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**Nicholas J. M. Popiel**

The University of Western Ontario

**Colin Metrow**

The University of Western Ontario

**Geoffrey Laforge**

The University of Western Ontario

**Adrian M. Owen**

The University of Western Ontario

**Bobby Stojanoski**

The University of Western Ontario

**Andrea Soddu** (✉ [asoddu@uwo.ca](mailto:asoddu@uwo.ca))

The University of Western Ontario

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## Research Article

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# Exploring electroencephalography with the aid of quantum mechanics

Nicholas J. M. Popiel<sup>a,b</sup>, Colin Metrow<sup>a</sup>, Geoffrey Laforge<sup>c</sup>, Adrian M. Owen<sup>c,d,e</sup>, Bobby Stojanoski<sup>c,d\*</sup> & Andrea Soddu<sup>a,c\*†</sup>

<sup>a</sup> The Department of Physics and Astronomy, The University of Western Ontario, London ON, N6A 5B7, Canada.

<sup>b</sup> Cavendish Laboratory, University of Cambridge, Cambridge, CB3 0HE, United Kingdom

<sup>c</sup> The Brain and Mind Institute, The University of Western Ontario, London ON, N6A 5B7, Canada.

<sup>d</sup> The Department of Psychology, The University of Western Ontario, London ON, N6A 5B7, Canada.

<sup>e</sup> The Department of Physiology and Pharmacology, The University of Western Ontario, London ON, N6A 5B7, Canada.

† asoddu@uwo.ca

\* authors equally contributed

27 **Abstract**

28

29 An outstanding issue in cognitive neuroscience concerns how the brain is organized  
30 across different conditions. For instance, during the resting-state condition, the brain  
31 can be clustered into reliable and reproducible networks (e.g., sensory, default,  
32 executive networks). Interestingly, the same networks emerge during active conditions  
33 in response to various tasks. If similar patterns of neural activity have been found  
34 across diverse conditions, and therefore, different underlying processes and  
35 experiences of the environment, is the brain organized by a fundamental organizational  
36 principle? To test this, we applied principles of quantum mechanisms to model  
37 electroencephalogram (EEG) data. We uncovered a tendency for EEG signals to be  
38 localized in anterior regions of the brain during “rest”, and more uniformly distributed  
39 while engaged in a task (i.e., watching a movie). Moreover, we found analogous values  
40 to the Heisenberg uncertainty principle, suggesting a common underlying architecture of  
41 human brain activity in resting and task conditions. This underlying architecture  
42 manifests itself in the novel constant  $K_{\text{Brain}}$ , which is extracted from the brain state with  
43 the least uncertainty. We would like to state that we are using the mathematics of  
44 quantum mechanics, but not claiming that the brain behaves as a quantum object.

45

46 **Introduction**

47 An important but outstanding issue in contemporary cognitive neuroscience is  
48 understanding the organizational properties of neural activity. For instance, is there a  
49 fundamental structure to the spatial-temporal patterns neural brain activity across  
50 different conditions? One common approach used to address this question is to  
51 examine the brain at “rest”. Measures such as functional connectivity, independent  
52 component analysis and graph theoretic metrics, have been applied to data recorded  
53 using different imaging techniques (e.g., functional magnetic resonance imaging (fMRI)  
54 and electroencephalography (EEG)), to cluster brain areas that exhibit similar activity  
55 patterns. Numerous studies have shown that brain activity during “rest” can be grouped  
56 into distinct networks across <sup>1,2</sup>; such as sensory (visual and auditory), default mode,  
57 executive, salience, and attentional (ventral and dorsal) networks that have been  
58 reliably reproduced across thousands of participants <sup>3</sup>, and are predictive of phenotypic  
59 measures like cognition and clinical diagnoses <sup>4-6</sup>. These results suggest these  
60 networks may be an intrinsic aspect of neural activity.

61  
62 Indeed, the same set of structured patterns of neural activity have been found during  
63 "active" states, such as, while completing different tasks <sup>7-9</sup>. For instance, there is a  
64 high degree of correspondence between networks extracted during rest and those  
65 extracted during tasks measuring sensorimotor <sup>10,11</sup> and higher-level cognitive abilities  
66 (i.e., working memory) <sup>12,13</sup>. Even completing a task as complicated as following the plot  
67 of a movie elicits the same network architecture as observed in the resting brain <sup>14</sup>. The  
68 correspondence between task and rest-based networks is so strong that task-based

69 fMRI network activity can be predicted from the resting state <sup>15</sup>, and rest-task network  
70 pairs can be identified at the individual level <sup>16</sup>. Together, these results suggest that rest  
71 and task-based patterns of brain activity likely share a similar underlying neural  
72 architecture, despite distinct experiences and cognitive processes <sup>17</sup>.

73

74 There are, however, important differences between the patterns of brain activity elicited  
75 during rest and task-based paradigms, and the set of experiences and cognitive  
76 processes associated with each <sup>18</sup>. For instance, the presence or absence of a task is  
77 accompanied by increases in variability across different scales including neuronal firing  
78 rates changes in field potentials <sup>19,20</sup>, variation in fMRI blood oxygen level dependent  
79 (BOLD signal) <sup>21</sup>, and in EEG frequency bands <sup>22</sup>. Furthermore, through transcranial  
80 direct current stimulation (tDCS) it has been shown that frontal-lobe stimulation  
81 increases one's proclivity to mind wander <sup>23,24</sup>. Importantly, these differences are  
82 associated with changes in properties of neural activity but not in changes in the  
83 underlying neural architecture.

84

85 Is there a way to identify the shared neural architecture underlying the cognitive  
86 processes associated with rest and active states while also quantifying how these  
87 processes diverge from that shared architecture of neural activity? In this paper, we  
88 applied the mathematical methods of quantum mechanics, and the concept of phase  
89 space to EEG recorded during rest and movie-watching to extract spatial and  
90 transitional properties of dynamic neural activity. Quantum mechanics was developed to  
91 describe the dynamics of the subatomic world in terms of probability amplitudes and

92 densities of states. Quantum systems are described by wavefunctions which square to  
93 a probability distribution leading to the loss of local determinism and the Heisenberg  
94 uncertainty principle (for an overview/intro to the subject see <sup>25</sup>). This uncertainty  
95 principle places a fundamental limit on the location and the momentum of a point  
96 particle <sup>26</sup>. In essence, if the position of a particle is known there is an underlying  
97 uncertainty in its momentum (one cannot precisely say how fast it is going) and vice  
98 versa. In addition to the adaptation of the wavefunction approach to quantum  
99 mechanics in this paper, we also employed a phase space model. Phase space is a  
100 widely used tool in the study of dynamical systems, where the positional variables are  
101 paired with their conjugate momenta which establishes a multidimensional space that  
102 describes all possible configurations of the given system. This space spans the entire  
103 range of states that a system can exist in, each point (in this hyper-space) represents a  
104 single state of the system. Phase space and its assorted formalisms are a classical  
105 concept, and we simply use it as another tool for analysing the EEG data. Herein, the  
106 mathematical methods of quantum mechanics are applied to EEG data to extract a  
107 proxy to phase space. This quasi-quantum approach naturally generates the concepts  
108 of ‘average’ position, ‘average’ momentum and culminates in an analogous Heisenberg  
109 uncertainty principle.

