, PS, QW  
 1202 Investigation: ID  
 1203 Supervision: PS, QW  
 1204 Writing—original draft: ID  
 1205 Writing—review & editing: ID, RAAI, PS, QW  
 1206

1207

1208