



## 36 1. Introduction

37 Abstract and concrete semantic representations form fundamental aspects of word meaning. For instance,  
38 concrete features (e.g., four legs, red fur), as well as abstract features (e.g., intelligent, aggressive),  
39 contribute to the representation of a fox in semantic knowledge (Borghesani & Piazza, 2017; Smith et al.,  
40 1974). Although the ability of the brain to retrieve these representations is at the core of human semantic  
41 knowledge, the neural underpinnings of this process are not completely understood.

42 To explain how various sorts of knowledge guide a broad range of behaviors, Dual Coding Theories  
43 (DCT; Paivio, 1986, 1991) put forward the idea that, in the brain, semantic knowledge is represented in a  
44 dual coding system comprising a linguistic code, and an imagistic/sensorimotor code. In DCT, abstract and  
45 concrete concepts can both be represented through the linguistic code, whereas the imagistic/sensorimotor  
46 code is available only for concrete aspects of meaning. In experimental psychology, the fact that concrete  
47 words are recognized faster (Kroll & Merves, 1986; Schwanenflugel et al., 1988; Schwanenflugel & Stowe,  
48 1989) and memorized better (Allen & Hulme, 2006; de Groot, 1989; Fließbach et al., 2006) than abstract  
49 words (i.e., the concreteness effect) has been traditionally taken as evidence in favor of the dual coding  
50 approach: only concrete concepts can activate both codes (linguistic and sensorimotor), a condition which  
51 gives them a processing advantage (Connell & Lynott, 2012; Paivio, 1986). However, the study of the  
52 concreteness effect in congenitally blind people has cast doubts on this interpretation (Bottini et al., 2021).  
53 Despite lacking a sensory code for visual features, early blind people processed visual unimodal-concrete  
54 words (e.g., “red,” “multicolor,” “transparent”) faster than abstract words, showing a concreteness effect that  
55 was indistinguishable from the one of sighted people (Bottini et al., 2021) and suggesting that the  
56 concreteness advantage is not driven by the availability of a double code for concrete words.

57 If, on the one hand, the study of blind people has shaken the confidence in psychological evidence  
58 considered a hallmark of dual coding models, on the other hand, it has revived the interest in DCTs from a  
59 neuro-cognitive perspective. Are sensory-derived and non-sensory-derived representations encoded in  
60 dissociable brain codes? A recent line of studies exploring the brain basis of visual knowledge in the  
61 absence of vision has provided alternative neurocognitive evidence for a dual code of semantic knowledge  
62 in the brain (see Bi, 2021). Two studies focusing on color representations in sighted and congenitally blind  
63 have shown that posterior brain areas in the V4 complex encode the similarity of color words, but only in  
64 sighted people. However, color similarity is also encoded in the dorsal anterior temporal lobe (ATL) in both  
65 sighted and blind (Bottini et al., 2020; X. Wang et al., 2020). Thus, the dorsal ATL seems to provide a non-  
66 sensory code to represent knowledge, both concrete and abstract, whereas a perceptual code for concrete  
67 representations relies on posterior perceptual regions and may not be available in the case of sensory  
68 deprivation (Bi, 2021).

69 Beyond research with populations devoid of specific aspects of perceptual experience, functional  
70 resonance imaging (fMRI) studies investigating topological as well as functional properties of the semantic  
71 network provide additional evidence in favor of a dual-code account of semantic knowledge in the brain  
72 (e.g., Bi, 2021; Xu et al., 2017). From a network perspective, the dorsal anterior temporal lobe (dATL) and  
73 posterior sensory and motor regions are components of dissociable brain systems. The dATL belongs to  
74 the high-level linguistic system in the left perisylvian network, encompassing the inferior frontal gyrus, the  
75 lateral temporal cortex, and the inferior parietal cortex (for instance, Fedorenko et al., 2011; Friederici,  
76 2011). It has stronger connections to the other regions in the language network than the sensorimotor  
77 regions (Jackson et al., 2016; X. Wang et al., 2020). The left perisylvian language network is consistently  
78 activated in semantic tasks (Binder et al., 2009; Xu et al., 2017), and is considered to play a role in  
79 language-supported semantic processing (Xu et al., 2017). Beyond DCTs, other models suggest that both  
80 codes are present in the ATL, arranged in a continuous transmodal gradient (e.g., Lambon-Ralph et al.,  
81 2017). That is, the ATL is considered a transmodal/graded hub with a linguistic neural code in its dorsal  
82 part, and a perceptual code in its ventral part (Hoffman et al., 2015; Visser & Lambon Ralph, 2011).

83 On the contrary, visual regions (including the color region V4) belong to the highly distributed  
84 sensorimotor brain system, (see Wang et al., 2020) which reflects relevant perceptual dimensions of the  
85 input such as visual, tactile, auditory, etc. (Barsalou et al., 2003; Binder et al., 2005, 2009; Binder & Desai,  
86 2011; Hoffman et al., 2015; Kana et al., 2012; Sabsevitz et al., 2005). These regions are usually more active  
87 for concrete compared to abstract concepts (Binder et al., 2005, 2009; Binder & Desai, 2011; J. Wang et  
88 al., 2010) and may host sensorimotor simulations of perceptual referents during semantic processing.  
89 However, as fMRI suffers from poor temporal resolution, several questions about the spatiotemporal  
90 dynamics of the dual code of knowledge in the brain remain unanswered. For instance, it is unclear whether  
91 transmodal/language-derived representations in the ATL are activated before, after, or at the same time as  
92 sensorimotor representations in perceptual regions. This missing information is crucial to understand the  
93 neural dynamics of conceptual processing and, in particular, how concreteness (abstractness) is encoded  
94 in the brain.

95 To answer these questions, we took advantage of the high temporal resolution of  
96 magnetoencephalography (MEG) signals combined with source-reconstruction techniques to assess the  
97 spatiotemporal dynamics of abstract and concrete semantic representations. Forty-six participants  
98 performed a semantic categorization task on 438 written words. Each word referred to a concept (e.g.,  
99 chair, dog, policeman) that was independently rated across 65 feature dimensions (e.g., color, shape,  
100 happiness, arousal, cognition, etc.; Binder et al. 2016). Using principal component analysis (PCA), we  
101 reduced the dimensionality of this feature space into one abstract and one concrete semantic principal  
102 component. We then used a combination of multiple linear regression analysis and source reconstruction  
103 methods to assess neural dynamics of abstract and concrete semantic representations while keeping into  
104 account other types of psycholinguistic information processed during visual word recognition.