110

111 It is important to note that we are not claiming that the brain behaves as a quantum  
112 object as some believe <sup>27-30</sup>. Rather, we have employed the analytical tools of quantum  
113 mechanics to the brain with the aim of gaining new insight into resting and task-based  
114 brain dynamics. Not only does devising this model probe questions into the functions of

115 the brain, but it also provides a novel approach to analysing the myriad of data available  
116 in neuroscience.

117

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122

123 **Results**

124 In this paper, we adapted the probability amplitudes of quantum mechanics to define  
125 new metrics for examining EEG data – the ‘average position’ and ‘average momentum’  
126 of the EEG signal. These were constructed from our definition of ‘brain states’ based on  
127 the quasi-quantum model. This allowed us to ascertain the frequency with which unique  
128 brain regions are entered by the pseudo-wavefunction, as well as explore the average-  
129 valued phase space. Finally, an analogous uncertainty relationship to that of quantum  
130 mechanics was established, with the full mathematical derivation described in the  
131 methods.

132

133 **Average Values**

134 The ‘average position’ of the EEG data was first extracted performing a Hilbert  
135 transform of the pre-processed time courses, and then applying a normalization  
136 constraint. Typically, the Hilbert transformed data is used to generate a metric of power  
137 dispersion or to extract the phase of the signal<sup>31–33</sup>. Instead, we imposed a new  
138 normalization condition, thereby creating an analogy to the wavefunctions of quantum  
139 mechanics. Denoting the Hilbert transformed time course of the  $j^{th}$  electrode as  $\Psi_j$ , this is  
140 equivalent to

141 
$$\Psi_j(t) = A_j(t)\exp\left(i\theta_j(t)\right)$$

142  $i$

143 With  $i = \sqrt{-1}$ . We then imposed the normalization condition,

144

$$\hat{\Psi}_j(t) = \frac{\Psi_j(t)}{\sqrt{\sum_{j=1}^{92} |\Psi_j|^2}}$$

145 2

146 The summation extends to 92, corresponding to the 92 electrodes selected from the  
 147 original 129 on the head cap (channels removed from the face and neck for this  
 148 analysis). This normalization constraint allowed us to define the probability at time  $t$  of  
 149 the  $j^{\text{th}}$  electrode as

150

$$P_j(t) = \hat{\Psi}_j^*(t) \times \hat{\Psi}_j(t)$$

151 3

152 With the \* denoting complex conjugation. <sup>25</sup>We then can describe each moment in time  
 153 as a 'brain state' that is fully described (in the context of this model) through the  
 154 wavefunction. This 'brain state' uniquely specifies the EEG signal, and hence the  
 155 dynamics of interest, at each moment in time. Using this definition of probability, we  
 156 defined two average quantities of interest. The average position and momentum are  
 157 given explicitly by,

159

158

160

$$\langle x(t) \rangle = \sum_{j=1}^{92} x_j P_j(t)$$

161

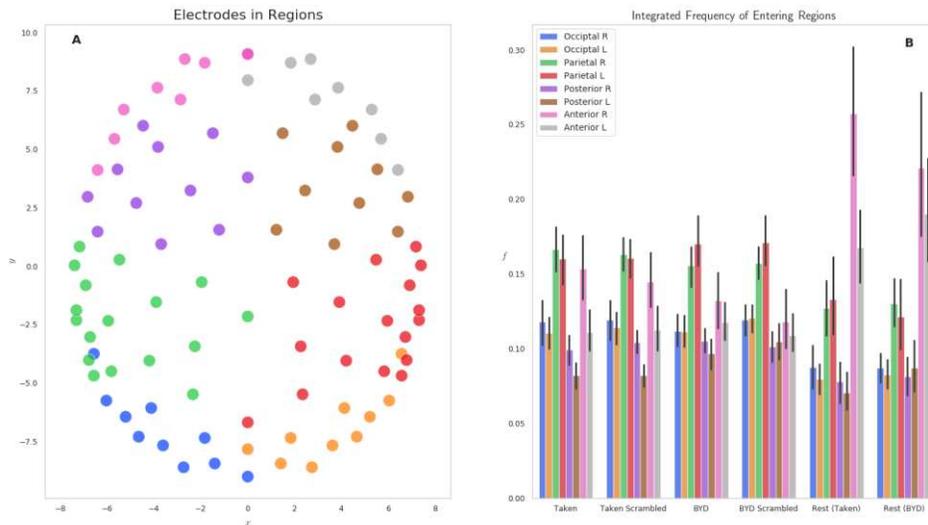
$$\langle p_x(t) \rangle = m \frac{d}{dt} \langle x(t) \rangle = m \sum_{j=1}^{92} x_j \frac{d}{dt} P_j(t)$$

162 4

163 With the same holding true for  $y$ . The second equation is an extension of Ehrenfest's  
 164 theorem, relating the average momenta of a particle to the time derivative of its average

165 position. Note that as the positions are fixed in space (positions of the electrodes) only  
166 the probability changes in time. Throughout this paper the mass  $m$  has been taking to  
167 be unity for both the  $x$  and  $y$  momenta. Each of the 92 electrodes were projected onto  
168 the horizontal plane, thus the  $j^{th}$  electrode was described by one unique  $(x_j, y_j)$  point.  
169  
170 We first examined this model by grouping the 92 electrodes into eight regions on the  
171 scalp: Anterior L/R, Posterior L/R, Parietal L/R, Occipital L/R and the probabilities of  
172 each electrode in the region were summed to give a region-level probability. Fig 1A  
173 shows the  $(x_j, y_j)$  locations of each electrode, with different colours representing each of  
174 the eight groups. Fig 1B displays the frequency of entering each region, grouped by the  
175 four task conditions and two resting conditions. This reflects the normalized count of  
176 regional probabilities integrated in time. We found that each anterior region was entered  
177 more frequently while at rest than when subjects were engaged in either movie.  
178 Specifically, the anterior left and right regions had significant within stimulus change,  
179 with  $P < 0.001$  (Tukey adjusted) for the *Taken Rest – Taken*, *Taken Rest – Taken*  
180 *Scrambled*, *BYD Rest – BYD* and *BYD Rest – BYD Scrambled*. This is in line with  
181 Axelrod and colleagues' findings which showed activation in the frontal region was  
182 associated with mind wandering<sup>23,24</sup>. We found frequency suppression in posterior  
183 regions, and an increase in anterior frequency in rest compared to the stimulated  
184 conditions, consistent with fMRI studies showing increased activation in the posterior  
185 cingulate cortex, and the medial prefrontal cortex during rest<sup>22,24,34–37</sup>. Thus, suggesting  
186 our model captures the frontal tendency associated with the brain activity while at rest.  
187

## 8 Brain Regions in EEG Space and Frequency Distribution



188

189 *Fig 1 (A) Electrode locations for each of the 92 electrodes on the Electrical Geodesics Inc. headcap. Electrodes were*  
 190 *projected onto a horizontal plane with the nose in the positive y direction. Electrodes have been colour-coded to*  
 191 *display the constituent parts of the 8 groups for the frequency analysis, namely, Occipital Left (Blue) / Right (Orange),*  
 192 *Parietal Left (Green) / Right (Red), Posterior Left (Purple) / Right (Brown) and Anterior Left (Pink) / Right (Grey). (B)*  
 193 *Histograms representing the frequency of entering each region are displayed for the six conditions tested. Significant*  
 194 *within stimulus change is present between each of the Anterior Left and Right regions when comparing the pre-*  
 195 *stimulus rest and the respective stimulated condition ( $P < 0.001$ , Tukey adjusted.). Error bars display the 1 standard*  
 196 *deviation confidence interval.*

