Capacity for movement is an organisational principle in object representations

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Abstract

The ability to perceive moving objects is crucial for survival and threat identification. The

association between the ability to move and being alive is learned early in childhood, yet not all

moving objects are alive. Natural, non-agentive movement (e.g., clouds, fire) causes confusion in

children and adults under time pressure. Recent neuroimaging evidence has shown that the visual

system processes objects on a spectrum according to their ability to engage in self-propelled, goal-

directed movement. Most prior work has used only moving stimuli that are also animate, so it is

difficult to disentangle the effect of movement from aliveness or animacy in representational

categorisation. In the current study, we investigated the relationship between movement and

aliveness using both behavioural and neural measures. We examined electroencephalographic (EEG)

data recorded while participants viewed static images of moving or non-moving objects that were

either natural or artificial. Participants classified the images according to aliveness, or according to

capacity for movement. Behavioural classification showed two key categorisation biases: moving

natural things were often mistaken to be alive, and often classified as not moving. Movement

explained significant variance in the neural data, during both a classification task and passive

viewing. These results show that capacity for movement is an important dimension in the structure of

human visual object representations.

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Capacity for movement is an organisational principle in object representations

The ability to categorise the world is crucial for efficiently interacting with the constantly changing environment around us, and is vital for survival. Knowing that objects in the same category share properties permits rapid decision-making, such aiding in deciding which animals to approach and which to flee, or determining which plants are edible and which are poisonous. This kind of generalisation is an efficient way to make use of our limited memory capacity and permeates all interactions with the visual world.

The ability to process the world through categories is so essential, it appears to develop early in infancy, even before language (Behl-Chadha, 1996; Quinn, 2004; Quinn et al., 2006). Previous work on categorical knowledge has shown that understanding of biological, or natural categories (Keil, 1987) such as animacy govern our representation of the visual world from early in childhood. Children show 'animistic' tendencies, and often attribute human processes like thinking and feeling to natural moving objects like the sun or clouds, (Piaget, 1929/2013). Based on findings that infants as young as 7 months old can distinguish animate motion (Träuble et al., 2014), some researchers have proposed that learning about animacy early in development is an adaptive system developed through evolution (Aslan & John, 2016). Neuroscience research has supported this idea, showing that animacy is automatically processed both the infant brain (Bayet et al., 2020; Deen et al., 2017), and the adult brain (Bao et al., 2020; Konkle & Caramazza, 2013; Kriegeskorte et al., 2008).

However, more recent research has shown that the structure of object representations in the brain is more complex than a simple binary animacy separation. Visual stimuli may be better represented as a spectrum, according to their similarity to humans (Contini et al., 2020) or their capacity for agency and goal-directed movement (Connolly et al., 2012; Sha et al., 2014; Thorat et al., 2019). Behavioural work has also shown the importance of movement in the conception of aliveness (Poulin-Dubois & Heroux, 1994; Richards & Siegler, 1986; Yorek et al., 2009; Yorek & Narli, 2009). These categories of aliveness and movement are fundamentally related, as most things

82   that are alive can move, yet they are not the same: not all moving objects are alive. In fact, the co-

83   occurrence of movement and aliveness is so common that it is the cause for classification error. In

84   particular, natural movement from things that are not alive (e.g., clouds, fire) causes confusion in

85   children and in adults under time pressure (Goldberg & Thompson-Schill, 2009). Linguistic research

86   suggests that these natural moving things are processed more similarly to other animate entities

87   compared to inanimate tools (Lowder & Gordon, 2015), as it is normal in English to form sentences

88   where inanimate natural forces are attributed agency (e.g., "the wind opened the door" (Wolff et al.,

89   2010)). Investigating items that violate this intuitive association between movement and aliveness

90   can provide insight into how these characteristics are coded by the brain, and help to understand how

91   everyday objects are categorised.

92   The tendency to categorise the natural world has a pervasive influence on the organisation of

93   object representations in the brain and on behaviour. Humans can automatically categorise stimuli,

94   from individual object identity to increasingly abstract conceptual categories within fractions of a

95   second (Cichy et al., 2014; Contini et al., 2017; Mohsenzadeh et al., 2018; Robinson et al., 2019).

96   Categorical distinctions such as animacy can be rapidly and subconsciously processed by the brain

97   (Carlson et al., 2013; Cichy et al., 2014; Connolly et al., 2012; Contini et al., 2017; Grootswagers et

98   al., 2018; Konkle & Caramazza, 2013; Kriegeskorte et al., 2008; Ritchie et al., 2015). Even at rapid

99   presentation rates, and when subjects are completing an unrelated task, there are distinct patterns of

100 brain activity associated with animate and inanimate objects (Grootswagers et al., 2021). An

101 advantage in processing animate stimuli is also revealed in behaviour. Compared to inanimate

102 stimuli, animate stimuli capture and hold attention for longer (Calvillo & Jackson, 2014; Pratt et al.,

103 2010), and are remembered better by both adults (Bonin et al., 2014; Gelin et al., 2017; Nairne et al.,

104 2013, 2017; VanArsdall et al., 2015) and children (Aslan & John, 2016). Animate stimuli are also

105 more frequently detected in both an attentional blink paradigm (Balas & Momsen, 2014), and a

106 change detection task (New et al., 2007). This rapid detection of animates may have been an

107 advantage in evolution, as the ability to monitor the environment for predators and prey increases

108 changes of survival (New et al., 2007). New et al. (2007) found no such detection advantages for

109   vehicles, suggesting that it is not simply the ability to move that captures our attention. However,

110   other work shows that much of the more overt bias towards animals appears to stem from animals'

111   capacity for movement and increased similarity to humans (Balding & Williams, 2016; Tam, 2014;

112   Tam et al., 2013; Yorek et al., 2009). Indeed, the brain processes simple geometric shapes moving in

113   'animate' ways in similar ways to animate stimuli, suggesting that movement is a key element in

114   conception of animacy (Martin & Weisberg, 2003). Clearly, the relationship between movement and

115   aliveness is complex, raising the question of exactly how important movement is in human

116   perception of aliveness and animacy.

117   Associations between movement and aliveness appear early in development. Young children

118   commonly base their judgements of 'aliveness' on whether an object can self-locomote, a trend

119   identified by Piaget (1929/2013) and reaffirmed by later study (e.g., Carey, 1985; Massey & Gelman,

120   1988). Young children report movement as the most important factor in making decisions about

121   whether something is alive or not from ages 4-11 (Carey, 1985; Richards & Siegler, 1986). However,

122   by adulthood capacity for movement is used less often to determine aliveness, overtaken by factors

123   taught in scientific education such as the ability to grow and reproduce (Richards & Siegler, 1986).

124   To investigate the characteristics of this transition from reliance on movement as a heuristic to

125   reliance on scientific knowledge, Goldberg & Thompson-Schill (2009) had university

126   undergraduates and biology professors rapidly classify object words as alive or not alive. Both

127   students and professors classified plants more slowly and less accurately compared to animals.

128   Similarly, items that were natural and able to move (e.g., clouds) were classified more slowly and

129   were more likely to be classified as alive compared to those that were unable to move (e.g., rock), or

130   artificial (e.g., car, mug). The authors suggest this is evidence for an intuitive biological framework

131   developed during childhood that remains present alongside formal education in biology. This

132   intuitive framework seems to be used in complex scientific decision-making across groups of high

133   school students (Coley et al., 2017), and college students (including biology majors; Coley &

134   Tanner, 2015; Nehm & Reilly, 2007; Shtulman & Harrington, 2016; Shtulman & Valcarcel, 2012).

135   This evidence suggests that while associations between movement and aliveness are learned early,

136   and remain throughout the lifespan, they are particularly relied upon under time pressure when

137   access to top-down scientific knowledge is limited.

138   It is clear that movement and aliveness are related, making it difficult to disentangle their

139   relationship in brain and behaviour. In the current study, we investigated the relationship between

140   movement and aliveness in neural categorisation and in behaviour by taking advantage of unusual

141   cases of natural movement that are often misclassified by children and adults under time pressure.

142   We used naturalistic image stimuli, including typical animate and inanimate stimuli as in prior

143   research, and also included natural moving objects (e.g., waves, fire) and plants (e.g., trees, vines).