105

## 106 **2. Material and Methods**

107

### 108 *2.1. Participants*

109 Forty-six native Italian speakers (29 female, aged  $24.8 \pm 4.2$  years) participated in the study. All  
110 participants were right-handed and had no history of neurological or psychiatric disorders. Before testing,  
111 participants gave their written informed consent and received monetary reimbursement for their  
112 participation. The experiments were conducted in accordance with the Declaration of Helsinki and were  
113 approved by the local ethical committee of the University of Trento.

114

### 115 *2.2. Experimental design*

116 We derived our stimulus set from a previous work by Binder and colleagues (Binder et al., 2016).  
117 Out of 535 English words filed in Binder et al.'s (2016) original work, 438 were translated into Italian (352  
118 nouns in the singular form, 54 verbs in the infinite tense, and 32 adjectives in the singular masculine form).  
119 Selected words could be unambiguously translated into Italian. Participants were instructed to categorize  
120 each stimulus as either related to sensory-perception (i.e., they express something that is related to one or  
121 more of the senses), or unrelated to sensory perception. Visual stimuli were projected on a translucent  
122 whiteboard (1440x1080 pixel resolution) using a ProPixx DLP projector (VPixxTechnologies, Canada) at a  
123 120 Hz refresh rate. Stimulus presentation was controlled via Psychtoolbox (Kleiner et al., 2007) running in  
124 a MATLAB 2015a environment. At the beginning of each trial, a 1s blank screen followed by a 0.5s fixation  
125 cross preceded stimulus appearance. Words appeared in a white monospaced bold font on a dark gray

126 background, covering on average 3.2 degrees of visual angle ( $SD = 0.8$ ). Stimuli remained on the screen  
127 for 0.3s, followed by a 1.7s blank screen. After this delay, a text (“Was it a word related to the senses? YES  
128 - NO”) prompted participants’ responses via button press operated with the dominant hand’s index and  
129 middle fingers. The response mapping was counterbalanced across participants. The maximum time given  
130 to respond was set to 2s and was followed by an interstimulus interval randomly jittered between 0.3s and  
131 0.6s. Participants were familiarized with a short version of the task (30 trials taken from a different stimulus  
132 set) on a portable PC outside the MEG chamber. Each testing session lasted approximately 2 hours and  
133 was divided into twelve seven-minutes runs separated by eleven short breaks and one 30 min break.

134

### 135 *2.3. MEG Data acquisition and preprocessing*

136 MEG data were recorded using a whole-head 306 sensor (204 planar gradiometers; 102  
137 magnetometers) Vector-view system (Elekta Neuromag, Helsinki, Finland). Five head-position indicator  
138 coils (HPIs) were used to continuously determine the head position with respect to the MEG helmet. MEG  
139 signals were recorded at a sampling rate of 1 kHz and an online band-pass filtered between 0.1 and 300  
140 Hz. At the beginning of each experimental session, fiducial points of the head (the nasion and the left and  
141 right pre-auricular points) and a minimum of 300 other head-shape samples were digitized using a  
142 Polhemus FASTRAK 3D digitizer (Fastrak Polhemus, Inc., Colchester, VA, USA).

143 The raw data were processed using MaxFilter 2.0 (Elekta Neuromag ®). First, bad channels  
144 (identified via visual inspection) were replaced by interpolation. External sources of noise were separated  
145 from head-generated signals using a spatio-temporal variant of signal-space separation (SSS). Last,  
146 movement compensation was applied, and each run was aligned to an average head position. All further  
147 analysis steps were performed in MATLAB 2019a using non-commercial software packages such as  
148 Fieldtrip (Oostenveld et al., 2011), Brainstorm (Tadel et al., 2011) and custom scripts. Continuous MEG  
149 recordings were filtered at 0.1 Hz using a two-pass Butterworth high-pass filter and epoched from -1.5 s  
150 before to 2s after stimulus onset. Time segments contaminated by artifacts were manually rejected (total  
151 data loss of  $M = 2.4\%$   $SD = 1.8\%$ ). A Butterworth low-pass filter at 40Hz was applied to the epoched data.  
152 Before encoding, each trial segment was baseline corrected with respect to a -500 to -100ms time window  
153 before stimulus onset.

154

### 155 *2.4. Multiple linear regression analysis*

156 Multiple linear regression analysis was applied to MEG data following the approach used in  
157 previous M/EEG studies (Chen et al., 2013, 2015; Hauk et al., 2006, 2009; Miozzo et al., 2015). The solution  
158 of a multiple regression provides the best least-square fit of all variables simultaneously to the data (Bertero  
159 et al., 1985). For each time point, channel and subject we calculated event-related regression coefficients  
160 (ERRCs) reflecting the contribution of each predictor to the MEG signal. We focused on four predictors  
161 spanning word-form, lexical and semantic aspects of word retrieval (i.e., word length/duration, word  
162 frequency and an abstract and a concrete semantic predictor obtained via dimensionality reduction  
163 techniques of a 65 features’ space, see 2.5.). Before entering the regression model, regressors of interest  
164 (i.e., word length, word frequency, abstract semantic component and concrete semantic component) were  
165 orthogonalized via varimax rotation. Before encoding the predictors of each model were converted to  
166 normalized z-scores and tested for multicollinearity using a condition number test (Belsley, 1982). The  
167 output of the test is a condition index, which in the present study never exceeded a threshold of 2 (with test  
168 values  $< 6$  collinearity is not seen as a problem).

169

## 170 2.5. Predictor variables

171 The aim of the present study was to investigate the contribution of abstract and concrete semantic  
172 dimensions of knowledge to concepts representations. On this account, we derived our stimulus set from a  
173 previous work by Binder and colleagues (Binder et al., 2016). These authors collected ratings of the  
174 salience of 65 biologically plausible features to word meaning (for a detailed description of the procedure  
175 see Binder et al. 2016). For every word in the database (e.g., lemon), more than one thousand participants  
176 were asked to rate how each of the features (e.g., color) was associated with that aspect of the experience  
177 (e.g., would you define a lemon as having a characteristic or defining color?). The result is a semantic space  
178 where concepts can be represented as single entities into a multidimensional space having perceptual (e.g.,  
179 sound, shape, smell) and conceptual (e.g., arousal, social, sad) features as dimensions. Crucially, features  
180 spanned both abstract and concrete domains of conceptual knowledge thus represent an ideal framework  
181 to operationalize our assumptions.