197

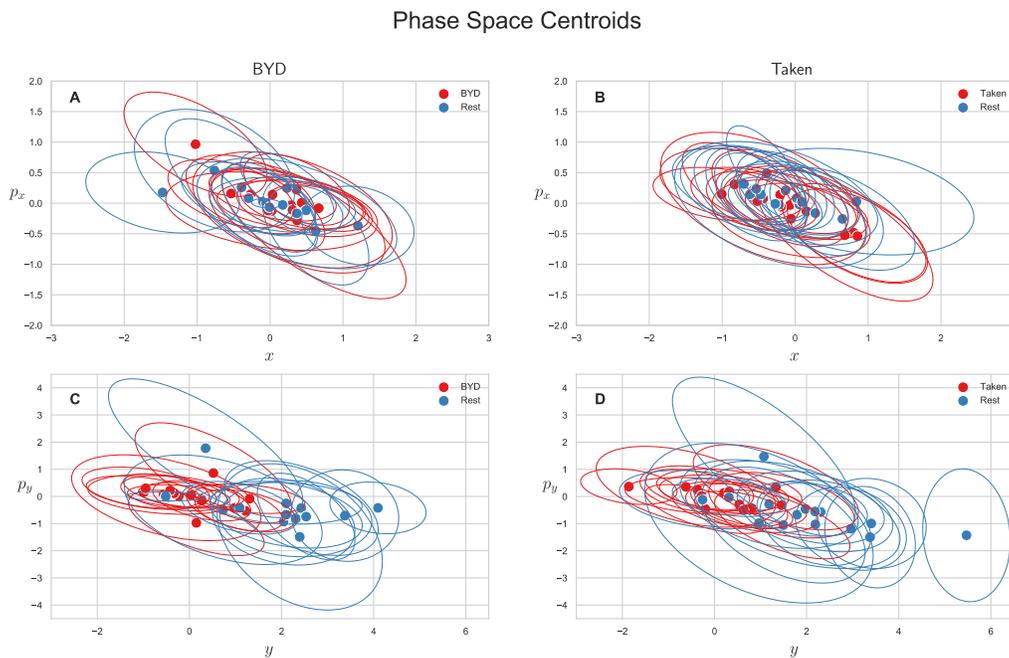
## 198 Phase Space

199 We also explored the average-valued phase space of this system. The phase space for  
 200 each subject was plotted as the average position and momentum along the x direction  
 201 ( $\langle x(t) \rangle$ ,  $\langle p_x(t) \rangle$ ) or as the average position and momentum along the y direction ( $\langle y(t) \rangle$ ,  
 202  $\langle p_y(t) \rangle$ ). Fig 2 shows the centroids of the phase space scatter plots for each subject  
 203 with an ellipse representing the one standard deviation confidence interval. Note that  
 204 values are only reported for the intact stimuli as an analysis of variance shows the

205 scrambled and intact movies are indistinguishable in phase space ( $P > 0.85$ , Tukey  
 206 adjusted). Fig 2A and 2B show the projection of the phase space centroid onto the  
 207 plane spanned by  $x$  and  $p_x$  for “Bang! You’re Dead” and “Taken” respectively, and Fig  
 208 2C and 2D ( $y$ ,  $p_y$ ) plane. The average position along the  $y$  axis ( $\langle y \rangle$ ) for the intact  
 209 stimulus (“BYD” and “Taken”) and their scrambled forms are significantly different from  
 210 the pre-stimulus rest counterparts with  $P < 0.001$  (Tukey adjusted) whereas the task-  
 211 positive and resting centroids are indistinguishable in the  $x$  plane ( $P > 0.05$ , Tukey  
 212 adjusted). The averages of the group are reported in Table 1 along with their standard  
 213 deviations.

214

215



216

217 *Fig 2 Mean phase space centroids for each subject. Ellipses represent the 1 standard deviation confidence interval.*

218 *Centroids for the scrambled stimuli were omitted as they are indistinguishable from intact stimuli ( $P > 0.85$ ) **A:***

219 *Centroids for “Bang! You’re Dead” along the  $x$  direction. **B:** Centroids for “Taken” along the  $x$  direction. **C:** Centroids*

220 for “Bang! You’re Dead” along the y direction. **D**: Centroids for “Taken” along the y direction. Differences are only  
 221 apparent in the y direction ( $P < 0.001$ , Tukey adjusted) indicative of the higher level of anterior activation as noted in  
 222 Fig 1.

223  
 224 This analysis revealed two notable findings. First, there was a lack of significant  
 225 differences in the momenta of the brain along the x and y direction. Second, the  
 226 averages in momenta were not significantly different from 0 at the group level. The  
 227 positive or negative momenta come from the competing time derivative of the probability  
 228 and location of the electrode. Since the momenta average to 0, there is an equal  
 229 number of anterior and posterior electrodes with both increases and decreases in  
 230 probability.

Stimulus	Group Averaged Centroids			
	$\langle x \rangle$	$\langle y \rangle$	$\langle p_x \rangle$	$\langle p_y \rangle$
Taken	$[-1.4 \pm 5.8] \times 10^{-1}$	$[2.4 \pm 8.0] \times 10^{-1}$	$[-5.8 \pm 27.0] \times 10^{-2}$	$[-1.0 \pm 4.1] \times 10^{-1}$
Taken Scrambled	$[-7.7 \pm 35.0] \times 10^{-2}$	$[1.1 \pm 9.3] \times 10^{-1}$	$[4.1 \pm 13.0] \times 10^{-2}$	$[6.3 \pm 35.0] \times 10^{-2}$
BYD	$[1.2 \pm 4.7] \times 10^{-1}$	$[3.5 \pm 74.0] \times 10^{-2}$	$[2.6 \pm 33.0] \times 10^{-2}$	$[-3.0 \pm 42.0] \times 10^{-1}$
BYD Scrambled	$[1.4 \pm 5.7] \times 10^{-1}$	$[-2.6 \pm 7.5] \times 10^{-1}$	$[-1.5 \pm 2.8] \times 10^{-1}$	$[-5.5 \pm 53.0] \times 10^{-2}$
Rest (Taken)	$[-1.3 \pm 4.6] \times 10^{-1}$	$[2.0 \pm 1.4] \times 10^0$	$[9.1 \pm 19.0] \times 10^{-2}$	$[-6.3 \pm 7.3] \times 10^{-1}$
Rest (BYD)	$[1.1 \pm 66.0] \times 10^{-3}$	$[1.9 \pm 1.2] \times 10^0$	$[1.0 \pm 26.0] \times 10^{-2}$	$[-4.3 \pm 7.5] \times 10^{-1}$

231  
 232 Table 1 Group averages of the Centroids. Significant differences are only noted for the rest acquired before Taken  
 233 and Bang! You’re Dead when comparing the average y location to either of their task counterparts (scrambled and  
 234 intact stimulus).

235  
 236 Further, we examined changes in the probability values in both resting and active  
 237 states. Animations of the probability distributions are present in Supplementary Material  
 238 1. In these animations, the differences in rest and task are apparent through the  
 239 evolution of probability in time.

