University of Trento

CIMeC – Centre for Mind/Brain Sciences

Doctoral School in Cognitive and Brain Sciences (XXXVII Cycle)

Exploring the Neural Representational Space of Abstract Concepts

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Academic year 2024-2025

Acknowledgements

To Costanza Papagno. Thank you for your supervision over these four years, for fostering and guiding me throughout this journey, for always pushing me to do better, and for placing your trust in me in the process.

To Paolo Belardinelli, for your valuable support and feedback on my final experimental project.

To Luigi Cattaneo and Manuela Piazza, for your meticulous feedback over the years, which greatly contributed to refining my research.

To Stefania Pighin, for supporting me during these years and mentoring me on how to navigate this career.

Finally, to Eleonora Catricalà and Valentina Borghesani, for reviewing this thesis and offering insightful feedback and suggestions on how to improve this work.

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ABSTRACT

Abstract concepts constitute a fundamental part of language, without which humans would not be able to express complex ideas, societal norms, scientific notions, their feelings and intentions. Nonetheless, they have been largely neglected in the neuroscientific literature, so that their representation in the human brain remains relatively uncharted compared to the extensive investigation that concrete concepts received, leaving many questions still open.

A major debate concerns whether abstract concepts are represented only in an amodal, linguistic format, or whether they are also grounded in sensorimotor, affective and social experiential features. A second open question concerns the categorisation of abstract concepts: although abstract concepts have been treated as a unitary domain, a growing body of evidence suggests that, based on their content, they can be differentiated into distinct categories relying on separate neural bases.

In this thesis, I addressed these issues using neuropsychological evidence, transcranial magnetic stimulation (TMS) and magnetoencephalography (MEG) methods. The results support a dynamic and context-dependent view of abstract concepts embodiment, whereby experiential features, either socio-affective or sensorimotor, are differentially recruited for abstract concepts representation depending on current requirements. Furthermore, while mixed evidence emerged in favour of a distinction of social and emotion concepts as two separate abstract categories, results also show that other abstract categories defined on the basis of classic taxonomy are not reflected in the brain representational space of abstract concepts.

Collectively, these findings suggest that more refined theoretical and methodological approaches are needed to capture the partitioning of the abstract semantic space, and indicate that abstract concepts are flexibly grounded in experiential information.

CHAPTER 1.

INTRODUCTION

Language is our most powerful instrument to comprehend the world, interact with each other, and exchange ideas and thoughts. The building blocks of language are concepts or words, units that express one or multiple meanings, which can be referents in the external world or experiences and notions that our mind can entertain. The meanings expressed by concepts, thus, vary in their level of concreteness, that is, how much their meaning is something that can be experienced with our senses and that we can physically interact with. Concepts can be extremely concrete (with words like bicycle, or persimmon, or daisy, which are used for referents that have very strong sensory qualities), or less so, with more abstract concepts that do not have a referent in the external world, but name intangible, internal ideas and notions such as democracy, love, or destiny. The bulk of neuroscientific research on language has focused on the first kind of concepts, the concrete ones, often neglecting the latter type in their research and the scope of their theories, despite abstract concepts making a relevant proportion of words in our languages (Lupyan & Winter, 2018).

In the first part of this introduction, I will examine theories exploring the principles of representation and the multidimensionality of abstract concepts. In the second part, I will review neuroimaging, neurostimulation and neuropsychological evidence showing how abstract concepts are represented in the brain, and whether and to what degree their results support these theories.

1.1 Abstract concepts: a review of theories

Concrete concepts offer some methodological advantage compared to less concrete items. First, they are easily classified into different subtypes or categories (e.g., animals, tools, food) based on their content features (Rosch, 1973): for example, 'squirrel' is easily categorised as an animal based on its features (e.g., being a living creature, breathing air, furred, etc.). The relevance of such concrete categories has been supported by a great number of neuropsychological and neuroimaging studies (Borghesani et al., 2016; Caramazza & Mahon, 2003; Fairhall & Caramazza, 2013; Pulvermüller et al., 2010) .

Most importantly, concrete concepts have that obvious, fixed sensory-motor counterpart that abstract concepts lack, and this has historically been pinpointed as the reason why concrete concepts are more easily processed than abstract ones, the so-called concreteness effect: participants respond more quickly and accurately to concrete compared to abstract concepts in a range of linguistic and semantic tasks, such as lexical decision, word-naming and recall tasks (Fliessbach et al., 2006; Hamilton & Rajaram, 2001; Romani et al., 2008). The Dual-Coding Theory (Clark & Paivio, 1987; Paivio, 1991) explained this effect, claiming that it is due to concrete concepts having a dual representation, both imagery-based and language-based, whereas abstract concepts only rely on one type of representation, the language-based one.