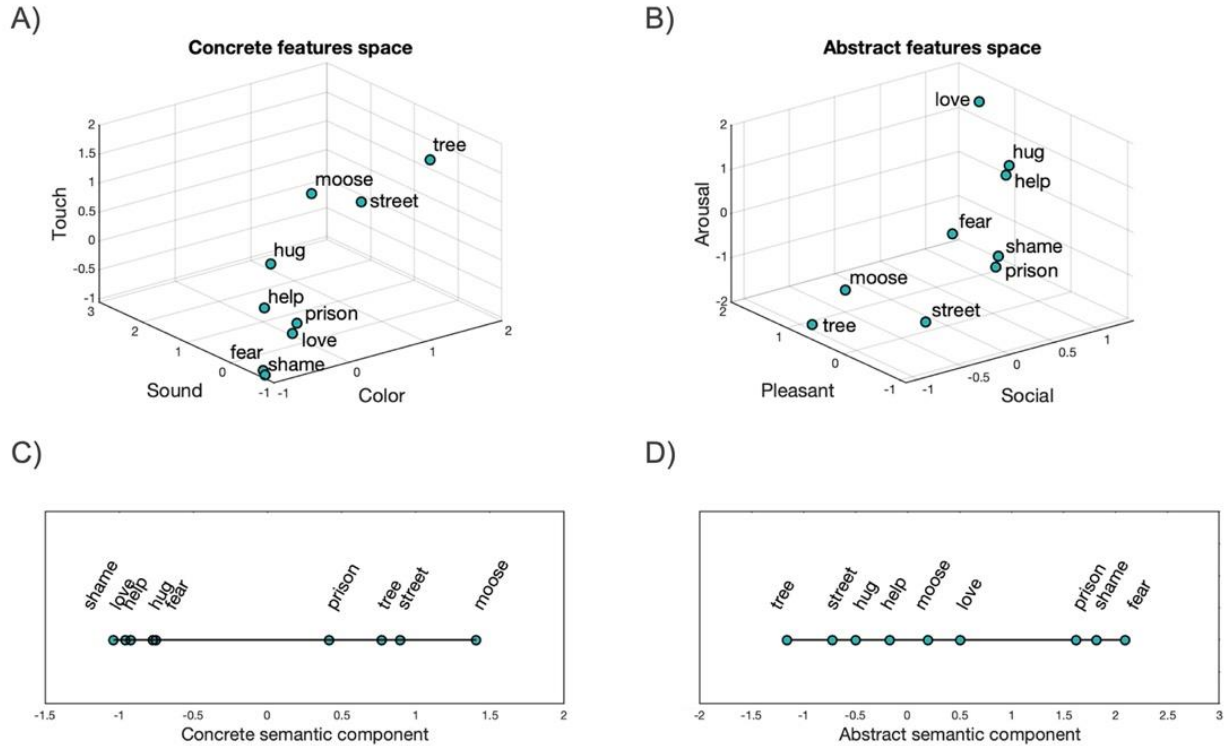
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### 183 2.5.1. Semantic components

184 As mentioned above, more than sixty features composed our semantic space. Encoding the entire  
185 space in one single model, however, would be suboptimal. In fact, features are highly intercorrelated with  
186 each other, leaving us with a multicollinearity issue. One way this can be avoided is through dimensionality  
187 reduction techniques (Cunningham & Yu, 2014), such as principal component analysis (PCA). PCA  
188 generates a series of principal components (PCs) representing the same data in a new coordinate system,  
189 with the first PC usually accounting for the largest percentage of data variance. Following the concrete  
190 versus abstract labeling provided in the original database (Binder et al., 2016), we separated the entire  
191 semantic space (65-features) into concrete features (N = 31, encompassing Vision, Somatic, Audition  
192 Gustation, Olfaction and Motor domains) and abstract features (N = 31, encompassing Spatial, Temporal,  
193 Causal, Social, Emotion, Drive and Attention domains). Three features (i.e., Complexity, Practice, Caused)  
194 were excluded due to incomplete ratings. Thus, each word could be considered as a point in a concrete  
195 semantic features' space (see Figure 1A), and in an abstract semantic features' space (see Figure 1B). We  
196 used PCA to reduce the dimensionality of the dataset and adopted the first concrete semantic component  
197 (Figure 1C; 24.7% of variance explained) and the first abstract semantic component (Figure 1D; 27.4% of  
198 the variance explained), to represent the same data in a new one-dimensional coordinate system.  
199 Importantly, the resulting semantic components do not simply reflect how concrete and how abstract a word  
200 is, but instead represents concrete and abstract aspects of concepts in a new low-dimensional space that  
201 encodes the most salient structural features of the high-dimensional space from which it is derived. For  
202 instance, in the concrete principal component, "moose" is more similar to "street" than to "hug", whereas  
203 the opposite is true in the abstract principal component (Figure 1, C-D).

204





205

206

207 **Figure 1. Dimensionality reduction.** A) Schematic representation of a 3-D semantic space where each word is viewed in a  
 208 coordinate system defined by concrete features such as Touch, Sound and Color (the actual multidimensional space  
 209 comprised 31 dimensions, here reduced to 3 for visualization purposes). B) Schematic representation of a 3-D semantic  
 210 space where each word is viewed in a coordinate system defined by abstract features such as Arousal, Pleasant and Social  
 211 (the actual multidimensional space comprised 31 dimensions). C) Words' weights along the first principal component of the  
 212 concrete space. D) Words' weights along the first principal component of the abstract space.

213

### 214 2.5.2. Linguistic features

215 For each of the selected words, we obtained psycholinguistic features: Word Frequency (in Zipf's  
 216 scale,  $M = 4$ ,  $SD = 0.8$ ; van Heuven et al. 2014) was calculated as the frequency of occurrence of a given  
 217 word in a large corpus of text samples (SUBTLEX-IT; Crepaldi et al. 2015). Word length was encoded as  
 218 the number of letters of each word ( $M = 6.9$ ,  $SD = 1.6$ ).