240

241

## 242 **Uncertainty Principle**

243 Despite the confirmation of previous neuroscientific results, and the apparent success of  
244 our quasi-quantum model, our research question as posed above remains only half  
245 answered. Using this model, we noted differences in the probability distributions and the  
246 phase space centroids in rest when compared to task. However, we still sought a  
247 parameter from the model that would remain the same in rest and task. To this end, we  
248 defined an analogous Heisenberg uncertainty principle of the form,

$$249 \quad \Delta x(t)\Delta p_x(t) \geq K_{\text{Brain}}$$

250 5

251 Table 2 displays the values of this constant ( $K_{\text{Brain}}$ ) acquired in all conditions, as well as  
252 the maximum value, mean value, and standard deviation. We found that this quasi-  
253 quantum model leads to a constant minimum value across  $\Delta x(t)\Delta p_x(t)$  and  $\Delta y(t)\Delta p_y(t)$   
254 of  $0.78 \pm 0.41 \frac{cm^2}{4ms}$  with (T=0, P=1). Note the unit of  $\frac{cm^2}{4ms}$  is a result of the EEG being  
255 sampled at 250 Hz and the mass being taken to be unity. Furthermore, the average  
256 value and standard deviation of these quantities remains consistent across conditions  
257 with an average value of  $9.3 \pm 4.4 \frac{cm^2}{4ms}$  (T=0, P=1) and a standard deviation of  $18 \pm$   
258  $29 \frac{cm^2}{4ms}$  (T=0, P=1). Notably, the maximum value does vary between conditions, with the  
259 largest value occurring while subjects watched the intact clip from *Bang! You're Dead*.  
260 Despite the average position of the signal along the y direction being different in rest  
261 than during a task (P<0.001), the quasi-quantum mathematical methodology leads to a

262 constant uncertainty value. Figure 3 displays the probability distribution at the time  
 263 corresponding to the minimum in uncertainty for both x and y.

264

265

266

Stimulus	Various Uncertainty Values							
	Min		Max		Average		STD	
	$\Delta x \Delta p_x$	$\Delta y \Delta p_y$	$\Delta x \Delta p_x$	$\Delta y \Delta p_y$	$\Delta x \Delta p_x$	$\Delta y \Delta p_y$	$\Delta x \Delta p_x$	$\Delta y \Delta p_y$
Taken	$[7.0 \pm 2.1] \times 10^{-1}$	$[7.2 \pm 1.8] \times 10^{-1}$	$[1.9 \pm 1.0] \times 10^3$	$[1.4 \pm 0.8] \times 10^3$	$[8.2 \pm 2.2] \times 10^0$	$[8.2 \pm 2.2] \times 10^0$	$[1.4 \pm 0.4] \times 10^1$	$[1.3 \pm 0.4] \times 10^1$
Taken Scrambled	$[6.4 \pm 2.6] \times 10^{-1}$	$[6.8 \pm 2.1] \times 10^{-1}$	$[1.7 \pm 1.2] \times 10^3$	$[2.1 \pm 2.2] \times 10^3$	$[8.1 \pm 1.9] \times 10^0$	$[7.8 \pm 2.0] \times 10^0$	$[1.4 \pm 0.4] \times 10^1$	$[1.4 \pm 0.7] \times 10^1$
BYD	$[7.6 \pm 4.9] \times 10^{-1}$	$[7.5 \pm 3.1] \times 10^{-1}$	$[0.1 \pm 3.1] \times 10^5$	$[0.7 \pm 1.4] \times 10^4$	$[9.4 \pm 6.7] \times 10^0$	$[8.3 \pm 3.6] \times 10^0$	$[4.1 \pm 8.9] \times 10^1$	$[2.7 \pm 3.9] \times 10^1$
BYD Scrambled	$[7.4 \pm 3.2] \times 10^{-1}$	$[7.1 \pm 2.9] \times 10^{-1}$	$[2.5 \pm 1.2] \times 10^3$	$[2.5 \pm 1.6] \times 10^3$	$[9.3 \pm 5.1] \times 10^0$	$[8.6 \pm 4.4] \times 10^0$	$[1.6 \pm 0.7] \times 10^1$	$[1.5 \pm 0.8] \times 10^1$
Rest (Taken)	$[9.7 \pm 4.2] \times 10^{-1}$	$[1.1 \pm 0.6] \times 10^0$	$[3.5 \pm 3.1] \times 10^2$	$[3.5 \pm 1.7] \times 10^2$	$[9.6 \pm 2.1] \times 10^0$	$[1.3 \pm 0.4] \times 10^1$	$[1.5 \pm 0.8] \times 10^1$	$[1.9 \pm 0.7] \times 10^1$
Rest (BYD)	$[6.3 \pm 3.7] \times 10^{-1}$	$[8.6 \pm 6.1] \times 10^{-1}$	$[3.7 \pm 2.0] \times 10^2$	$[4.3 \pm 2.5] \times 10^2$	$[8.7 \pm 3.3] \times 10^0$	$[1.2 \pm 0.6] \times 10^1$	$[1.4 \pm 0.5] \times 10^1$	$[1.9 \pm 0.8] \times 10^1$

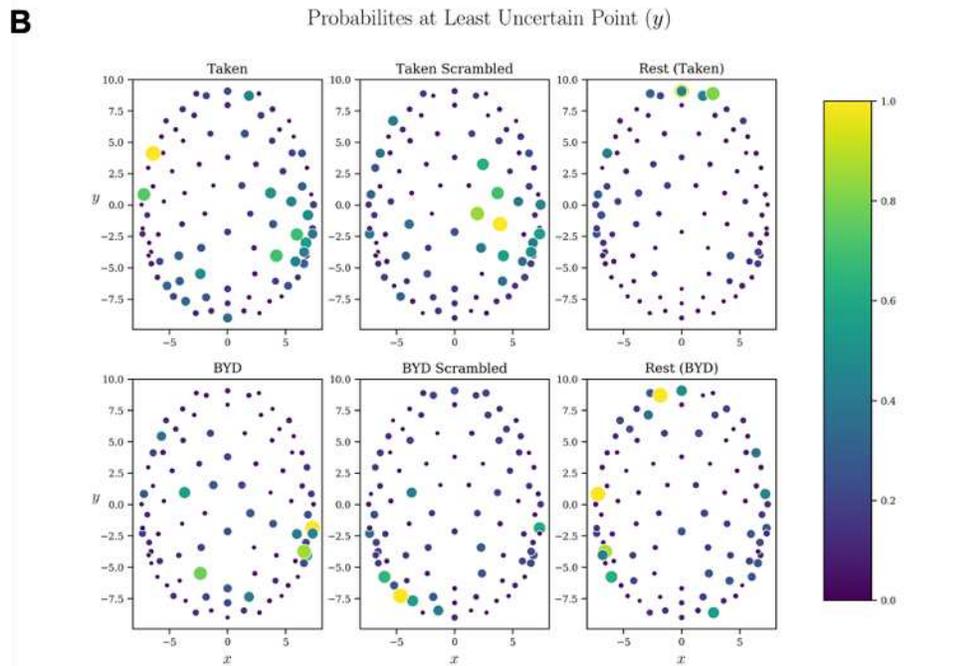
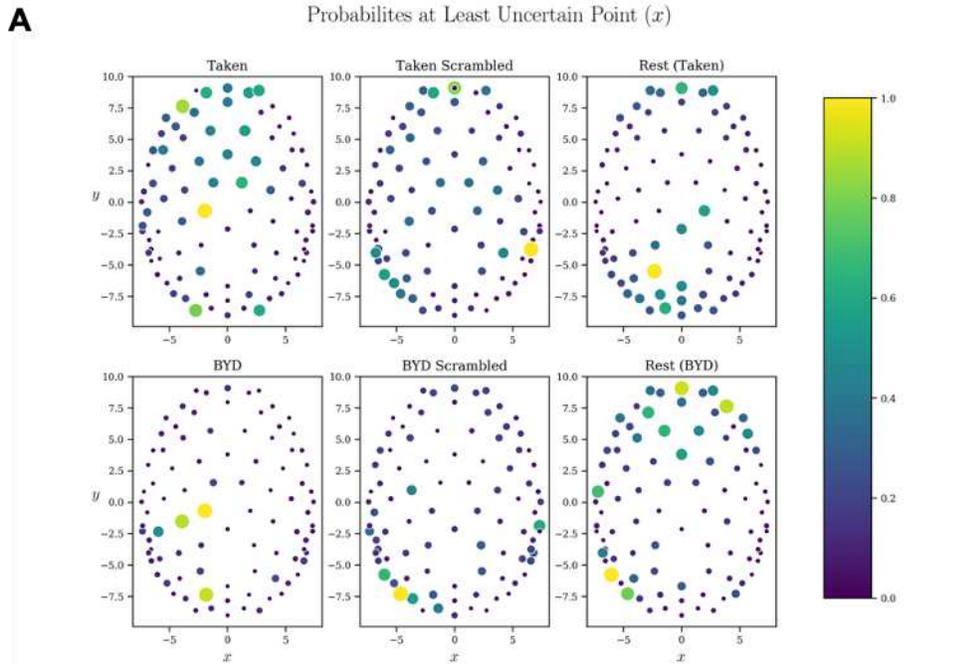
267