The Context Availability theory (Schwanenflugel & Shoben, 1983), instead, claims that concrete concepts are associated with more readily retrievable contexts, which makes it easier to understand and recall them, whereas abstract ones are more difficult to associate with appropriate contexts. This theory is supported by studies showing that the processing disadvantage of abstract concepts disappears when they are placed in a context, for example, within a meaningful sentence (Schwanenflugel & Shoben, 1983; Schwanenflugel & Stowe, 1989).

However, the Dual Coding and the Context Availability theories (1) do not explain the reversal of the concreteness effect, i.e., a better performance with abstract than with concrete concepts, which has been observed in specific neuropsychological conditions (Breedin et al., 1994; Papagno, Capasso, et al., 2009; Yi et al., 2007), and (2) they only treat concrete and abstract concepts as a dichotomy of two unitary opposites.

Another earlier approach to explain conceptual representation is that of amodal theories of language, which claim that all linguistic concepts are stored in an symbolic format and defined by their relations to other words (Landauer & Dumais, 1997; Levelt, 1993), processed in amodal semantic ‘hubs’ (Patterson et al., 2007), and that the activity observed in sensory-motor areas for concepts’ processing is only an epiphenomenon that does not really affect the concept representation (Mahon & Caramazza, 2009).

Embodiment accounts of semantic representation, on the contrary, deem the sensory-motor qualities of concepts a central part of their representation (Barsalou, 2008; Gallese & Lakoff, 2005; Hauk et al., 2004; Meteyard et al., 2012; Muraki et al., 2023; Pulvermüller, 2001;

Pulvermüller et al., 2005): according to these approaches, processing a concept is based on the reactivation of the same modality-specific, sensory-motor cortices activated during the experience of that concept (e.g., the concept 'jogging' reactivates areas in the motor cortex that are active when we go for a run). This embodiment account has been supported by several neuroimaging and neurostimulation studies, which showed a correspondence between concept and modality-specific motor, visual and other sensory areas (Fernandino et al., 2016; Kiefer & Pulvermüller, 2012; Pulvermüller et al., 2005; Simmons et al., 2003; Tong et al., 2022).

However, applying an embodied framework to abstract concepts is challenging because they do not possess obvious sensory-motor qualities in the way concrete concepts do. A variety of theoretical approaches have been developed to resolve this theoretical issue and to extend embodied accounts to abstract concepts.

Barsalou (Barsalou et al., 2018) critiques the very distinction of concrete and abstract concepts as two separate domains. In the Situated Conceptualisation Framework (Barsalou et al., 2018; Barsalou & Wiemer-Hastings, 2005; Wilson-Mendenhall et al., 2013), both concrete and abstract concepts are used to describe real-world situations and integrate the different elements that constitute them. While concepts traditionally defined as more concrete usually describe single, external elements of situations, concepts described as abstract (e.g., 'truth') are typically used to (a) integrate different situational elements, linking together sometimes very concrete aspects of the situations, or (b) they are used to describe single internal elements of situations (e.g., emotion concepts) (Barsalou et al., 2018).

Other approaches similarly highlight that abstract concepts are usually developed to describe internal experiences.

According to the Words as Social Tools approach (WAT), proposed by Borghi (Borghi et al., 2019), abstract concepts, compared to more concrete ones, rely heavily on the social and linguistic context in which they are acquired and used. Their meaning, the authors argue, would be grounded on those linguistic and social experiences, and on internal experiences such as interoception and metacognition, therefore signals from within our body as well as cognitive monitoring processes. The authors claim that abstract concepts would also be associated with the mouth effectors, given the importance of inner speech to tell ourselves the meaning of abstract words.