219

### 220 2.6. Source reconstruction

221 Distributed minimum-norm source estimation (Hämäläinen & Ilmoniemi, 1994) was applied  
 222 following the standard procedure in Brainstorm (Tadel et al., 2011). Anatomical T1-weighted MRI images  
 223 were acquired during a separate session in a MAGNETOM Prisma 3T scanner (Siemens, Erlangen,  
 224 Germany) using a 3D MPRAGE sequence, 1-mm<sup>3</sup> resolution, TR = 2140ms, TI = 900ms, TE = 2.9ms, flip  
 225 angle 12°. Anatomical MRI images were processed using an automated segmentation algorithm of the  
 226 Freesurfer software (Fischl, 2012). Co-registration of MEG sensor configuration and the reconstructed scalp

227 surfaces was based on ~300 scalp surface locations. When no individual MRI was available (6 participants),  
228 we warped participants' head shapes to a standard ICBM152 brain template. The data noise covariance  
229 matrix was calculated from the baseline interval (-500ms to -100ms) of the different trials. The forward  
230 model was obtained using the overlapping spheres method (Huang et al., 1999) as implemented in the  
231 Brainstorm software. We then: i) Estimated current density maps for event-related regression coefficients  
232 onto a 15000 vertices boundary element. Dipole sources were assumed to be perpendicular to the cortical  
233 surface. ii) Normalized current density values with respect to a -500ms to -100ms baseline period (z-  
234 transform). iii) Rectified current density values (converted to absolute values). iv) Spatially smoothed the  
235 source maps using an 8mm full width at half the maximum smoothing parameter (FWHM) and, finally, v)  
236 the individual results were projected to a default template (ICBM152).

237

## 238 *2.7. Sensor-level statistical analysis and visualization*

239 In line with previous studies (Chen et al., 2013, 2015; Hauk et al., 2006, 2009; Miozzo et al., 2015),  
240 we depicted the time course of different regressors as the root-mean-square (RMS) of the signal-to-noise  
241 ratio (SNR) of ERRC. The SNR was computed on the grand mean of all subjects by dividing the MEG signal  
242 at each channel and time point by the standard deviation of the baseline. This provided a unified  
243 (magnetometers and gradiometers are combined together) and easy-to-interpret measure of sensor-level  
244 activity. Statistical significance was assessed with t-test from -.5s to 1s after stimulus onset (FDR corrected  
245 for multiple comparisons,  $p < .05$ , Benjamini & Hochberg, 1995) on ERRC, separated for magnetometers  
246 and planar gradiometers (see Groppe et al., 2011). We additionally imposed temporal (a minimum duration  
247 of 20ms) as well as spatial (at least 2 concurrently significant channels) constraints on the reported results.

248

## 249 *2.8. Source-level statistical analysis and visualization*

250 Cortical responses to individual predictors (i.e., abstract semantic component, concrete semantic  
251 component, word frequency and word length; Figures 2 to 5, B) are illustrated as 20ms averages of source-  
252 reconstructed brain activity thresholded to the 80% of the local maxima. We additionally imposed temporal  
253 (a minimum duration of 20ms) as well as spatial (a minimum cluster size of 10 adjacent vertices) constraints  
254 on the reported results. Source-magnitude statistical maps (i.e., Concrete > Abstract, Figure 6) were  
255 computed using whole-brain t-tests (two-tailed), on consecutive 100ms average time windows (FDR  
256 corrected for multiple comparisons,  $p < .05$ , minimum number of 10 vertices).

257

## 258 **3. Results**

259

### 260 *3.1. Behavioral results*

261 Participants were instructed to categorize each stimulus as either related to sensory perception  
262 (i.e., they refer to something that can be easily perceived with the senses, like "red" and "telephone"), or  
263 unrelated to sensory perception (i.e., they refer to something that cannot easily be perceived with the  
264 senses, like "agreement" and "shame"). We expected participants to categorize relatively concrete words  
265 as related to sensory perception and relatively abstract words as unrelated to sensory perception. To  
266 assess this, we correlated participants' responses with the semantic principal components (see below). The  
267 results indicated a significant association between participants' responses and our semantic dimensions  
268 (concrete semantic dimension:  $r(436) = .80$ ,  $p < .001$ ; abstract semantic dimension:  $r(436) = -.23$ ,  $p < .001$ ).

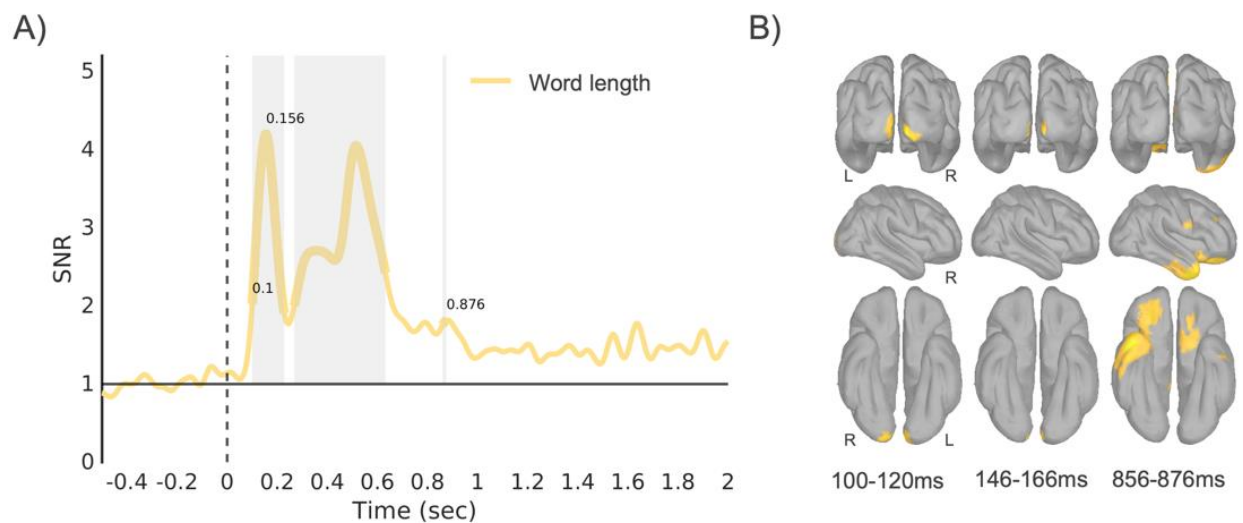
269 We did not analyze reaction times because participants' responses were delayed in order to avoid motion-  
270 related artifacts in the MEG signal (i.e., see Material and Methods for details).

271

### 272 3.2. Neural dynamics of lexical and semantic features

273 We first localized, in space and time, the encoding of the word length regressor (i.e., number of  
274 letters in a word). As predicted, this low-level visual information was encoded in and around primary visual  
275 cortices (bilaterally, Figure 2B), starting approximately 100ms after word appearance, peaking shortly after  
276 and remaining sustained up until 600ms after word onset (see Figure 2A). Such a highly predictable result  
277 served as a manipulation check for our source-localization procedure. At late time stages, word length  
278 information encoding saw the contribution of left inferior frontal and right anterior temporal and middle frontal  
279 brain systems.