268 *Table 2 Various values extracted from the time courses of the products  $\Delta x(t)\Delta p_x(t)$  and  $\Delta y(t)\Delta p_y(t)$ . Considering*  
 269 *the minimum value these products reach for each subject, we see a constant value in both x and y of  $0.78 \pm$*

270  *$0.41 \frac{cm^2}{4ms}$ , an average value of the  $9.3 \pm 4.4 \frac{cm^2}{4ms}$ , and a constant standard deviation of  $18 \pm 29 \frac{cm^2}{4ms}$ . The unit of  $\frac{cm^2}{4ms}$*

271 *arises from the sampling of 250 Hz. Maximum values differ across stimulation. Values are reported as mean across*  
 272 *subjects plus or minus 1 standard deviation.*

273



274  
 275 *Fig 3 Probability maps corresponding to the least uncertain time point for each of the six experimental conditions. A: The*  
 276 *probabilities which lead to the minimum uncertainty as defined by the minimum of  $\Delta x(t)\Delta p_x(t)$ . B: The probabilities which lead*  
 277 *to the minimum uncertainty as defined by the minimum of  $\Delta y(t)\Delta p_y(t)$ . One subject is displayed for all Taken stimuli, and*  
 278 *another for all Bang! You're Dead stimuli.*

279

280 **Discussion**

281 In the current study, we investigated the spatial-extent and the associated transitional  
282 properties of neural activity in the brain during active and resting conditions, and  
283 whether similar underlying network properties exist. We found that applying the Hilbert  
284 transformation to the EEG data and normalizing it (Equation 2) imposes a probabilistic  
285 structure to the EEG signal across the brain (Equation 3), which we used to identify  
286 probability of spatial patterns of activity along with transitions in activity across the scalp.  
287 We found more anterior activity during rest relative to the movie watching, in both  
288 amplitude and phase space. This finding is in line with previous results showing  
289 increased activation in anterior region during rest<sup>20–22,34,37,38</sup>. Moreover, by normalizing  
290 the Hilbert transformed EEG signals and extracting average values akin to those of  
291 quantum mechanics, we were able to compute uncertainty in the ‘position’ and  
292 ‘momentum’ during rest and movie-watching, which is set by the new constant  $K_B =$   
293  $0.78 \pm 0.41 \frac{cm^2}{4ms}$ ,

294

295 It is alluring to associate the constant related to the ‘position’ and ‘momentum’ of neural  
296 activity to a fundamental principle, such as, the Heisenberg uncertainty principle.  
297 However, it is still unclear what this uncertainty means. It could imply limits to the  
298 degree to which the brain is accessible; increasing information about the precise  
299 location of the brain state (as described by our quasi-quantum wavefunctions) will  
300 produce a bigger uncertainty about where it will be at a subsequent time. These results  
301 offer an interesting perspective on the link between neural function and cognitive  
302 processes. For instance, as the wavefunction becomes localized in space along a train

303 of thoughts, we become distracted to increase the uncertainty, which may explain why  
304 minds wander and thoughts are fleeting?  
305 Is the  $K_B$  value we found constant across different stimulus conditions, and independent  
306 of the number of electrodes used to acquire the data? To test this, we down sampled  
307 the EEG electrodes from 92 to 20 and performed the same analysis as in the main text.  
308 In line with 92 channels, we found the anterior tendency in rest, but we found reducing  
309 the electrodes to 20 resulted in a different constant  $K_B = 0.03 \pm 0.02 \frac{cm^2}{4ms}$  (See  
310 Supplementary Material). This demonstrates that the model is able to capture the  
311 differences of rest/task, but a montage-dependent normalisation condition may need to  
312 be introduced.

313

314 It is important to note that uncertainty values of this form are inherent to any Fourier  
315 conjugate variables, as a value spreads out in one variable, it localizes in the other. This  
316 suggests that after defining the square of the Hilbert transformed EEG electrode time  
317 course to be the probability and imposing the properties of a Hilbert space onto the  
318 electrode signals, an uncertainty values can be extracted. In quantum mechanics, this  
319 uncertainty sets the limit for the scales that cannot be observed. This approach was  
320 inspired from the need in neuroscience for novel models to help interpret neuroimaging  
321 data. While this is an interesting methodological step forward, we still must determine if  
322 the observed uncertainty in the EEG data is supported by a new fundamental principle  
323 like in quantum mechanics, or if it is just the outcome of having built two new Fourier  
324 conjugate variables from the EEG signal.

325

326 Further work must be done to explore this constant with respect to the rich taxonomy of  
327 tasks and stimuli and varying states of consciousness that are routinely used in  
328 cognitive neuroscience. This methodology could be extended into fMRI, where the  
329 BOLD time courses could be Hilbert transformed creating a three-dimensional analog of  
330 the EEG model presented in this paper.

331 Ultimately, this paper presented a novel methodology for analysing EEG data.  
332 Normalizing the data and treating it as a probability amplitude led to parameters that  
333 changed with the presence or lack of stimulus, while simultaneously establishing a  
334 constant value independent of stimulus. We have successfully applied the mathematical  
335 formalisms of quantum mechanics to the resting and task paradigm in EEG (without  
336 claiming the brain is a quantum object). As neuroscience continues to evolve, the  
337 analytic tools at its disposal must also progress accordingly. We hope that this analytical  
338 tool, along with the advances in modelling and machine learning will aid in our  
339 understanding of the nature of consciousness.

