# Neural Dynamics and Representational Content across Abstract and Concrete Concepts

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#### Abstract

Concrete concepts are represented in the brain linguistic, according to experiential and taxonomic organizational principles, but it is not clear how much these principles contribute to the representation of the abstract domain. Moreover, compared to their spatial location in the brain, little is known about the temporal unfolding of these processes. In this study, we use Magnetoencephalography (MEG) and semantic models to investigate the localisation and temporal unfolding of concrete and abstract concepts. Concrete and abstract words were presented visually to the participants during MEG Data were analysed recording. through (RSA), Representational Similarity Analysis separately for concrete and abstract words. The semantic models were based on linguistic, experiential, and taxonomic information. We collected data from 6 participants, and data collection is ongoing. We expect significant correlations between the MEG signal and the distributional model for abstract and concrete concepts. This correlation is expected to temporally precede correlations with the experiential models. Concrete concepts signal is expected to correlate with the sensorimotor experiential model, while abstract concepts signal with the emotional one. Taxonomic models are expected to correlate with concrete but not with abstract concepts signal.

**Keywords:** concrete concepts; abstract concepts; MEG, semantics; RSA

#### Introduction

While concrete concepts have been argued to rely on both a linguistic and a perceptual format, abstract concept representation has been considered purely linguistic for a long time (Paivio, 1991). However, more recent embodied cognition accounts claim that abstract concepts too rely on experience, in particular the emotional one (Kousta et al., 2011). Concrete concepts have also been divided into clear-cut categories derived from taxonomic information. While the literature highlighted the existence of different abstract categories (Conca et al., 2021), the separation of these categories is fuzzy and often relies on experiment-specific measurements (Villani et al., 2019; Persichetti et al., 2024). In our study, we used MEG to record neural responses during words' visual comprehension, and used RSA to correlate distributional, experiential, and taxonomic models separately on concrete and abstract word-to-word sensor and source-localized MEG responses. We investigated: (i) which information (i.e., which model) is encoded during concept comprehension, (ii) when, and (iii) where the information is encoded.

### Methods

#### **Experimental Design**

Stimuli consist of 80 Italian nouns (3-10 letters), taken from Repetto dataset (Repetto et al., 2023). Half of these words are abstract and half concrete (<5.5 and >7 on the concreteness scale, respectively). Similarities between these words were obtained using three kinds of models: a distributional model, two experiential models, and two taxonomic models. These similarities are stored in representational dissimilarity matrices (RDMs), where each column/row references one word, and each offdiagonal cell contains the distance between each pair of words according to each model. The distributional model is based on Word-Embeddings Italian Semantic Space (Marelli, 2017), a word2vec model trained on an Italian text corpus, where the distance between word vectors reflects co-occurrence patterns of words in the text. The experiential models were computed based on semantic ratings obtained from Repetto and colleagues' dataset on sensory (vision, touch, audition, smell, taste and interoception), motor (head, foot/leg, hand/arm, mouth/throat, torso) and emotional (valence, arousal, dominance) dimensions. The taxonomic models leverage WordNet. In WordNet, concepts are organized according to taxonomic relations, with a hypernyms and hyponyms hierarchical structure. We computed two models based on WordNet: a path model based on Wu-Palmer similarity and a categorical model with hypernyms as the category labels. Concrete categories are Animal, Person, Structure and Device; abstract categories are Act, Quality, Cognition and Feeling. Words across all categories were balanced in terms of: number of letters, frequency, number of orthographic neighbors, mean frequency of the orthographic neighbors. Moreover, we computed control RDMs based on word frequency and length to regress out in the RSA. Continuous MEG data was acquired during word visual presentation. Words were presented for 300 ms, followed by a blank screen lasting for a jittering intertrial interval of an average of 900 ms, and a fixation cross of 1000 ms. To ensure participants' compliance, 15% of trials were followed by catch trials, in which a pair of nouns was presented, and subjects were asked to choose whether the two words were semantically associated with the last presented word by pressing a right or left-hand button (Borghesani et al., 2016, 2019).

### Analysis

RTs and accuracy from the semantic relatedness task were analyzed to verify participants' compliance. MEG data were preprocessed and segmented into 1.2-second epochs around word onset (-0.2, 1). RSA (Kriegeskorte et al., 2008) was performed between the semantic models and the sensor-level and source-localized MEG pseudo-trials. Source-level estimates for each pseudo-trial were obtained using Minimum Norm Estimates (MNE) constrained to the cortical surfaces (Hultén et al., 2021). The volume conduction model and the cortical sheet-based source model are based on individual T1-weighted MRI and obtained using FreeSurfer software and successively decimated with the HCP Workbench. We first created MEG RDMs by correlating the neural between pseudo-trials with activity Pearson correlation r across all possible word pairs, using 1-r as the dissimilarity between each pair. This procedure was performed for each participant, time bin and set of sensors/source-level vertices, using a searchlight approach (Figure 1). The RSA was computed using partial correlation to compare MEG-RDMs and each semantic model RDM. The statistical significance of these maps was assessed using a cluster-based permutation test (Maris and Oostenveld, 2007).

### **Results and Discussion**

We expect: (i) correlations between neural responses and the distributional model both for abstract and concrete concepts (Hultén et al., 2021; Kaiser et al., 2022; Vignali et al., 2023); (ii) these correlations to be localised in frontotemporal linguistic regions, and to temporally precede correlations with the experiential models (Vignali et al., 2023); (iii) correlations between neural signals in occipital and posterior temporal regions and the sensorimotor experiential model for concrete concepts, and to a lesser extent for abstract concepts (Vignali et al., 2023). In line with the Affective Embodiment account, (iv) the opposite pattern is expected for the emotional experiential model, with correlation only with abstract concepts, localised in IPL and Superior Temporal Sulcus (Meersmans et al., 2020; Montefinese et al., 2021). We expect (v) the taxonomic models to correlate with neural signals elicited by concrete concepts, and this correlation to be spatially located in category-selective areas, but no strong predictions are suggested for a correlation with abstract concepts (Fernandino et al., 2022).



1 - correlation between pairs of trials

#### Neural Representational Dissimilarity Matrices (RDMs)



Figure 1. Searchlight MEG RDMs.

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