280



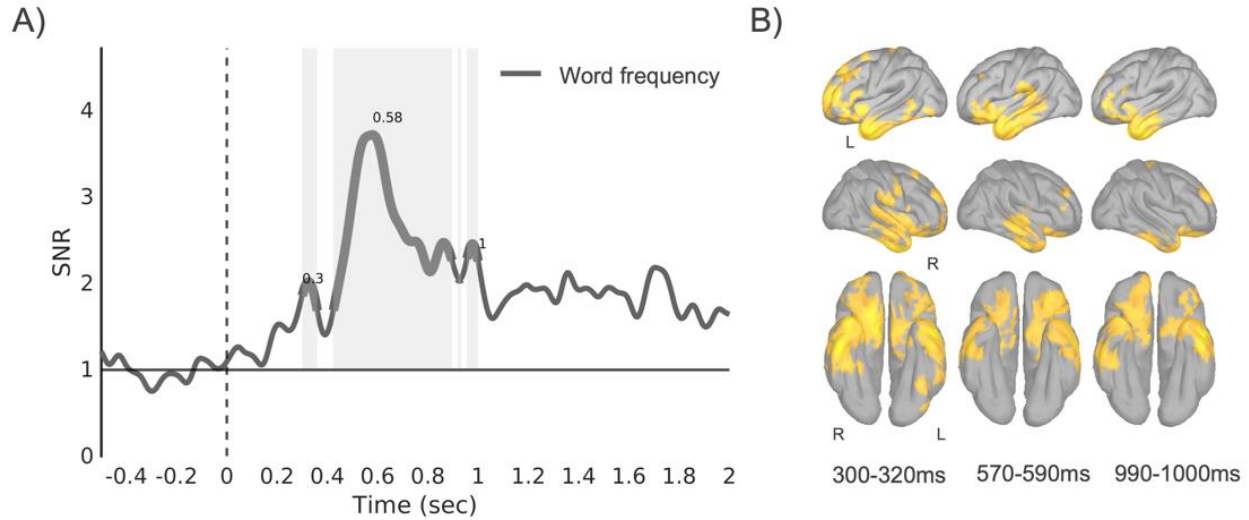
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282 **Figure 2. Spatiotemporal dynamics of word length information encoding. A)** Sensor-level results depicted as the root-mean-  
283 square of the SNR of ERRC of the word length predictor. Significant time intervals (FDR corrected,  $p < .05$ ) are indicated with  
284 a thicker line and a shadowed gray area. 0s = stimulus onset. **B)** Source-reconstructed maps of the word length predictor  
285 displayed as 20ms time averages (threshold 80% of local maxima, min cluster size 10, min duration 20ms) around the first  
286 significant time point (100-120ms), the peak of activation (146-166ms) and the last significant time point (856-876ms).

287

288 Lexical access occurred shortly after processing of word-form related information. This is illustrated  
289 in Figure 3A, where encoding of the word frequency predictor (Zipf; van Heuven et al. 2014) begins around  
290 300ms after visual word presentation, peaks at 580ms and continues until one second after stimulus onset.  
291 Source-level results are illustrated in Figure 3B. Encoding of information related to how frequent a word is  
292 in the language involves generators in the left ventral occipitotemporal cortex (approximately in the location  
293 of the Visual Word Form Area; Cohen et al. 2002) and anterior frontal brain regions. At the peak  
294 (approximately 600ms after word onset), these encompassed inferior frontal, anterior temporal, middle  
295 temporal and superior temporal brain areas with an overall moderate left lateralization. At later time points,  
296 the word frequency predictor was encoded in inferior frontal and anterior temporal brain areas, bilaterally  
297 (see Figure 3B).



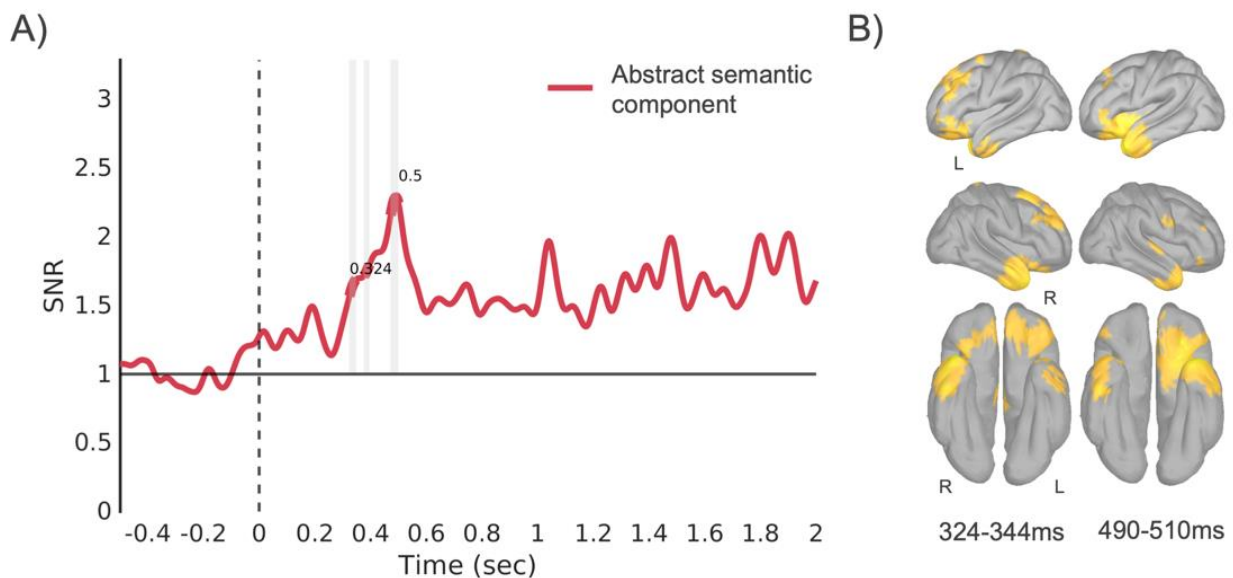


298

299 **Figure 3. Spatiotemporal dynamics of word frequency information encoding.** A) Sensor-level results depicted as the root-  
300 mean-square of the SNR of ERRC of the word frequency predictor. Significant time intervals (FDR corrected,  $p < .05$ ) are  
301 indicated with a thicker line and a shadowed gray area. 0s = stimulus onset. B) Source-reconstructed maps of the word  
302 frequency predictor displayed as 20ms time averages (threshold 80% of local maxima, min cluster size 10, min duration  
303 20ms) around the first significant time point (300-320ms), the peak of activation (570-590ms) and the last significant  
304 time point (990-1000ms).