340 **Methods**

341 **Data Acquisition**

342 Twenty-eight healthy subjects were recruited from The Brain and Mind Institute at the  
343 University of Western Ontario, Canada to participate in this study. Informed written  
344 consent was acquired prior to testing. Ethics approval for this study was granted by the  
345 Health Sciences Research Ethics Board and the Non-Medical Research Ethics Board of  
346 The University of Western Ontario. The study has been performed in accordance with  
347 the relevant guidelines and regulations and in accordance with the Declaration of  
348 Helsinki. Two suspenseful movie clips were used as the naturalistic stimuli in this study.  
349 A video clip from the silent film "*Bang! You're Dead*" and an audio excerpt from the  
350 movie "*Taken*" were shown to 13 and 15 subjects respectively in both their original  
351 intact and scrambled forms. Prior to the two acquisitions, a section of rest was acquired  
352 where the subjects were asked to relax, without any overt stimulation. Stimulus  
353 presentation was controlled with the Psychtoolbox plugin for MATLAB<sup>39-41</sup> on a 15"  
354 Apple MacBook Pro. Audio were presented binaurally at a comfortable listening volume  
355 through Etymotics ER-1 headphones.

356

357 EEG data were collected using a 129-channel cap (Electrical Geodesics Inc. [EGI],  
358 Oregon, USA). Electrode impedances were kept below 50k $\Omega$  with signals sampled at  
359 250Hz and referenced to the central vertex (Cz). Using the EEGLAB MATLAB toolbox  
360<sup>42</sup>, noisy channels were identified and removed, then interpolated back into the data. A  
361 Kolmogorov-Smirnov (KS) test on the data was used to identify regions that were not  
362 Gaussian. Independent components analysis (ICA) was then used to visually identify

363 patterns of neural activity characteristic of eye and muscle movements which were  
364 subsequently removed from the data. EEG pre-processing was performed individually  
365 for each subject and condition.

366

367 Of the two movie clips tested, the first was an 8-minute segment from Alfred Hitchcock's  
368 TV silent movie "*Bang! You're Dead*". This scene portrays a 5-year-old boy who picks  
369 up his uncle's revolver. The boy loads a bullet into the gun and plays with it as if it were  
370 a toy. The boy (and viewer) rarely knows whether the gun has a bullet in its chamber  
371 and suspense builds as the boy spins the chamber, points it at others, and pulls the  
372 trigger. As an alternative to visual stimulation, a 5-minute audio excerpt from the movie  
373 "*Taken*" was also used. This clip portrays a phone conversation in which a father  
374 overhears his daughters' kidnapping.

375

376 Furthermore, two "scrambled" control stimuli were used – one for each movie. This  
377 separates the neural responses elicited by the sensory properties of watching or  
378 listening to the movies from those involved in following the plot. The scrambled version  
379 of "*Bang! You're Dead*" was generated by isolating 1s segments and pseudorandomly  
380 shuffling the segments, thereby eliminating the temporal coherence of the narrative <sup>14,43</sup>.  
381 The scrambled version of "*Taken*" was created by spectrally rotating the audio, thus  
382 rendering the speech indecipherable <sup>43,44</sup>. The scrambled movie clips were presented  
383 before the intact versions to prevent potential carry-over effects of the narrative. Prior to  
384 subjects watching/listening to the scrambled stimulus a short segment of resting EEG  
385 was acquired.

386 **Model**

387 Each of the  $j$  electrodes is described by an ordered pair  $(x_j, y_j, z_j)$  in 3-dimensional  
388 space. To complete this analysis, the electrodes were first projected onto the  $(x, y)$   
389 plane, removing the depth of the head. Fig 1A shows the locations of each electrode in  
390 this 2d-space. Following this projection, the time courses for each of the 92 electrodes  
391 were Hilbert transformed and then normalized following the procedure listed using  
392 Equation 2. A probability was defined in this electrode-position space as the square of  
393 the Hilbert transformed time course (Equation 3), analogous to the wavefunctions of  
394 quantum mechanics. Eight regions Anterior L/R, Posterior L/R, Parietal L/R, Occipital  
395 L/R) were then defined by grouping the 92 electrodes, and the frequencies of entering  
396 each region were obtained by summing the probabilities electrodes within the group,  
397 then integrating in time.

398 
$$\text{Prob}_G(t) = \sum_{k=1}^N \Psi_k^*(t) \times \Psi_k(t)$$

399 6

400 
$$f_G = \frac{1}{T} \sum_{t=1}^T \text{Prob}_G(t)$$

401 Where each of the eight groups denoted by the subscript  $G$  have a different number of  
402 constituent electrodes  $N$ . In the occipital left and right there are 10 electrodes each, in  
403 the parietal left and right there are 17 electrodes each, in the posterior left and right  
404 there are 10 and 11 electrodes respectively, and in the anterior left and right there are 8  
405 and 9 electrodes respectively.

406 Upon getting the group level frequencies average values for position and momentum  
 407 were calculated using Equation 4 and 5 (with identical expressions for y). Finally, to  
 408 ascertain our analogous uncertainty principle, we sought expressions of the form

409

$$410 \quad \Delta x = \sqrt{\langle x^2(t) \rangle - \langle x(t) \rangle^2}$$

411

$$412 \quad \Delta p_x = \sqrt{\langle p_x^2(t) \rangle - \langle p_x(t) \rangle^2}$$

413 7

414

415 The expression for  $\Delta x$  can be readily applied to the probabilities and positions as  
 416 defined above, resulting in the first term given by

417

$$418 \quad \langle x^2(t) \rangle = \sum_{j=1}^{92} P_j(t) x_j^2$$

419 8

420

421 And the second term given by the square of Equation 4. The second term of  $\Delta p_x$  is  
 422 given by the square of Equation 5, but the first term is more nuanced. This is owing to  
 423 the complex number returned when acting the derivative operator twice on the  
 424 probability. To overcome this, Fourier transforms were used to change Equation 5 into  
 425 the momentum basis which then allowed for the efficient calculation of  $\langle p_x^2(t) \rangle$ . Denoting  
 426  $\tilde{P}_j(t)$  as the momentum-space probability obtained through a 2-dimensional, non-  
 427 uniform Fourier transform of the position space pseudo-wavefunction, Equation 5 can  
 428 be rewritten as,

429

430

$$\langle p_x(t) \rangle = \sum_{j=1}^{92} \tilde{P}_j(t) p_j$$

431 9

432

433 Leading to the first term in the  $\Delta p_x$  expression to be written as,

434

435

$$\langle p_x^2(t) \rangle = m^2 \sum_{j=1}^{92} \frac{x_j^2}{\tilde{P}_j(t)} \left[ \frac{d}{dt} P_j(t) \right]^2$$

436 10

437

438 The FINUFFT python wrapper was used to take the Fourier transform using a type 3, 2d

439 non-uniform FFT <sup>45,46</sup>, and the minimum value in time of the uncertainty relation was

440 found. Points in momentum space were sampled on  $p_x \in [-4,4]$  and  $p_y \in [-4,5]$  along

441 with the two additional points (-5,-4) and (-4,-5). Fig 4 shows the position and