144   These natural stimuli that violate the association between movement and aliveness allow us to

145   investigate how movement and aliveness are processed in the brain and how this relationship

146   manifests in behaviour. To investigate how movement, aliveness and naturalness affected

147   classifications of images, we ran an online experiment (Experiment 1) where participants had

148   unlimited time to categorise images by one of these three dimensions. In Experiments 2 and 3, we

149   gathered electroencephalography (EEG) data obtained while participants completed the same

150   categorisation task, but under time pressure. For the first EEG experiment, participants classified

151   images according to whether they were alive or not, and for the second, participants classified

152   images by whether they could move or not. To determine whether representations were task-

153   dependent, we also collected EEG data from when participants were viewing but not actively

154   classifying the same images. Using multi-variate pattern analysis techniques, we examined

155   similarities and differences in the temporal dynamics of visual processing and decision-making based

156   on a stimulus' capacity for movement, and whether it is alive or not. These methods were used to

157   examine if, and when, movement (including natural, non-agentive movement such as from fire, or

158   waterfalls) is represented in the brain, and whether this is dependent on the categorisation task being

159   completed. We find that capacity for movement explained significant variance in the EEG data,

160   during both passive viewing of stimuli and when classifying them. The findings suggest that

161   movement is an important organisational principle for object representation in the brain.

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Methods

165   This section reports three experiments: one behavioural study (Experiment 1, unlimited response

166   time), and two EEG studies (Experiments 2 and 3, time-pressured responding). All experiments used

167   the same stimuli. Stimuli, analysis scripts, results and anonymised raw EEG data are publicly

168   available at https://osf.io/jxhcs/ (Experiment 1), https://doi:10.18112/openneuro.ds003885.v1.0.0

169   (Experiment 2) and https://doi:10.18112/openneuro.ds003887.v1.0.0 (Experiment 3). This study was

170   not preregistered.

171

172   **Stimuli**

173   Stimuli were 400 realistic colour images collected from free online image databases

174   (www.pixabay.com, www.pexels.com) under Creative Commons 0 licenses (free to use and

175   distribute without credit) and were used in all three experiments. All text in images (e.g., brand

176   names on cars) was blurred manually using GIMP (v2.10.14, 2020), then each image was cropped

177   and resized to 256 by 256 pixels. Stimuli were gathered in six superordinate categories based on

178   those in Goldberg & Thompson-Schill (2009): animals, plants, still artificial things, still natural

179   things, moving artificial things, and moving natural things (shown in Figure 1A). For animals and

180   plants, there were 10 object categories. For all other superordinate categories, there were five object

181   categories. The extra plant and animal categories were included to ensure there was an equal number

182   of images that were alive and not alive, as well as equal numbers of moving and still images. Within

183   each category (e.g., cat, bench), there were 10 different images (e.g., cat1, cat2, … cat10). There

184   were 400 images in total, each classified according to aliveness (200 living and 200 non-living),

185   movement (200 moving and 200 still), and naturalness (300 natural and 100 artificial). For objects

186   that are able to move, the stimulus was shown in motion in the image (e.g., birds and helicopters

187   shown flying, see Figure 1A).

188

189   **Experiment 1: Online behavioural**

190   To investigate how people categorise objects in terms of aliveness, movement and naturalness, and

191   validate the stimulus set, we ran an online experiment using Amazon's Mechanical Turk platform,

192   guided by Grootswagers (2020), programmed using jsPsych (de Leeuw, 2015) and hosted on

193   Pavlovia (Peirce et al., 2019, https://www.pavlovia.org/).

194

195   ***Participants and methods***

196   Mechanical Turk (MTurk) workers were recruited from the U.S.A. and Canada to complete the 15-

197   minute experiment in return for cash payment. Participants were randomly allocated to answer one of

198   three questions about each of the 400 stimuli: (1) "Is the thing in the image alive, or not alive?", (2)

199   "Can the thing in the image move, or is it still?", or (3) "Is the thing in the image naturally occurring

200   or man-made?" Data was gathered from 50 participants for each question. Participants were shown

201   one image at a time and instructed to press the 'F' and 'J' keys on their keyboard to indicate their

202   response to the question for that image. The instructions stated that participants should "try to be fast

203   and accurate." Each image appeared after a 500ms fixation cross and remained on the screen until

204   participants responded (Figure 1B).

205

206   ***Analysis***

207   To ensure we were only using data where participants were completing the task properly, we

208   removed seven subjects whose overall accuracy (based on expected classification) was less than

209   50%. We also removed 15 participants who responded in less than 100ms on more than 25% of

210   images, as participants are unlikely to be making valid responses in such a short time period. After

211   these exclusions, there were 42 participants that classified by aliveness, 48 participants that classified

212   by movement capacity, and 38 participants that classified by naturalness. For these remaining

213   participants, any trial that had a reaction time more than 3 standard deviations above the mean or less

214   than 100ms was also removed. Median reaction time per stimulus was calculated based on all

215   remaining trials.

216

217   **Experiments 2 and 3: EEG**

218   To investigate how aliveness and movement are represented in the brain, we recorded

219   electroencephalography (EEG) while participants were completing the same task as the behavioural

220   experiment above, but under time pressure. We conducted two EEG experiments consisting of a

221   categorisation task in which participants classified images, and passive viewing, in which

222   participants viewed stimuli in rapid streams. The structure of both experiments was identical,

223   including the passive viewing blocks. The only difference was the categorisation task. In Experiment

224   2, participants classified images based on "whether they are alive or not". In Experiment 3,

225   participants classified images based on "whether they can move or not". Different participants

226   completed each experiment. Unless stated otherwise, the description of the methods below applies to

227   both EEG experiments.

228

229   *Participants*

230   In Experiment 2, 24 undergraduate psychology students (15 females, 9 males) at the University of

231   Sydney, Australia, participated in exchange for course credit. The mean age was 19.58 (range 18-

232   26), and all but one were right-handed. In Experiment 3, 24 undergraduate psychology students (16

233   females, 7 males, one non-binary person) at the University of Sydney participated for course credit.

234   The mean age was 19.71 (range 18-26), and all but one were right-handed. All participants in both

235   experiments had normal or corrected-to-normal vision, were neurologically healthy, and were not

236   colour-blind. Informed written and oral consent was obtained from all participants prior to

237   participation. The study was approved by the University of Sydney Ethics Committee.

238

239   *Apparatus*

240   Images were shown in the centre of a 1920x1080 pixel Asus gaming monitor with a refresh rate of

241   60Hz. Participants responded using the two outermost buttons on a four-button button box produced

242   by The Black Box ToolKit Ltd (layout as shown in Figure 1C, 1D). They were seated approximately

243   55cm away from the screen and stimuli subtended approximately 5° of visual angle. EEG was

244 recorded at 1000Hz on a 128 channel BrainVision ActiCap system (Brain Products GmbH), with

245 electrodes located in positions consistent with the 10-5 extension of the 10-20 system (Oostenveld &

246 Praamstra, 2001). Data were recorded with an online reference of FCz.

247

248 ***Procedure***

249 Participants in both experiments completed 8 blocks of trials, alternating between passive viewing (4

250 blocks) and the categorisation task (4 blocks) and always beginning with passive viewing.

251

252 **Categorisation task.** To see how focusing on aliveness and movement affected neural

253 processing, participants completed a categorisation task (Figure 1D). Each trial consisted of a

254 fixation cross for a random duration between 500ms and 1000ms, followed by an image in the centre

255 of the screen for 100ms. Participants had 1000ms from stimulus offset to respond on the button box.

256 For Experiment 2, participants decided whether the image was alive or not alive. For Experiment 3,

257 participants decided whether the stimulus could move or not. The response mapping changed over

258 each block, such that the side of the button corresponding to 'alive' or 'able to move' switched

259 between left and right every block, and the order of the mapping was counterbalanced across

260 participants. When a participant responded, the fixation spot filled in to indicate that a response had

261 been recorded (Figure 1D). If there was no response in this time, the screen displayed "Too late!",

262 and advanced to the next trial. For each of the four categorisation blocks, trials (single image

263 presentation and response, as described above) were chunked into 10 sequences. One sequence

264 contained 40 trials, so that each sequence contained one image from each category (e.g., one dog,

265 one fire). Thus, across the 10 sequences in each block, all 400 images were shown. Each sequence

266 lasted approximately 1-2 minutes, and participants were told to take a break between sequences and

267 advance at their own pace.