305

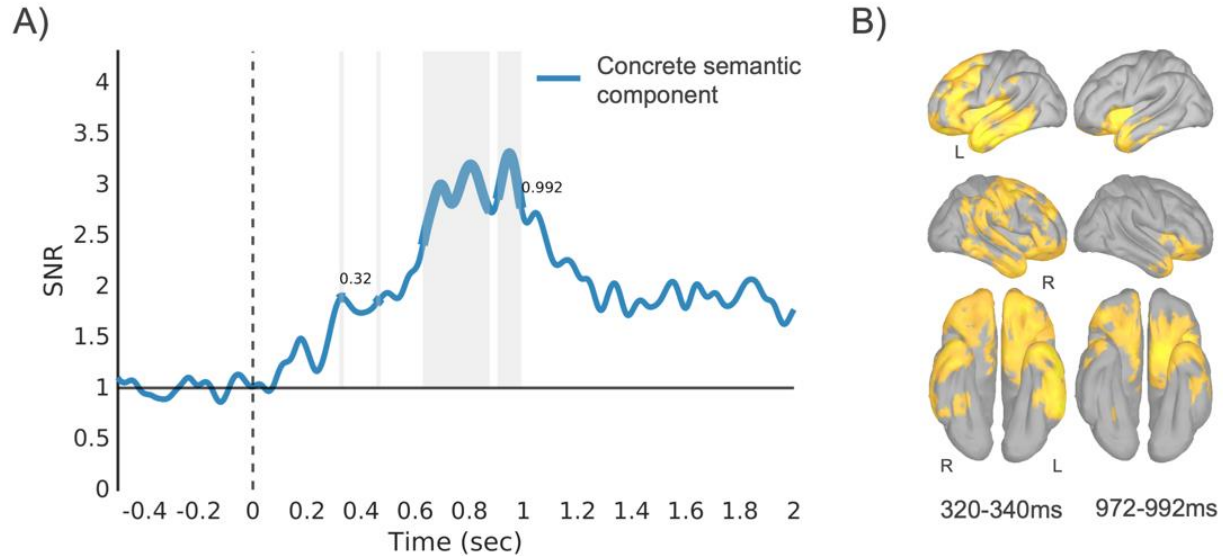
306 Abstract semantic information processing began approximately 300ms after stimulus onset to peak  
307 200ms after (see Figure 4A) and involved generators in prefrontal, inferior-frontal and anterior-temporal  
308 brain areas, bilaterally (see Figure 4B).



309

310 **Figure 4. Spatiotemporal dynamics of abstract semantic information encoding.** A) Sensor-level results depicted as the root-  
311 mean-square of the SNR of ERRC of the abstract semantic component. Significant time intervals (FDR corrected,  $p < .05$ ) are  
312 indicated with a thicker line and a shadowed gray area. 0s = stimulus onset. B) Source-reconstructed maps of abstract  
313 semantic information encoding predictor displayed as 20ms time averages (threshold 80% of local maxima, min cluster size  
314 10, min duration 20ms) around the first significant time point (324-344ms) and the peak of activation (490-510ms).

315 Encoding of concrete semantic information showed transient responses in the 300 to 500ms time  
316 window and a more sustained response from 600ms to 1s after stimulus onset (see Figure 5A). Source-  
317 level activation maps showed that concrete semantic information is encoded in prefrontal, inferior frontal  
318 and anterior temporal brain areas bilaterally (see Figure 5B).



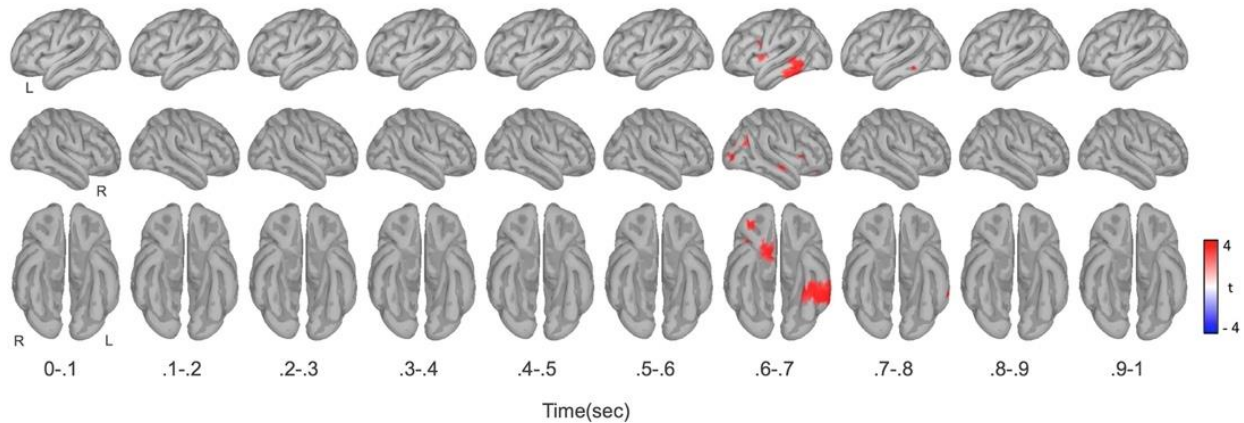
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320 **Figure 5. Spatiotemporal dynamics of concrete semantic information encoding. A)** Sensor-level results depicted as the root-  
321 mean-square of the SNR of ERRC of the concrete semantic component. Significant time intervals (FDR corrected,  $p < .05$ )  
322 are indicated with a thicker line and a shadowed gray area. 0s = stimulus onset. **B)** Source-reconstructed maps of concrete  
323 semantic information encoding predictor displayed as 20ms time averages (threshold 80% of local maxima, min cluster size  
324 10, min duration 20ms) around the first significant time point (320-340ms) and the last significant time point (972-992ms).

325

326 Last, we investigated source-magnitude activity of abstract and concrete semantic regressors which  
327 allowed us to describe in statistical terms brain areas showing greater responses to one or the other type  
328 of information. Results are illustrated in Figure 6 and evidenced greater activations for concrete semantic  
329 information in a distributed network of regions encompassing occipital, ventral occipito-temporal, inferior  
330 fusiform cortex and inferior-frontal brain areas approximately 700ms after word presentation. In line with a  
331 dual-coding approach, no brain region showed a greater activation for abstract compared to concrete  
332 features.