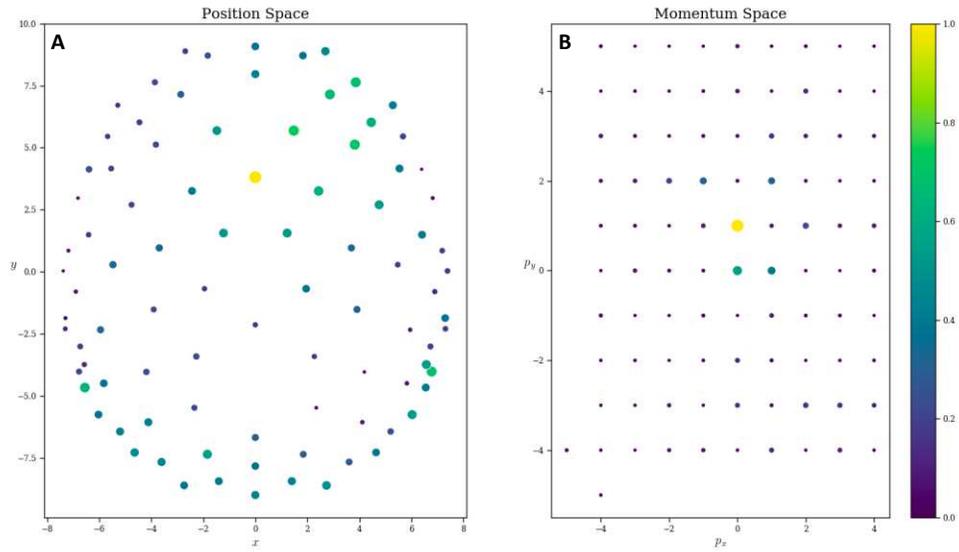
442 momentum probabilities respectively in their own basis. An animation showing how

443 these evolve in time for the different conditions is presented in Supplementary Material

444 2.

445

Probabilities in the Position and Momentum Bases



446

447 *Fig 4 A Probability distribution for a single subject in the position basis. B Momentum basis probability distribution for*  
448 *a single subject. The momentum values used for the Fourier transform are indicated by the point locations. Points are*  
449 *colour- / size-coded to represent the probability value at that location.*

450

451

452 To compute the values reported in Table 2, the corresponding value was found for each

453 subject, and these were used to calculate the group average reported here.

454

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459 Brain, Mind, and Consciousness Program.  
460

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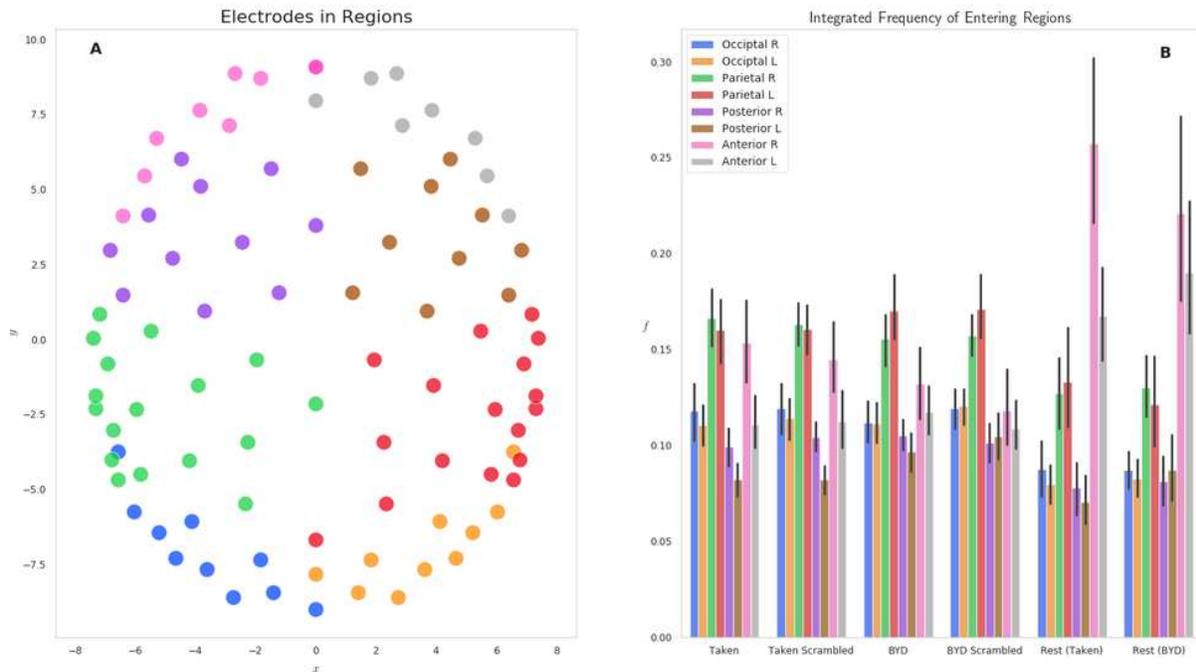
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# Figures

## 8 Brain Regions in EEG Space and Frequency Distribution



**Figure 1**

(A) Electrode locations for each of the 92 electrodes on the Electrical Geodesics Inc. headcap. Electrodes were projected onto a horizontal plane with the nose in the positive y direction. Electrodes have been colour-coded to display the constituent parts of the 8 groups for the frequency analysis, namely, Occipital Left (Blue) / Right (Orange), Parietal Left (Green) / Right (Red), Posterior Left (Purple) / Right (Brown) and Anterior Left (Pink) / Right (Grey). (B) Histograms representing the frequency of entering each region are displayed for the six conditions tested. Significant within stimulus change is present between each of the Anterior Left and Right regions when comparing the pre-stimulus rest and the respective stimulated condition ( $P < 0.001$ , Tukey adjusted.). Error bars display the 1 standard deviation confidence interval.