The Affective Embodiment account (AEA) also focuses on the inner experience associated with abstract concepts, in particular, the importance of internal affective experience as the base of their experiential grounding (Kousta et al., 2011; Newcombe et al., 2012; Vergallito et al., 2019; Vigliocco et al., 2014). Based on the results of their studies, the authors argue that abstract concepts are more emotionally valenced than concrete ones, and that, controlling all other variables, this greater emotional association gives the abstract concepts the advantage, nullifying the usually observed concreteness effect (Kousta et al., 2011; Vigliocco et al., 2014). Using distributional linguistics methods, Lenci and colleagues (Lenci et al., 2018) also found that abstract concepts have a stronger emotional connotation and co-occur in context with higher emotional value. The Affective Embodiment account, by giving a central spot to the emotional features of abstract concepts, is also compatible with another approach, which emphasises the importance of interoceptive information, such as inner sensations associated with emotional states, for the sensory grounding of abstract concepts (Connell et al., 2018; Vergallito et al., 2019).

Together, all these embodied, grounded approaches point to the importance of other experiential modalities (situational, social, emotional) in the grounding of abstract concepts. By placing importance on the different modalities whereby these concepts are experienced, they allow for the characterisation of the abstract domain not as a single, monolithic domain, but as a multi-faceted space where different kinds of abstract concepts exist.

1.2 Multidimensionality of abstract concepts

Abstract concepts are not a monolithic whole, but they can be differentiated into distinct classes, such as emotions, social, or magnitude concepts (Conca et al., 2021; Desai et al., 2018), using a categorical approach. However, classes or categories of abstract concepts are hard to define, in that most abstract words could belong to multiple classes, as they show a significant overlap of multiple dimensions (e.g., internal, social) and are therefore sometimes categorised in one class or in another depending on the experimental paradigm (Borsa et al., 2025). For example, the concept ‘honour’ can be considered a social concept but is also associated with moral and emotional qualities. This within-category multidimensionality of abstract concepts might also be the reason why the neural bases of specific classes of abstract concepts vary greatly across experiments: the investigation of one class of abstract concepts (e.g., mental states) might overlook significant associations with social, emotional or introspective dimensions of experience, which might vary depending on the specific set of mental state concepts in one experiment with respect to another (Borsa et al., 2025). For this reason, other approaches have been developed to characterise the multifaceted abstract conceptual domain:

abstract concepts are characterised according to multiple semantic and sensorimotor dimensions (Binder et al., 2016; Repetto et al., 2023; Troche et al., 2014), and their profile and similarities are defined in a multidimensional space which considers all dimensions together. Another approach, which shares similarities with the semantic ratings approach described above, consists of features listing, namely asking participants to list features associated with abstract concepts (Barsalou & Wiemer-Hastings, 2005; Harpaintner et al., 2018). Compared to the semantic ratings approach, whereby dimensions are defined by the experimenters a priori, this feature listing approach (also called 'property generation') is more explicit and data-driven, because it directly asks participants to think of features they associate with the concepts. However, this approach also includes a more theoretically guided component, whereby the listed features can be organised under dimension labels, and the stimuli clustered based on similarities of the listed features into meaningful classes (Harpaintner et al., 2018).

In the following sections, I will describe each of these three methods: the semantic ratings, the feature listing, and the categorical methods.

1.2.1 Semantic ratings

In semantic ratings studies, participants are typically presented with concepts ranging the spectrum of concreteness and they are asked to rate these concepts on various semantic dimensions on a Likert scale. Specifically, they are asked to rate affirmations like: "I relate this word to *definition of the dimension"* (Troche et al., 2017) or reply to questions such as "To what extent do you experience this word through *name of sensory modality* / through an action of *name of body part* (Connell et al., 2018; Repetto et al., 2023). The dimensions investigated in these studies range from only perceptual/motor dimensions (Banks & Connell, 2023; Connell et al., 2018; Repetto et al., 2023; Vergallito et al., 2020), only affective (Montefinese et al., 2014), both abstract and concrete dimensions, but with a predominance of dimensions chosen for the abstract domain (Crutch et al., 2013; Troche et al., 2014; Villani et al., 2019), and a balanced set of dimensions to characterize the whole range of concepts, both concrete and abstract (Binder et al., 2016; Troche et al., 2017). Across studies including abstract dimensions, similar clusters/categories of abstract concepts emerge, typically including a distinction between concepts reflecting emotional/inner state processes and sociality, quantitative/magnitude concepts and concepts more related to the senses (Binder et al., 2016; Harpaintner et al., 2018; Persichetti et al., 2024; Troche et al., 2014; Villani et al., 2019). Results about the emotional qualities and social ones are mixed, as they are sometimes considered part of only one, socio-affective axis/cluster (Troche et al., 2014), or as two separate dimensions, with emotional qualities considered as more inward and social ones as more outward features (Villani et al., 2019).