333



334

335

336 **Figure 6. Analysis of source-level magnitude activations. Source-reconstructed statistical maps of the contrast Concrete >**  
337 **Abstract (paired-sample t-test (two-tailed), FDR-corrected  $p < .05$ , min cluster size 10) in consecutive 100ms average**  
338 **intervals.**

339

#### 340 4. Discussion

341 We took advantage of the high spatiotemporal resolution of MEG signals to test when and where  
342 abstract and concrete information is processed in the human brain. Using a multiple linear regression  
343 analysis of MEG-recorded brain activity, we obtained for every time point, channel, and subject event-  
344 related regression coefficients (ERRC) reflecting the contribution of each predictor to the data. Predictors  
345 of interest included variables associated with low-level visual information (the number of letters), lexical  
346 information (the frequency), as well as semantic properties (abstract and concrete feature dimensions) of  
347 each word.

348 Typically, the early stages of visual word recognition are dominated by the processing of low-level  
349 features (Carreiras et al., 2014). This is illustrated in Figure 2, where encoding of information related to the  
350 length of a word begins 100ms after stimulus onset and peaks shortly after (for similar findings, see Dufau  
351 et al., 2015; Hauk et al., 2009). Source analysis localized this result in bilateral occipital areas, reflecting  
352 the visual nature of these early contributions (see also Dhond et al., 2007; Hauk et al., 2009; Marinkovic et  
353 al., 2003). Sub-lexical information encoding was followed (~200ms after) by lexico-semantic information  
354 encoding. That is, the word frequency predictor, the abstract semantic predictor, and the concrete semantic  
355 predictor all showed significant effects at around 300ms after stimulus onset (see Figures 3-4-5, A). The  
356 present findings reflect the cascade of underlying processes involved in visual word recognition (Grainger  
357 & Holcomb, 2009). A feedforward sweep of information cascades across sub-lexical and lexico-semantic  
358 stages resulting in parallel activations of lexical and semantic information approximately 300ms after word  
359 presentation (for similar findings, see Chen et al., 2015; Halgren et al., 2002; Pylkkänen & Marantz, 2003).  
360 At these latencies, the processing of information related to word frequency involved frontotemporal and left  
361 ventral occipitotemporal brain areas, consistent with functional imaging results of reading material (see, for  
362 instance, Kronbichler et al., 2004; Schurz et al., 2010; Schuster et al., 2016). Abstract and concrete  
363 semantic information processing, instead, involved a distributed network of brain areas encompassing both  
364 anterior frontal, anterior temporal and posterior brain areas (for similar findings, see Binder et al., 2009;

365 Kana et al., 2012; Lambon-Ralph et al., 2017; Sabsevitz et al., 2005; Striem-Amit et al., 2018; J. Wang et  
366 al., 2010).

367         Recent dual coding accounts of knowledge suggest that meaning is represented in the brain by a  
368 double code, which comprises language-derived representations in the (dorsal) ATL and sensory-derived  
369 representations in perceptual and motor regions (Bi, 2021). This approach further predicts that anterior  
370 temporal regions should encode both concrete and abstract features, whereas perceptual and motor  
371 regions (e.g., occipital cortex) should encode mostly concrete features. Our results are in keeping with this  
372 view and provide additional information with respect to the temporal dynamics possibly underlying this  
373 cognitive model: As illustrated in Figures 4 and 5, encoding of both abstract and concrete semantic  
374 information showed early (300ms after word onset) engagement of anterior temporal and inferior frontal  
375 brain areas, suggesting that representations of word's concreteness is not initially contingent on the  
376 activation of sensorimotor simulations or imagistic representations in perceptual and motor regions of the  
377 brain (Hauk et al., 2006; Hultén et al., 2021). Moreover, source-level analysis contrasting the abstract and  
378 concrete semantic regressors revealed that: (i) there was no brain region that was activated more by  
379 abstract compared to concrete features, as predicted by DCT; (ii) fusiform, lateral occipitotemporal,  
380 precentral and orbitofrontal regions preferentially encode concrete semantic features over abstract ones,  
381 in keeping with the prediction of DCT; (iii) finally, this neural signature emerged relatively late, around  
382 700ms from word onset, suggesting a late activation of the sensorimotor/imagistic code during semantic  
383 processing.

384         Contrary to previous studies, a direct comparison of abstract and concrete semantic information  
385 encoding did not evidence stronger activations to abstract semantic information (see Figure 6). Whereas  
386 this result is in line with DCT, which predicts no differences between abstract and concrete representation  
387 in linguistic coding, greater activations to abstract concepts as to concrete concepts were reported in the  
388 linguistic areas in the inferior frontal cortex and the anterior temporal lobe (see, for instance, Binder et al.,  
389 2005; Hoffman et al., 2015). Our results did not confirm these observations, and this discrepancy might be  
390 due to task-induced mechanisms. Whereas our semantic categorization task ("Was it a word related to the  
391 senses? YES - NO") put large emphasis on perceptual and motor representations of word meaning, several  
392 previous studies adopted tasks that emphasize linguistic properties of the stimuli (e.g., a lexical decision  
393 task, synonym judgment task; see for instance Binder et al., 2005; Hoffman et al., 2015). Wilson-  
394 Mendenhall et al. (2013) showed that under task conditions which require deeper conceptual processing,  
395 the linguistic system did not show stronger engagement with abstract concepts as compared to concrete  
396 concepts, in line with our results. It is possible that language-related tasks show greater sensitivity to  
397 symbolic/linguistic representations of abstract words, inducing a greater activation for such items in the  
398 language/symbolic network (Wilson-Mendenhall et al., 2013). However, it is also possible that lexical  
399 decision or synonym judgment foster the processing of lexical-semantic features such as semantic diversity  
400 (Hoffman et al., 2013), age of acquisition (Brown & Watson, 1987) or contextual availability  
401 (Schwanenflugel et al., 1988; Schwanenflugel & Stowe, 1989) which are often unbalanced between  
402 abstract and concrete words (abstract words usually have higher semantic diversity, lower contextual  
403 availability and are learned later in life). In this case, the higher activation of the language/symbolic network  
404 by abstract words could be due to the sensitivity of the network to such properties more than the preferential  
405 encoding of abstract semantic features per se.