268

269 **Passive viewing.** To provide a task-independent visual representation of each stimulus,

270 participants viewed a series of rapid presentation sequences (Figure 1C). In each of the four passive

271   viewing blocks, participants were shown three repetitions of each image during passive viewing

272   sequences, equating to 12 total repetitions of each stimulus across the experiment. These were split

273   into 15 short sequences of 80 images each (~12 seconds each), to minimise fatigue and eye blinks.

274   All 400 images were displayed in the first five sequences, then shuffled and repeated over the next

275   five, and shuffled and repeated over the final five sequences. This ordering ensured that no image

276   appeared twice in the same sequence, and that images were distributed within each block.

277   Participants were instructed to press a button as quickly as possible whenever they saw the

278   fixation spot (a bullseye, two concentric black circles, shown in Figure 1) change colour to red. The

279   concentric circles of the bullseye were used to ensure there was sufficient contrast with all stimuli to

280   distinguish colour changes. This task ensured that participants maintained a central fixation and paid

281   sufficient attention to the screen but were not explicitly focused on the semantic properties or

282   categories of the images. There were two to four randomly located colour changes in the middle 60

283   presentations of each sequence of 80 images.

284

Figure 1.

Experimental paradigm for all three experiments: Experiment 1 online, and Experiments 2 and 3 with EEG. Sample stimuli are shown in (A). For the online experiment shown in (B), participants classified images by either aliveness, capacity for movement, or naturalness. During passive viewing trials of both EEG experiments in (C), participants viewed a rapid stream of images and responded to the fixation spot changing to red by pressing a button "as quickly as possible". During categorisation trials for both EEG experiments in (D), participants rapidly categorised images. In EEG Experiment 2, participants responded based on whether each image depicted something that was alive or not alive. In EEG Experiment 3, participants responded based on whether each image showed something that could move or could not move. Note that all images are magnified here for clarity; for presentation they occupied a smaller proportion of the screen.
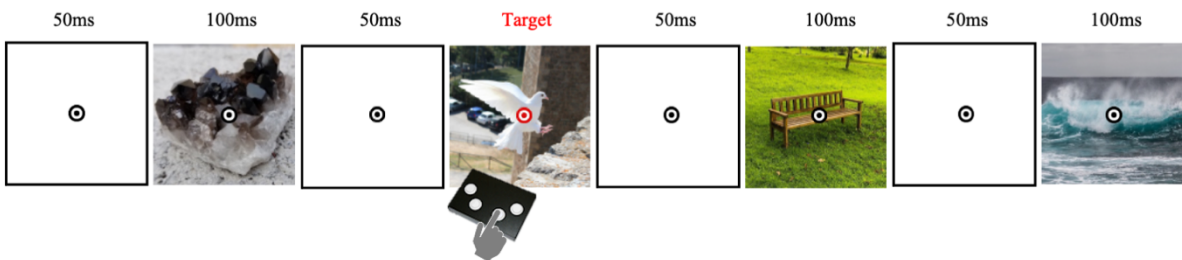
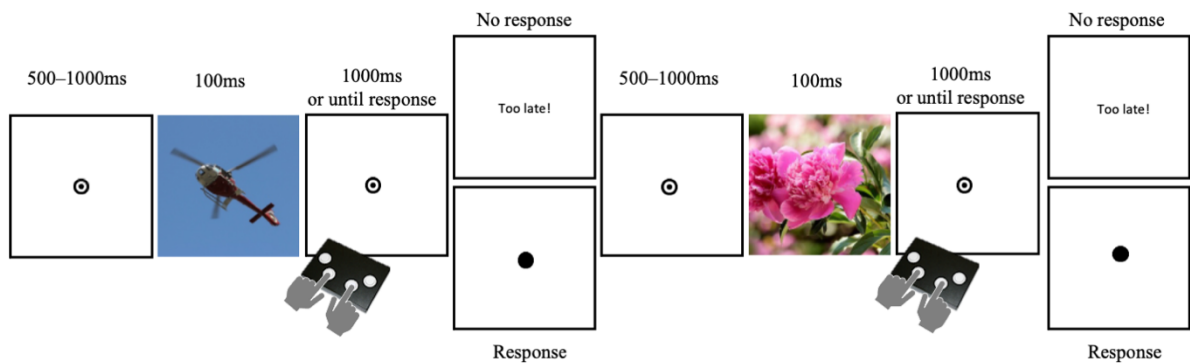**(A) Sample stimuli**
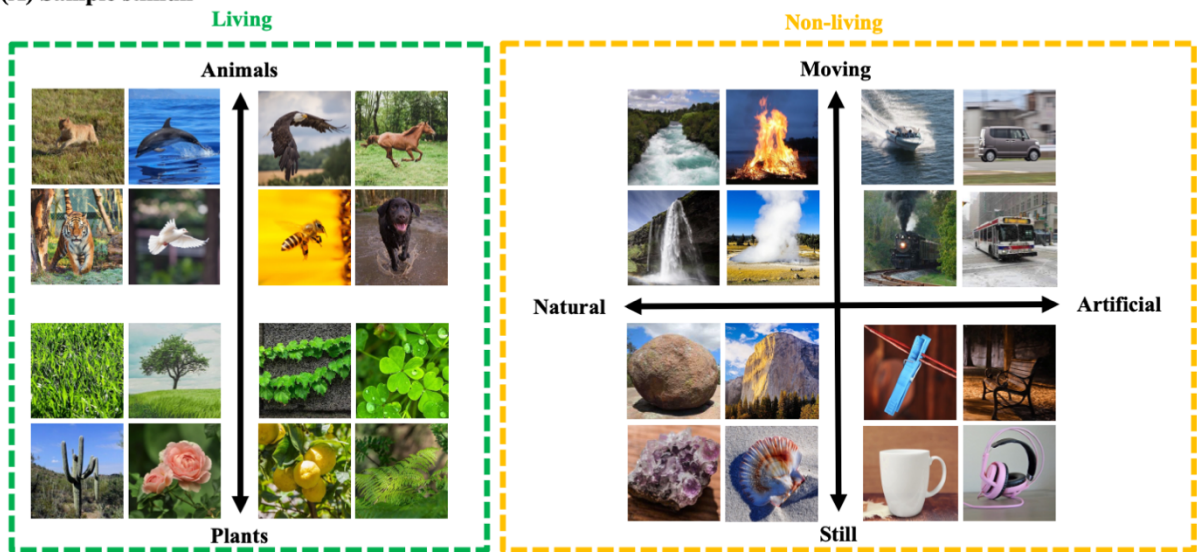
(B) Experiment 1: online (alive/not alive, moves/still, natural/artificial)
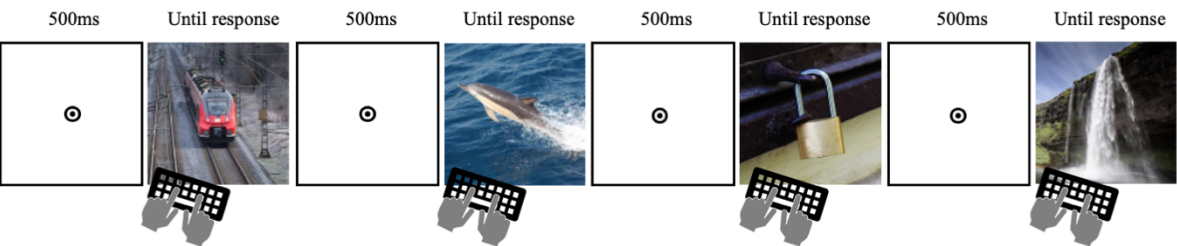
(C) Experiments 2 and 3: EEG (passive viewing)

(D) Experiment 2: EEG (alive/not alive) and Experiment 3: EEG (moves/still)

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288   *Data Analysis*

289   **EEG preprocessing.** As in prior work, we used a minimal pre-processing pipeline

290   (Grootswagers et al., 2021; Grootswagers, Robinson, & Carlson, 2019; Grootswagers, Robinson,

291   Shatek, et al., 2019; Robinson et al., 2019; Shatek et al., 2019). Using custom scripts for EEGLab

292   (Delorme & Makeig, 2004) in MATLAB (The MathWorks Inc., version 2020a), data were re-

293   referenced to an average reference, low pass filtered at 100Hz, high pass filtered at 0.1Hz, then

294   down-sampled to 250Hz. Epochs of data were created from 300ms before each stimulus appeared on

295   the screen to 1000ms after stimulus onset.