## Phase Space Centroids

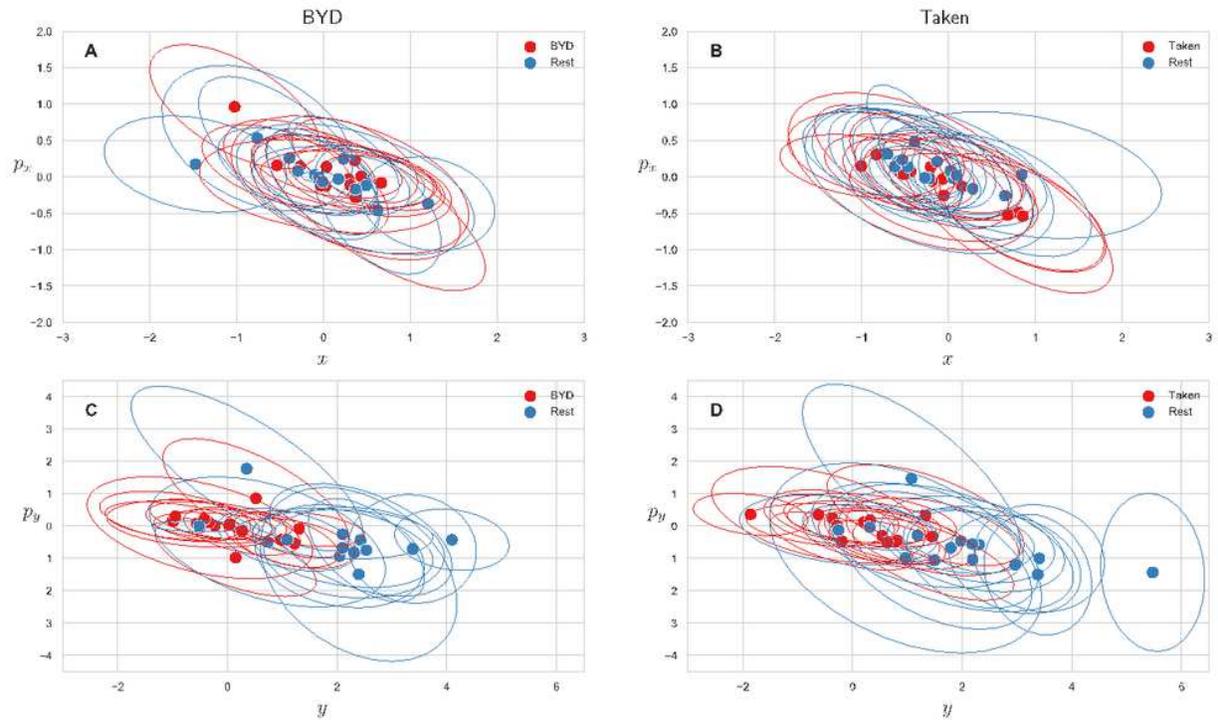
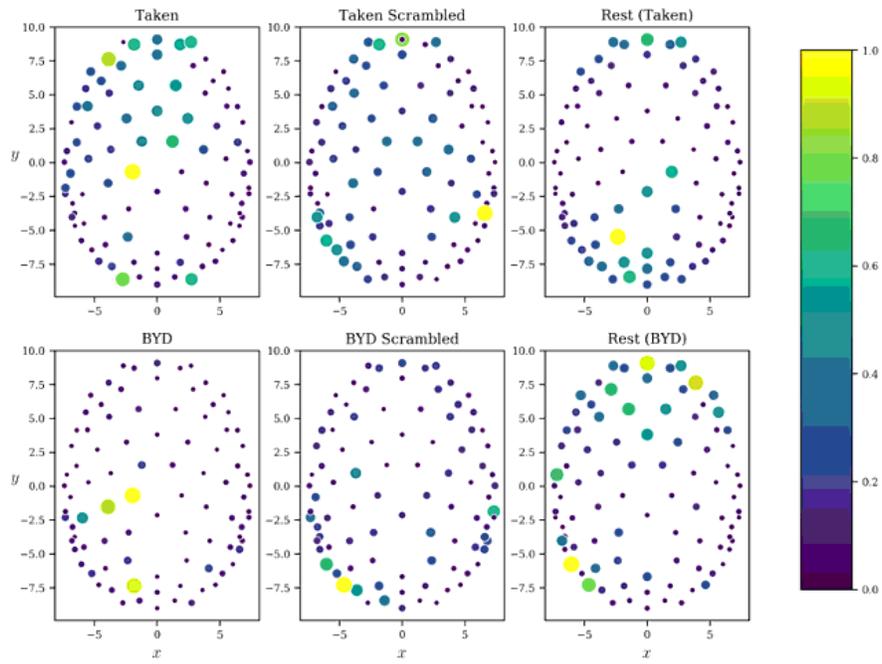
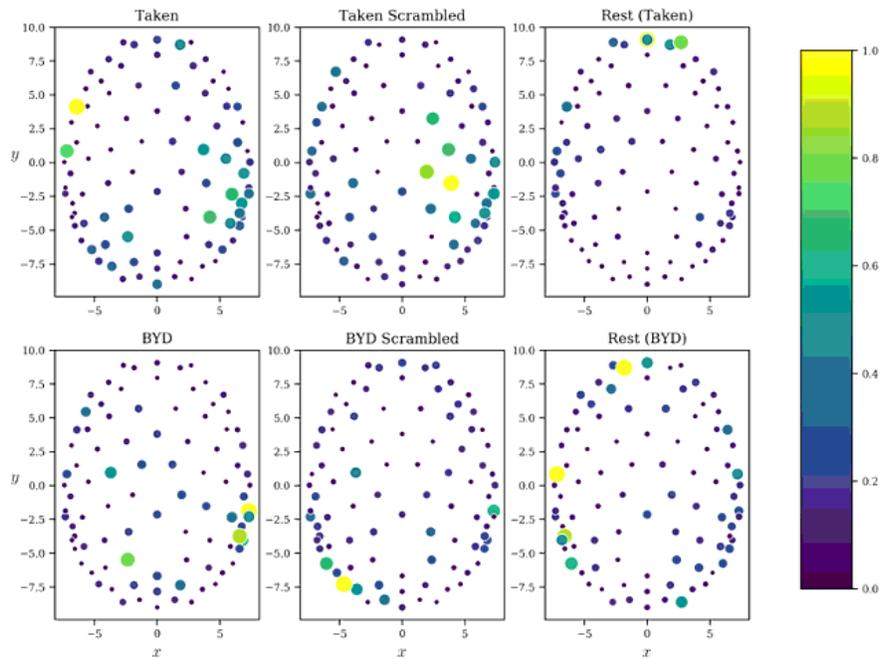


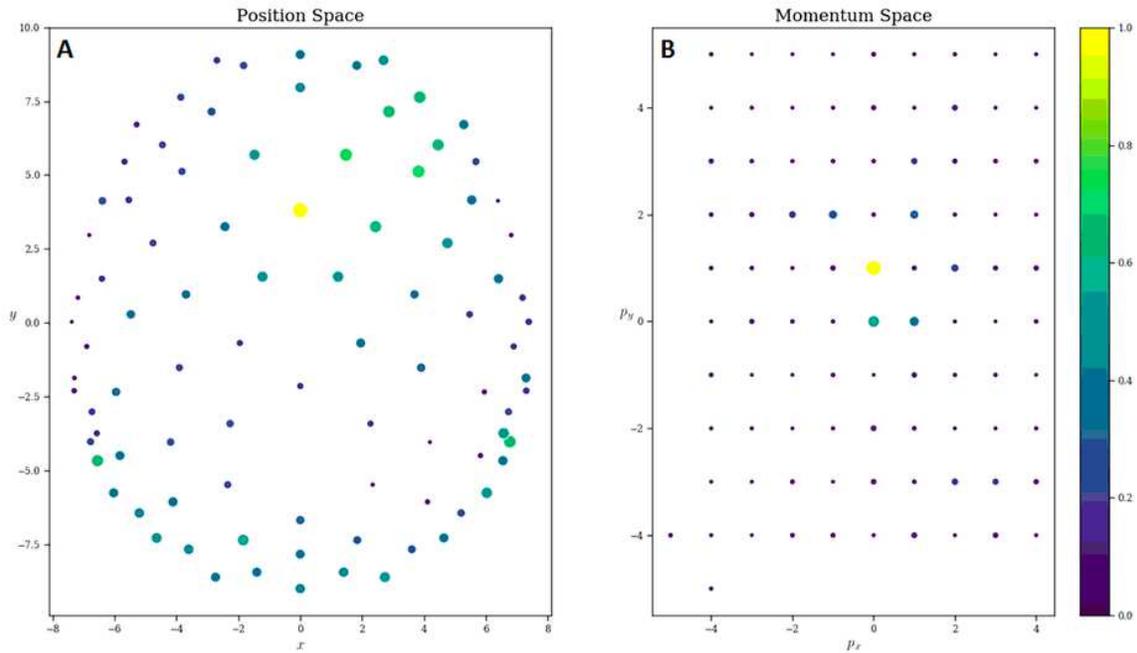
Figure 2

Please see the Manuscript PDF file for the complete figure caption

**A**Probabilities at Least Uncertain Point ( $x$ )**B**Probabilities at Least Uncertain Point ( $y$ )**Figure 3**

Please see the Manuscript PDF file for the complete figure caption

## Probabilities in the Position and Momentum Bases



**Figure 4**

A Probability distribution for a single subject in the position basis. B Momentum basis probability distribution for a single subject. The momentum values used for the Fourier transform are indicated by the point locations. Points are colour- / size-coded to represent the probability value at that location.

## Supplementary Files

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