406         Overall, the present findings suggest that contributions from a transmodal/linguistic code, housed  
407 in the perisylvian brain network, precede those of the imagistic/sensorimotor code in perceptual and motor  
408 regions, at least in the case of semantic concreteness. We cannot, however, exclude the prospect that,  
409 under different circumstances, this sequence of events would unfold differently. The case of action verbs  
410 may be a paradigmatic one, with many studies showing an early (~200ms) activation of primary motor



411 regions (e.g., M1) in response to action verbs (Hauk et al., 2008; Pulvermüller, 2013; Pulvermüller et al.,  
412 2005; van Elk et al., 2010). For instance, Garcia and colleagues (García et al., 2019), have recently shown  
413 that a machine learning classifier can distinguish action verbs (e.g., grasping) from nonaction verbs (e.g.,  
414 sleeping), in M1, as early as 150ms after word onset. Interestingly, the same classification was found in  
415 ATL, but only later, around 250-300ms, thus revealing a reversed time course (sensorimotor regions before  
416 ATL) than the one we report here. Although their analyses were limited to these two regions of interest  
417 (ROIs), without control regions, and a limited number of participants, this data suggest that action verbs  
418 can activate simulations in primary motor regions during the very early stages of word processing (actually,  
419 as early as the peak of activation we found in primary visual cortex for word length; Figure 2).

420 However, taking into account the relevant exception of action verbs, in this experiment we showed  
421 that even when the task emphasized perceptual and motor representations of word meaning, posterior  
422 temporal, lateral occipital and precentral regions associated with a sensorimotor/imagistic code are  
423 preferentially activated by concrete features only during later stages of word processing. This finding  
424 supports the hypothesis that the concreteness advantage observed behaviorally during the early stages of  
425 word recognition can hardly be attributed to the activation of a sensorimotor/imagistic code in the  
426 sensorimotor regions of the brain (Bottini et al., 2021).

427 Dual code theories of knowledge in the brain successfully account for a large number of behavioral  
428 as well as neuroimaging findings (Bi, 2021; Paivio, 1986). Several aspects of this model, however, are still  
429 to be uncovered. It is for example unclear what is the exact nature of conceptual representations in the  
430 (dorsal) ATL? Is it really a language-based code that is “necessarily ‘amodal,’ ‘symbolic’ and independent  
431 from sensory experience” (Bi, 2021, p. 8)? In this view, the type of meaning supported by the linguistic code  
432 would be similar to the one encoded by current computational models in the field of natural language  
433 processing (NLP) and based on the statistical relationships with other words in speech (for a review Günther  
434 et al., 2019). In other words, the meaning is supported in language contexts (Barsalou et al., 2008; Vigliocco  
435 et al., 2009; Xu et al., 2017). However, this state of affairs begs the actual question behind the grounding  
436 problem (Harnad, 1990): If the linguistic code is ultimately granted by links between word forms, how can  
437 they entail meaning in the sense of referring to something beyond other words? Under this assumption, if  
438 congenitally blind people could rely only on the amodal, ungrounded and sensory independent linguistic  
439 code to understand the meaning of “red” they would find themselves trapped in the Chinese Room (Searle,  
440 1980).

441 To solve this problem, several influential theories focus on the link between the two codes. One  
442 such example is “hub and spokes mode (H&S; Patterson et al., 2007). H&S assumes that modality-specific  
443 sources of information (i.e., “spokes”), distributed across neocortical regions, encode different information  
444 sources (e.g., visual information in the occipital cortex, haptic in the sensorimotor cortex, linguistic in the  
445 perisylvian regions) that are integrated in the ATL “hub” (Lambon-Ralph et al., 2017; Patterson et al., 2007).  
446 In this model, the ATL is considered the home of transmodal representations that are not strictly language  
447 derived (language regions are one of the spokes in the model and simply one source of such integrated  
448 representations) but abstracted enough to affect all domains of knowledge (A. R. Damasio, 1989; H.  
449 Damasio et al., 1996; Patterson & Erzinçlioğlu, 2008; Rogers & Patterson, 2007). Studies on functional  
450 connectivity corroborate this interpretation. By applying a graph-theoretic approach to the semantic brain  
451 network, Xu et al. (2017) highlighted two segregated systems for different types of semantic  
452 representations: a multimodal experiential content system in the default mode network and language  
453 supported content system in the perisylvian brain network. In this framework, anterior temporal areas are  
454 not the house to either linguistic or sensorimotor representations but are where these two representations  
455 converge (Xu et al., 2017). It has been also proposed that the ATL hub is organized according to a gradient  
456 of abstractness: The dorsal ATL would be more active for abstract concepts, given its preferential



457 connectivity with perisylvian language regions; Whereas the ventro-medial ATL would be more active for  
458 concrete concepts given its connections with visual brain regions. However, the spatial resolution of MEG  
459 is limited and makes the distinction between subparts of the ATL difficult to achieve. Finally, our design,  
460 does not allow to disentangle whether linguistic, or integrated representations (or both) encoded abstract  
461 and concrete semantic features in anterior temporal regions.

462

## 463 **5. Conclusions**

464 To conclude, the present findings shed new light on the spatiotemporal dynamics of abstract and concrete  
465 semantic representations in the brain. At early processing stages, abstract and concrete semantic  
466 information encoding was underpinned by common neural substrates in the anterior temporal lobe, whereas  
467 at later latencies, sensory-motor areas showed preferential responses to concrete information only. We  
468 suggest that concreteness is encoded in the brain via the early contribution of a transmodal/linguistic code  
469 (housed in frontotemporal brain systems), followed by the activation of an imagistic/sensorimotor code in  
470 perceptual regions. Results are broadly consistent with a dual-coding approach, although the strictly  
471 linguistic nature of ATL representations remains putative and waits for further empirical studies.

472

## 473 **Author contributions**

474 **L. Vignali:** Conceptualization, Data curation, Formal analysis, Investigation, Software,  
475 Methodology, Visualization, Writing - Original draft. **Y. Xu:** Conceptualization, Formal analysis, Writing –  
476 Review & Editing. **J. Turini:** Investigation, Resources, Data curation. **O. Collignon:** Conceptualization,  
477 Writing – Review & Editing, Supervision, Funding acquisition. **D. Crepaldi:** Conceptualization, Writing –  
478 Review & Editing, Supervision, Funding acquisition. **R. Bottini:** Conceptualization, Writing – Review &  
479 Editing, Supervision, Project administration, Funding acquisition.

480

## 481 **Declaration of competing interest**

482 The authors declare that they have no known competing financial interests or personal relationships  
483 that could have appeared to influence the work reported in this paper.

484

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