296

297   **Decoding image category.** To investigate how the different object categories are represented

298   in the brain, we used multivariate decoding applied to the EEG data in response to each image. All

299   decoding analyses were run in MATLAB using functions from the CoSMoMVPA toolbox

300   (Oosterhof et al., 2016), using all 128 channels from each participant. To test if individual images

301   (e.g., tree1, cat1), objects (e.g., tree, cat) and categories (e.g., plant, animal) were distinguishable

302   from the EEG recording, we conducted pairwise decoding analyses. All analyses were conducted

303   timepoint by timepoint relative to when each image was displayed. At the individual image level

304   (e.g., tree1, cat1), we trained a Linear Discriminant Analysis (LDA) classifier on each pair of images

305   from all but one block and tested on those same images from the left-out block. This was repeated

306   over all pairs of images, for each block as the test data. Separate analyses were conducted for

307   categorisation and passive viewing.

308   At the category (e.g., tree, cat) and super-ordinate level (e.g., plant, animal), we conducted a

309   similar pairwise analysis still leaving two images out to test on, but also excluded these two images

310   from the training set. For example, to compare tree and cat at the category level, a classifier was

311   trained on blocks 1-3 using all trees and cats except tree1 and cat1 (i.e., train on cats/trees 2-10). This

312   classifier was then tested on the remaining image (tree1, cat1) trials from block 4. This process was

313   repeated so each pair of images was left out in each block.

314

315   **Representational Similarity Analysis.** To investigate how neural activity was related to

316 behavioural classifications of the stimuli, we used Representational Similarity Analysis (RSA) to

317 generate models of categorical and visual attributes of the images, as well as similarity in neural

318 representations (Kriegeskorte et al., 2008). Behavioural models were generated from responses of

319 online participants by averaging the percentage of responses towards the affirmative decision ('alive'

320 or 'moves') for each image and calculating the Euclidean distance between each pair of images. This

321 400 x 400 matrix was then averaged over all images within a category to create a 40 x 40

322 Representational Dissimilarity Matrix (RDM).

323   We also computed RDMs for low-level visual features, including a model for colour based on

324 MATLAB's image processing toolbox (The MathWorks Inc., version 2020a) in CIE colour-space

325 (cielab) and a greyscale model. To control for rectilinear biases in animacy, we also included a

326 measure of rectilinearity from Nasr et al. (2014), calculated using publicly available code from

327 [https://github.com/cechava/Rectilinearity_Toolbox]. These models were calculated on an image-

328 level basis; a 400 x 400 model was formed by calculating the Euclidean distance between each pair

329 of images, then averaged across category to form a 40 x 40 model.

330   To calculate RDMs for the neural data, we used an LDA classifier at every time point to

331 compute decoding accuracy for each pair of categories (e.g., cats vs rocks), resulting in a 40x40

332 neural dissimilarity matrix for each time point. This classifier used the same partitioning structure as

333 category decoding above, in which each pair of images was left out as the testing set for each block

334 and for each pair of categories. Separate RDMs were created for passive viewing and categorisation

335 trials.

336

337   **Linear modelling.** To investigate how categories of aliveness, movement and naturalness

338 account for neural responses to objects, we used linear modelling. A generalised linear model was

339 run at each time point, including all of the conceptual models based on the online behavioural data

340 from Experiment 1 (aliveness, movement, naturalness), as well as the low-level visual models

341 (colour, greyscale, rectilinearity) described above, with the neural RDMs as the outcome variable.

342   This was completed separately for each participant, for the categorisation trials and passive viewing

343   trials, then the beta values were averaged across all participants for each time point.

344   Prior research has indicated that animate stimuli have distinct patterns of neural activity, and

345   that these differences can be attributed at least to some extent to low- and mid-level visual features

346   (Grootswagers, Robinson, Shatek, et al., 2019; Long et al., 2018). To ensure that the visual

347   characteristics included in our linear model were sufficient to control for these features, we ran an

348   additional GLM including the neural RDM from the same time point of the passive viewing trials,

349   and a binary model of animacy (animals coded as 1, all other categories coded as 0). The passive

350   viewing blocks provided an ideal visual control for the categorisation task, as these are recorded

351   without task-related judgements, using the exact same images, presented for the same period of time.

352   A model of animacy was also included, as this is the dominant model in the literature, and has been

353   shown to outperform 'living' classifications (Contini et al., 2020).

354   To ensure that multicollinearity was sufficiently low to interpret the output of the model, we

355   calculated the variance inflation factors for each model based on a downloaded MATLAB function

356   (Vasilaky, 2021). A measure of multicollinearity, the variance inflation factor indicates the impact

357   on the variance of the model of adding a particular variable, compared to if it were independent to all

358   the other variables (Montgomery et al., 2012). A variance inflation factor of 1 would indicate that the

359   variable is independent from the other elements in the model, with lower factors indicating fewer

360   potential issues with multicollinearity (Thompson et al., 2017).

361

362   ***Statistical analysis***

363   We used Bayesian inference to examine differences in accuracy and reaction time across stimulus

364   categories.

365   For all comparisons, we used the BayesFactor package in R (Morey et al., 2018). Following

366   recommendations in Teichmann et al. (2021), we used a JZS prior (Rouder et al., 2009) with a scale

367   factor of 0.707. This is the default prior and scaling in the BayesFactor package because it makes

368 minimal assumptions about the expected effect size, and serves as a "non-informative default"

369 (Rouder et al., 2009, p. 232).

370   To calculate behavioural statistics for the differences between animals and plants, we used

371 the Bayesian equivalent of t-tests (Rouder et al., 2009). We also used Bayesian linear models to

372 determine if naturalness and capacity for movement influenced reaction times or accuracy. Models

373 were built to express all combinations of each variable, in addition to participant ID. To determine

374 whether naturalness and movement had an effect on reaction times and accuracy, we compared an

375 additive model (movement + naturalness + subject ID) to a model without each variable in turn (for

376 movement, naturalness + subject ID). A larger Bayes Factor would indicate that the inclusion of that

377 variable makes a model that is more likely given the data (Rouder et al., 2012). This can be

378 interpreted similarly to the main effect in a traditional ANOVA.

379   For decoding analyses, we used a series of t-tests using the ttestBF function (Morey et al.,

380 2018) from the BayesFactor package with the parameters described above. The alternate hypothesis

381 is that the decoding is above chance (50%), and the null-interval was effect sizes from negative

382 infinity up to 0.5, as effect sizes during baseline periods prior to stimulus onset from previous work

383 have shown this to be most appropriate (Teichmann et al., 2021). This formed a one-sided hypothesis

384 that the effect size for alternate hypothesis should be positive. For linear modelling, in which both

385 negative and positive results are meaningful, we used the same procedure with the alternative

386 hypothesis that the betas are different to zero, with a two-sided prior from -0.5 to 0.5.

387   Bayes Factors are interpreted according to Jeffreys (1961/1998), where Bayes Factors larger

388 than 30 are very strong evidence for the alternate hypothesis, Bayes Factors larger than 10 are strong

389 evidence for the alternate hypothesis, Bayes Factors larger than 3 provide some evidence for the

390 alternate hypothesis, and Bayes Factors smaller than 1/3 provide evidence for the null hypothesis.

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393   **Results**

394   To investigate how aliveness and movement are processed by the brain, we looked at behavioural

395   and neural measures across three experiments. In the online experiment (Experiment 1), participants

396   had unlimited time to classify images according to aliveness, movement or naturalness. In the two

397   EEG experiments, participants rapidly classified images according to aliveness (Experiment 2) or

398   capacity for movement (Experiment 3).

399

400   **Behavioural: Categorisation task**

401   To examine the relationship between movement and aliveness in categorisation of naturalistic image

402   stimuli, we used behavioural metrics (reaction time, classification accuracy) and multivariate pattern

403   analysis of neural data. Here we report the results of the online experiment and both EEG

404   experiments together, so that results can be compared across tasks.

405   Overall, for the EEG experiments, the time pressure was effective in encouraging rapid

406   responding while allowing a large number of trials. There were very few trials in which participants

407   did not respond before the time out: only approximately 1% of trials were missed on average (~16 of

408   1600 trials per participant) for both experiments. Though some participants had low 'accuracy'

409   scores, these always arose from consistent classification in the opposite direction from what was

410   predicted (e.g., consistently responding that plants were not alive in Experiment 2, or consistently

411   responding that moving natural stimuli did not move in Experiment 3).

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430 **Table 1**
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432 *Bayes Factors for analyses of accuracy and reaction times for the aliveness and movement*
433 *classification tasks. First, objects that were alive were assessed (top) to determine the differences*
434 *between animals and plants, calculated using Bayesian t-tests. Next, we analysed images of objects*
435 *that are not alive (moving natural, moving artefact, still natural, still artefact). Linear modelling was*
436 *applied to assess the effect of naturalness and movement dimensions in the images.*
437

| Analysis	Aliveness task		Movement task	
	EEG	Online	EEG	Online
Alive (t-tests, plants vs animals)				
Accuracy	16.66**	7.51*	0.68	397.51***
Reaction time	1.09	1.3×10^{-3}	3.17	550.55***
Not alive (linear modelling)				
Naturalness				
Accuracy	184.70***	873.54***	66.50***	2.29×10^4 ***
Reaction time	3757.79***	1.31×10^6 ***	0.92	1.28×10^4 ***
Movement				
Accuracy	132.28***	0.87	1815.09***	3.29
Reaction time	667.90***	0.17	0.29	0.25
Interaction Terms				
Accuracy	1.07	0.87	168.70***	8.77
Reaction time	1.79	0.49	2.98	6.60

438 * Bayes Factors greater than 3 indicate some evidence for the alternate hypothesis
439 ** Bayes Factors greater than 10 indicate strong evidence for the alternate hypothesis
440 ***Bayes Factors greater than 30 indicate very strong evidence for the alternate hypothesis
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Figure 2.

Median response times and classifications of stimuli from online and EEG experiments. Data from participants considering whether the stimulus was alive or not is shown in the left column (A, C) and data from classifying images by capacity for movement are shown in the right column (B, D). Participants in the EEG experiments (bottom row) were under time pressure to respond quickly, whereas in the online experiment (top row) there was no time pressure.
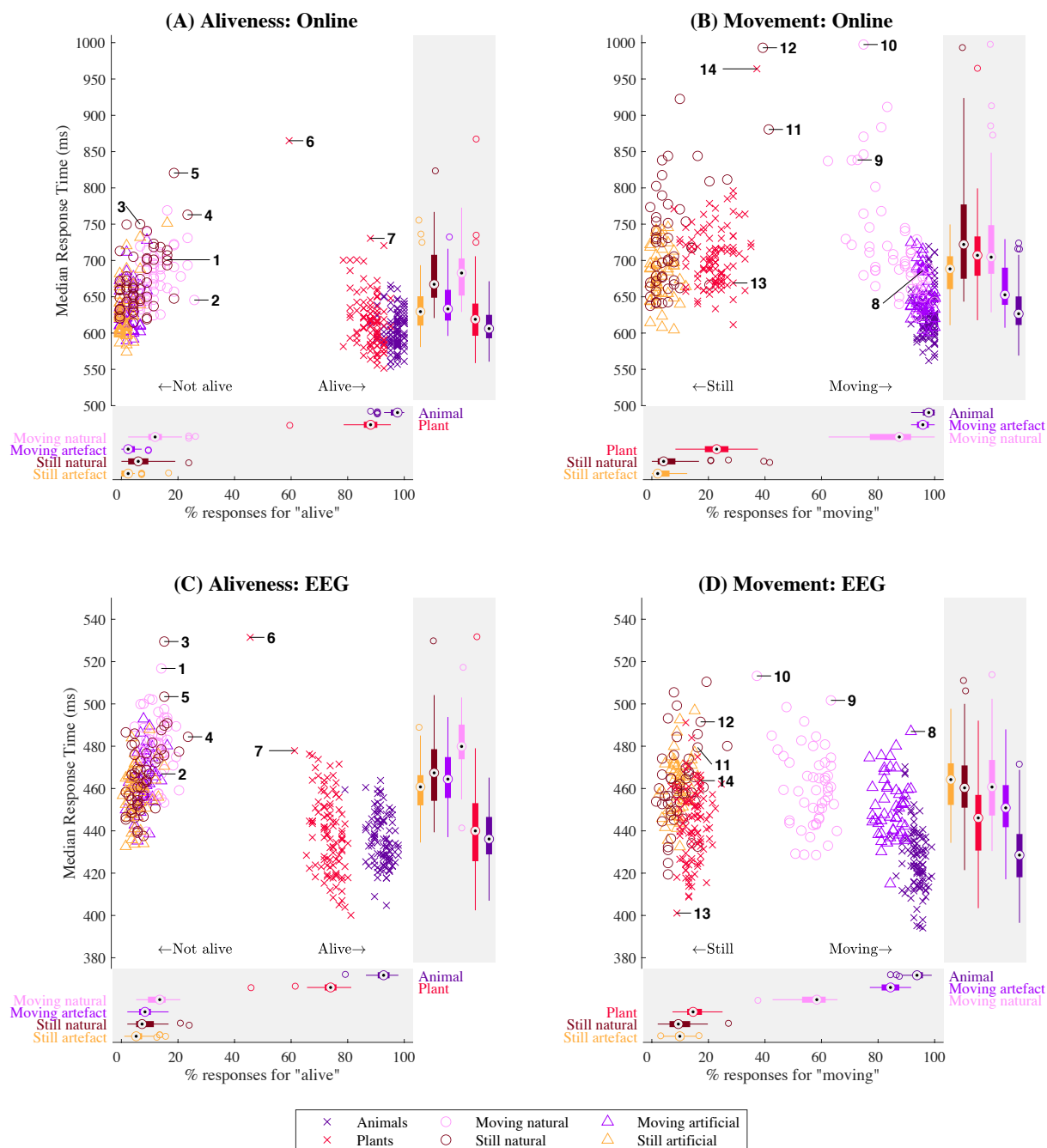
445   *Classifying by aliveness*

446   We were interested in how image category influenced how participants categorised images

447   according to whether they were alive or not in Experiments 1 and 2. First, we assessed performance

448   for the alive images, which consisted of animals and plants, as previous work has shown that animals

449   are considered 'more alive' than plants (Yorek et al., 2009). Bayesian t-tests were used to evaluate

450   whether there were significant differences in reaction time and classification between plants and

451   animals (Table 1, top). For both online Experiment 1 and EEG Experiment 2, there were no

452   differences in reaction time between plants and animals. However, there was strong evidence that

453   plants were mistaken as "not alive" more often than animals for EEG participants (Figure 2C), and

454   some evidence in the same direction for online participants (Figure 2A). This suggests that plants are

455   considered 'less alive' compared to animals, and this difference is particularly evident when

456   participants are under time pressure.

457   For the stimuli that are not alive, we used Bayesian linear modelling to investigate how

458   moving and natural stimuli influenced aliveness judgements compared with still and artificial stimuli

459   (Table 1, bottom). In both online Experiment 1(Figure 2A) and EEG Experiment 2(Figure 2C),

460   natural stimuli were mistakenly classified as alive more often and more quickly than artificial

461   stimuli. This is somewhat expected, given that all of the stimuli that are alive are also natural.

462   Capacity for movement also influenced responding, but only for the time-pressured EEG experiment.

463   For EEG participants (Figure 2C), non-living moving stimuli were classified as alive more often and

464   more slowly compared to still stimuli. However, for participants with unlimited time in the online

465   experiment (Figure 2A), there were no differences in responding between moving and still stimuli.

466   These results are in line with use of intuitive biological knowledge under time pressure, mistaking

467   moving and natural stimuli for being alive.

468

469   *Classifying by movement*

470   We were also interested in how image category influenced movement classification in

471   Experiments 1 and 3. For plants and animals, the presence of time pressure was important. In the

472   EEG experiment (Figure 2D), there were no differences in time or accuracy in classifying plants and

473   animals as moving or non-moving (Table 1, top). However, when participants had unlimited time to

474   make a decision in the online experiment, animals were classified as moving more often than plants

475   were classified as still. In the online experiment, participants also classified animals more quickly

476   than plants. Together these findings suggest that without time pressure, people were much better at

477   classifying animals as moving than plants as non-moving.

478   For non-living stimuli, we investigated the impact of capacity for movement and naturalness

479   on movement classification using the Bayesian equivalent of an ANOVA. For both online and EEG

480   experiments, natural stimuli were classified more slowly and less accurately (Table 2, bottom). For

481   the EEG experiment, moving stimuli were also classified less accurately. Crucially, there was a

482   significant interaction effect in the EEG experiment, suggesting that stimuli that are both moving and

483   natural were responded to less accurately. This difference is clear in Figure 2D (pale pink circles),

484   showing the low agreement across participants on whether these natural moving stimuli are moving

485   or not.

486

487   **EEG (Experiments 2 and 3): passive viewing**

488   In the passive viewing task, participants performed an orthogonal fixation change task. Behavioural

489   performance on the passive viewing blocks of both EEG experiments indicated that participants were

490   engaged with the task. Participants correctly identified the target colour change within 600ms on

491   93.77% of occurrences for Experiment 2 (SE = 0.93, range 79.07% - 100%) and on 95.76% of

492   occurrences for Experiment 3 (SE = 0.54, range 88.04%- 98.89%).

493

494   **EEG (Experiments 2 and 3): Decoding image category**

495   We were interested in the temporal dynamics of visual information processing in the brain, from

496   low-level image identity to general object representations, to category level representations. To test if

497   individual images (e.g., tree1, cat1), objects (e.g., tree, cat) and categories (e.g., plant, animal) were

498   distinguishable from the EEG recording, we used a linear discriminant classifier to classify stimuli at

499   these three levels. Neural responses contained information about image identity (e.g. dog1), object

500   identity (e.g. dog) and superordinate classification (e.g. animal) from 90-120 milliseconds after

501   stimulus onset, characteristic of early stage visual processing (Carlson et al., 2013; Cichy et al.,

502   2014). Both when participants were passively viewing images and when they were classifying them,

503   information about stimulus identity remained present for more than 400ms after stimulus offset. This

504   is in line with prior work demonstrating enduring neural representation after stimulus offset in rapid

505   serial visual presentation sequences (Grootswagers, Robinson, & Carlson, 2019; Mohsenzadeh et al.,

506   2018; Robinson et al., 2019).

507   In both EEG experiments, participants completed the same passive viewing task (Figure 3B,

508   D, E). At all levels of classification, neural data revealed similar information was present over time

509   for the passive trials in both experiments. This similarity indicates that there are unlikely to be major

510   differences in data quality between the two experiments, suggesting that differences in time course of

511   neural processing in the categorisation task are more likely to be task-related.

512

Figure 3.

Decoding stimulus identity. Plots show pairwise decoding accuracy from an LDA classifier over time for image-level (A, B), category-level (C, D) and superordinate-level (E, F) classification. The dashed line at 0.5 indicates chance decoding. Blue lines show data from Experiment 2 (aliveness task) and green lines show data from Experiment 3 (movement task). Shaded areas indicate standard error across subjects (N=24 for each experiment). Bayes Factors (BF) above 30 (very strong evidence) are shown in the filled coloured dots, BF between 10 and 30 (strong evidence) are shown as unfilled coloured dots, BF between 1/3 and 10 are shown in grey, and BF below 1/3 (evidence for the null) are shown in black. Red dots indicate very strong evidence for a difference between the two experiments (BF>30). For passive viewing blocks (B, D, F) the task was the same across both experiments. For categorisation trials (A, C, E) participants classified stimuli by aliveness in Experiment 2 (blue) and by capacity for movement in Experiment 3 (green).
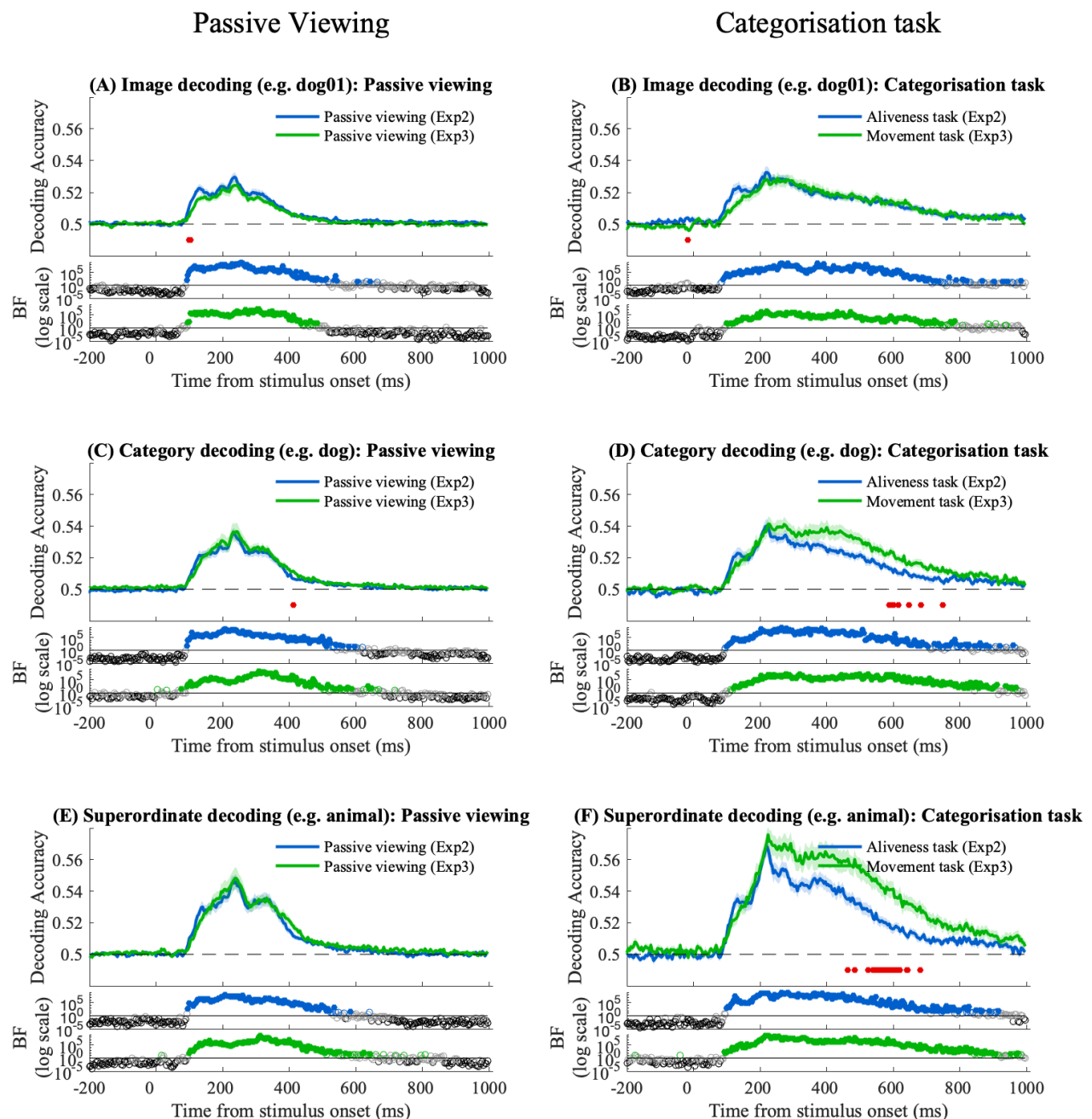
515   **Figure 4.**

Linear modelling of data from both EEG experiments shows that the movement model explains a significant proportion of brain activity during the categorisation task and passive viewing. Panels A-D show beta estimates over each time point for the first linear model, combining theoretical models of aliveness (A/B), movement (C/D) and naturalness, and image-level models (greyscale, colour, rectilinearity). Panel E shows beta estimates for movement from a second linear model, which included the behavioural and image-level models as in the first, as well as a model of animacy and the passive viewing RDM from the corresponding time point. Shaded regions show standard error across subjects (N=24 for each experiment). Bayes Factors (BF) above 30 (very strong evidence) are shown in the filled coloured dots, BF between 10 and 30 (strong evidence) are shown as unfilled coloured dots, BF between 1/3 and 10 are shown in grey, and BF below 1/3 (evidence for the null) are shown in black. Red dots indicate very strong evidence for a difference between the two experiments (BF>30).
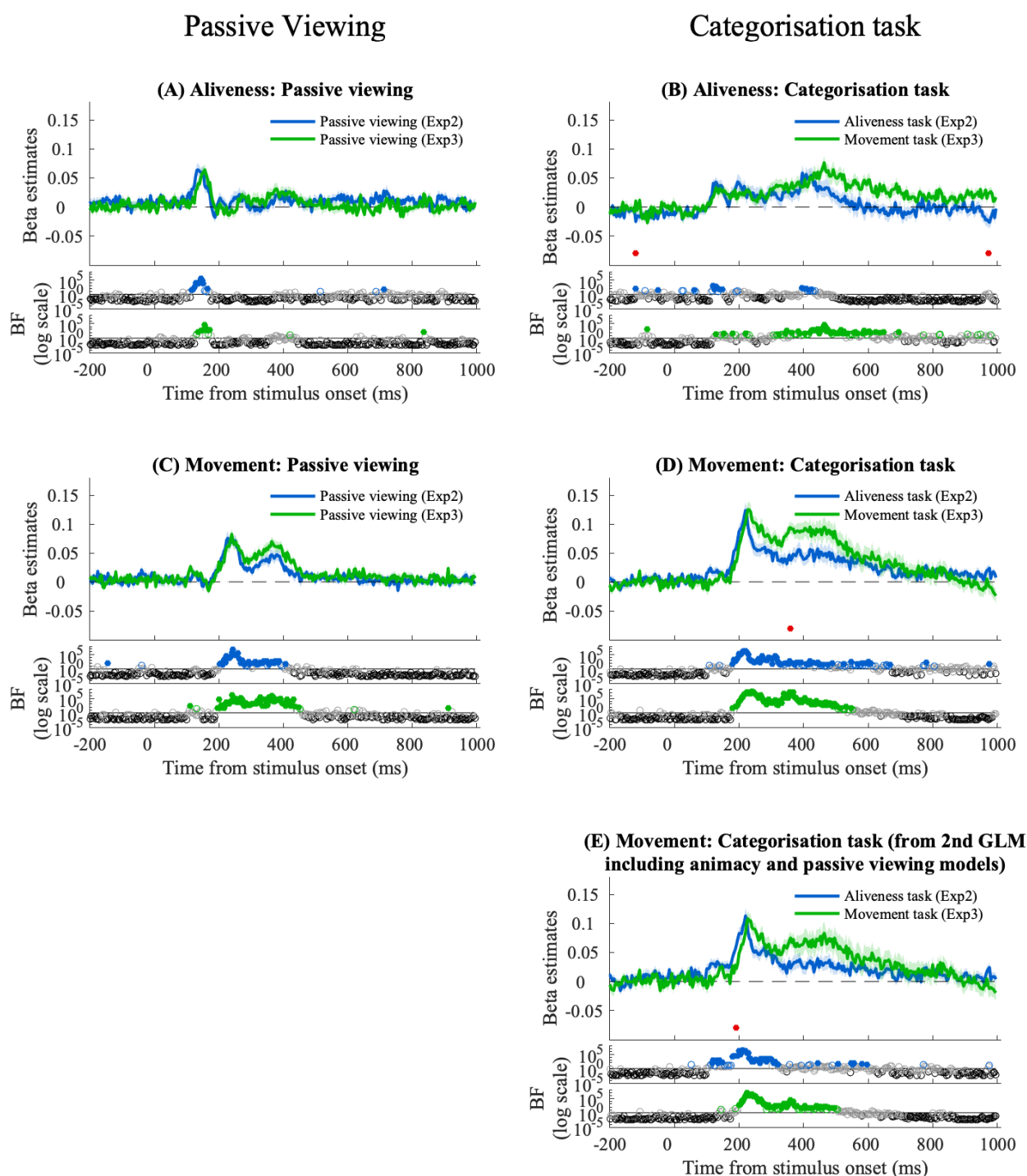
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518   **EEG: Linear modelling**

519   To investigate how much each of the conceptual categories of movement, aliveness, and naturalness

520   explained brain activity while classifying and viewing object stimuli, we used a linear model to see

521   which theoretical models best explained patterns of brain activity over time (Figure 4). These models

522   were based on the behavioural data from Experiment 1 (online). The variance inflation factors for all

523   variables were low (ranging from 1.01 for movement to 1.40 for naturalness), indicating low

524   multicollinearity between the models.

525   For passive viewing, aliveness explained patterns of neural activity 120ms after stimulus

526   presentation (Figure 4B), for a brief period of approximately 50ms. In contrast, information about

527   movement was present slightly later, from 180ms, and for a longer period of time (approximately

528   200ms; Figure 4D).

529   When participants were actively classifying images, the timing of these representations

530   changed and was affected by the dimension participants were classifying the stimuli on. During

531   categorisation tasks, information about movement was present from a similar time point as the

532   passive blocks, for a slightly longer period of time but still with the same 230ms - 240ms peak

533   (Figure 4C). The shift from the passive viewing to classification task was dramatic for aliveness; the

534   early effect of aliveness in the passive viewing is considerably reduced and shifted later (Figure 4A).

535   These significant points surround the median reaction times for each experiment, around 450ms,

536   suggesting these later periods of significance may be associated with decision-making.

537   Information about both aliveness and movement was present in the brain for a longer duration

538   when participants were categorising stimuli by movement (Experiment 3) compared to categorising

539   by aliveness (Experiment 2). For Experiment 2, even though participants were focusing on aliveness

540   classification, representations of aliveness were only significant for a very short period of time

541   around 400ms. In contrast, information about aliveness was present from 400ms to 570ms when the

542   focus is on movement classification. This suggests that aliveness is automatically considered when

543   participants are processing whether something moves.

544   As previous research has shown that animate stimuli have distinct low- and mid-level

545   features (Grootswagers, Robinson, Shatek, et al., 2019; Long et al., 2018), we ran a second linear

546   model to ensure that the visual characteristics included were sufficient to account for systematic

547   visual differences between categories. This model was identical to that used for the categorisation

548   task above, but also included the corresponding time point of the passive trials and a model of

549   animacy. When calculated independently for each time point to account for the changing passive

550   blocks, the maximum variance inflation factors for each model were also low (from maximum 1.19

551   for movement to maximum 1.70 for naturalness), indicating that factors were sufficiently

552   independent to interpret the results. Once accounting for the low-level characteristics of stimuli,

553   movement and aliveness still accounted for substantial proportion of the neural signal, albeit with a

554   shorter length of time for which information about movement was evident in neural signal (Figure

555   4E).

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557

558   **Discussion**

559   In this study, we used a combination of one behavioural and two neuroimaging experiments to

560   investigate the contribution of movement and aliveness in categorisation. Previous work has focused

561   on animacy as a major dimension in visual object processing, but animacy tends to co-occur with

562   movement, raising the question of how much these object features contribute to representational

563   categorisation. Here, we show that movement appears to be an important organisational principle in

564   the brain. We use naturalistic image stimuli including moving elements of the natural landscape (e.g.,

565   waterfall, fire) to show that the brain processes movement associated with non-living kinds as well as

566   animate movement. Behavioural results reveal that participants have difficulty classifying moving

567   non-living natural stimuli in terms of aliveness and movement, likely because these stimuli violate

568   common associations that non-living natural stimuli tend not to move, and moving stimuli tend to be

569   alive. Neural data revealed that information about capacity for movement was represented in the

570   brain while participants were passively viewing stimuli, as well as when they were actively

571   categorising the stimuli. Together, the results show that capacity for movement is an important

572   dimension in human visual object perception.

573   The design of the current study is optimal for examining the interaction between movement

574   and aliveness. The categorisation of plants and natural items were of particular interest in this study

575   because most prior work has focused on the separation between animals and artificial items, which

576   completely overlap in terms of their categorisation as animate/inanimate, moving/non-moving and

577   natural/artificial. The stimulus set used in the current experiment, including 'edge cases' such as

578   plants and moving natural items, can be informative in constructing a deeper understanding in the

579   structure of object representations, particularly as these stimuli often cause errors of categorisation

580   (Goldberg & Thompson-Schill, 2009). Use of full images of objects in naturalistic backgrounds

581   rather than segmented images facilitated inclusion of these natural stimuli (plants, and non-living)

582   which are more difficult to isolate from the background and are rarely used in prior research.

583   Furthermore, these naturalistic images reduce the reliance on mid-level visual features such as

584   curvature which perceptually distinguish animates from inanimates (Grootswagers, Robinson,

585   Shatek, et al., 2019; Long et al., 2018; Papale et al., 2020; Zachariou et al., 2018). Finally, the use of

586   static images allows us to examine the concept of movement while controlling for perceptual

587   differences in the kind, direction and speed of movement across all categories. These design

588   strengths allow clear separation of movement and aliveness by task and category. Our results clearly

589   show that capacity for movement is represented in the brain and also influences categorisation

590   behaviour.

591   Behavioural data revealed two key biases: an association between movement and aliveness,

592   and a tendency to perceive elements of the natural landscape as still. Firstly, things that move were

593   more likely to be judged as alive. Plants were considered to be alive less often than animals, and

594   moving natural stimuli were mistaken to be alive more often than still and artificial stimuli. These

595   trends are in line with prior work showing that under time pressure, adults may rely on intuitions

596   about the world (Goldberg & Thompson-Schill, 2009; Kelemen et al., 2013; Shtulman & Harrington,

597   2016; Shtulman & Valcarcel, 2012; Young & Shtulman, 2018). The current results build on these

598   prior findings to show that application of scientific intuition in adulthood is not limited to the

599   complex judgements about the accuracy of complex statements about physics and chemistry or

600   judgement of words that are used in prior work, but also extends to basic judgements of aliveness

601   and to naturalistic pictorial visual stimuli. Crucially, movement only influenced judgements when

602   participants were under time pressure to categorise images, suggesting that scientific knowledge may

603   override these intuitions with sufficient decision-making time.

604   The results also revealed a second bias in judgement: moving natural stimuli like fire were

605   judged as moving less often than moving man-made objects like cars, demonstrating a bias towards

606   perceiving elements of the natural landscape as still. Similar to the association between aliveness and

607   movement, this effect was only present under time pressure. Given the evidence of neural processing

608   of goal-directed movement and agency (Thorat et al., 2019) it is possible that this effect occurs

609   because there is no obvious agent causing natural movement. This is in contrast to all the other

610   moving stimuli, which can generate spontaneous goal-directed movement (animals) or move with the

611   intervention of humans (all the moving man-made stimuli were vehicles). Future studies may

612   evaluate whether moving artificial stimuli that move without clear human intervention (e.g., clocks,

613   fireworks) show similar response patterns. Together, these biases show that moving natural things

614   are an unusual case, unusual in their ratings of both movement and aliveness compared to the other

615   stimuli. The presence of these biases under time pressure may reflect that they are adaptive in most

616   situations in both modern times and for our ancestors (New et al., 2007); assuming that moving

617   things are alive allows for rapid reactions even when these assumptions are wrong (e.g., moving

618   away from an oncoming car). These biases are also reflected in the language we use to describe

619   naturally moving phenomena (Wolff et al., 2010), which can use the same linguistic constructions to

620   connote causation as animate things (compare the acceptable "the sunlight dried the towel", to the

621   slightly more unusual "the broom cleaned the room"). These behavioural results suggest therefore

622   that natural movement is uniquely positioned in a spectrum of movement because of its ambiguous

623   causal relationships.

624   A possible alternate explanation for these biases is that it is simply difficult to isolate the

625   moving natural things as 'objects' in a landscape, and therefore participants have difficulty

626   classifying these stimuli regardless of the task. However, items in the still natural category have

627   similar integration with the background, such as sand or cliffs, so this is unlikely to be the sole

628   explanation. Together, these behavioural results provide support for reliance on intuitive scientific

629   judgements under time pressure, and further suggest that movement is an important organisational

630   concept in our intuitive understanding of the world.

631   Though behavioural results suggest movement and aliveness are related in making

632   judgements about stimuli, the neural decoding shows that they are processed differently in the brain.

633   Information about movement was present in neural activity shortly after stimulus onset, regardless of

634   the task. Even after accounting for more stringent visual controls, the movement model still

635   explained a large portion of variance in brain activity, for both passive viewing and categorisation,

636   indicating that capacity for movement is an inherent feature of object representations. For passive

637   viewing, aliveness was processed early and information about movement was available later (Figure

638   4B, D). However, when participants actively considered semantic attributes of the stimuli as part of

639   the categorisation task in both experiments, the onset of information about aliveness came later than

640   information about movement, the reverse order compared to passive viewing blocks. This distinction

641   reflects prior evidence that higher-order top-down processes related to the task can constrain

642   processing of visual stimuli (Harel et al., 2014), and further shows that these effects generalise to

643   realistic naturalistic stimuli in scenes.

644   Curiously, information about movement and aliveness was present for longer in Experiment 3

645   when participants classified by movement compared to in Experiment 2 when participants classified

646   by aliveness (compare significant time points in Figure 4A and 4C). This could indicate that when

647   judging if something moves, the brain automatically processes whether it is alive. Animate

648   movement is reasonably distinct from inanimate movement, in terms of having a goal-directed

649   trajectory (Gergely et al., 1995), predictability of movement (Pratt et al., 2010), the speed and angle

650   of directional changes (Tremoulet & Feldman, 2000), among other things. This ability to detect

651   animate movement is present early in infancy (Csibra et al., 1999; Poulin-Dubois et al., 1996).

652   Hence, it is possible that when we are judging if something is moving, we are inherently judging the

653   quality and type of the movement to provide clues about aliveness. This is particularly interesting

654   given that participants were viewing still images where all movement is implied.

655   Alternatively, it is possible that the movement task was more cognitively demanding, so

656   participants were processing all semantic associations of the stimuli more deeply, not just those

657   relevant for the task. For example, participants could complete the aliveness task by pressing alive

658   whenever they identify a 'plant' or 'animal'. No such shortcut existed for the movement task, in

659   which the categorical groupings do not have a clear label and are less 'natural' (Rhodes & Gelman,

660   2009). However, reaction times and accuracies across the two EEG experiments were very similar on

661   average, so this does not seem likely. Though task may affect the duration of processing certain

662   characteristics, the linear modelling clearly shows that the visual system automatically processes

663   information about whether a stimulus can move, during passive viewing and active categorisation of

664   images.

665   Each participant responded consistently to items across the course of the experiment, but

666   there was less consistency between participants, suggesting that understanding of the concepts 'alive'

667   and 'can move', or potentially the interpretation of the instructions may have varied across

668   participants. For example, there were four participants in Experiment 2 who consistently responded

669   that plants were not alive. The term 'alive' can colloquially be interpreted to mean 'animate'

670   (Leddon et al., 2009) particularly in childhood, so it is possible that these participants interpreted the

671   instructions as such. Similarly, in Experiment 3, some participants consistently classed the moving

672   natural things as still, potentially because they interpreted 'can move' to refer only to self-generated

673   movement. However, these same participants also reliably classified vehicles as moving, so it is

674   unclear whether this is a semantic or lexical distinction that is important. Further research is required

675   to fully understand the impact of lexical factors on classification behaviour in the current context.

676   Converging evidence from neuroscience and behaviour has shown that animacy and aliveness

677   are best described as represented on a continuum according to capacity for goal-directed movement

678   (Connolly et al., 2012; Contini et al., 2020; Sha et al., 2014; Thorat et al., 2019; Yorek et al., 2009).

679   However, it is difficult to distinguish the contribution of movement when most prior work has

680   contrasted animate stimuli with still artificial objects. In the current study, we show that capacity for

681   movement is an important dimension in human visual object perception, not only for animate

682   movement, but also for movement in the natural world. Information about an object's capacity for

683   movement was present in neural activity during active classification as well as passive viewing of

684   stimuli, after accounting for visual similarities within categories. Capacity for movement also

685   influenced behavioural judgements, showing a pervasive influence of movement on object

686   categorisation in the brain and in behaviour.

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