When it comes to sensory-motor dimensions, instead, studies show that both abstract and concrete concepts are grounded in composite sensory-motor dimensions (Banks & Connell, 2023), and that interoception seems to be particularly relevant for abstract compared to concrete concepts. Abstract concepts are experienced through interoception more than concrete ones (Banks & Connell, 2023; Connell et al., 2018; Repetto et al., 2023), are less associated with vision and touch (Repetto et al., 2023), and more associated with hearing, and movements of the head and the mouth (Banks & Connell, 2023), in line with Borghi's proposal of the importance of the subvocal pronunciation for inner speech, and therefore mouth movements to tell ourselves abstract words' meanings (Borghi et al., 2019).

Moreover, interoceptive grounding is not uniform in the abstract domain, as emotional/inner states' abstract concepts are more grounded in interoception than external or social ones (Banks & Connell, 2023), or more neutral ones (Repetto et al., 2023). As with the more abstract dimensions, these behavioural findings on the importance of the sensory modality of interoception for abstract concepts and its relation to emotion support the embodied theoretical approaches outlined above, in particular the Affective Embodiment Account (Kousta et al., 2011; Vigliocco et al., 2014).

1.2.2 Feature-listing

Although most studies exploring the dimensionality of abstract concepts require participants to make explicit judgements about abstract dimensions chosen by the researchers, based on a theory-driven approach, a few studies (Barsalou & Wiemer-Hastings, 2005; Borghi et al., 2016; Caramelli & Setti, 2005; Harpaintner et al., 2018) adopted a more data-driven approach: feature-listing or property-generation. In this approach, adapted from research on concrete concepts, participants are asked to name properties or features they associate with the concepts, and these properties are organised under labels such as 'introspective', 'situational', or 'emotion' properties, based on the experimenters' coding.
In the seminal work of Barsalou and Wiemer-Hastings (Barsalou & Wiemer-Hastings, 2005), the authors investigated only a limited set of concepts (3 abstract, 3 intermediate, and 3 concrete concepts), and classified the listed properties as either taxonomic, entity, setting/event, and

introspective properties. With this study, they were interested in investigating the type of situational content associated with concrete vs abstract concepts.

Harpaintner and colleagues (Harpaintner et al., 2018) asked participants to write down properties associated with the 296 abstract concepts, and classified those properties as 'sensorimotor feature', 'social constellation', 'internal state and emotion', 'association', or an unspecific 'other abstract concepts' for properties that could not be classified. Their coding scheme reflected current proposals on the grounding role of experiential, emotional and social dimensions for abstract concepts.

Compared to the semantic ratings approach, the feature listing enables capturing more fine-grained characteristics of the concepts, reveals not only how much a concept is related to a certain dimension, but also how many different features are generated that could be related to that dimension, and relies to a lesser degree on a priori hypotheses. Still, in order to identify significant profiles or clusters of abstract concepts, as illustrated by the two studies described above, experimenters usually organise the generated features into dimensions which reflect the current theoretical approaches.

1.2.3 Categorical

Finally, abstract concepts can be divided into distinct categories (Catricalà et al., 2020; Conca et al., 2021; Desai et al., 2018). These categories can be defined with different methods: experimenters can select stimuli as belonging to one category if they present a high score on the dimension corresponding to the category (e.g., abstract words categorised as 'emotions' if they present high scores on valence/arousal/emotional associations) (Binney et al., 2016; Skipper & Olson, 2014; Vigliocco et al., 2014; Zahn et al., 2007), or they categorise them based on established taxonomy (Della Rosa et al., 2014; Fernandino et al., 2022) defined in datasets such as WordNet (Fellbaum, 2010), using hypernyms as category labels. This type of characterisation of concepts is relatively easy and fast to achieve, compared to semantic ratings or feature listing procedures, and has been widely adopted in research on the neural bases of different types of abstract concepts (Conca et al., 2021; Desai et al., 2018). While the categorical approach offers a clear-cut organisation of the abstract conceptual space, it overlooks the overlap of different dimensions in the same concept: 'friendship', for example, could be classified as a social concept, as it refers to a relationship between people, but at the same time, it includes strong associations with emotional experiences. Based on recent evidence highlighting how a single dimension cannot represent the full meaning of most abstract concepts (Borsa et al., 2025), this approach might not be best suited to the comprehension of the multidimensionality of the abstract semantic space, and future research on the neural bases of abstract concepts should take into account this multidimensionality (for example, by using multivariate methods such as RSA with semantic models reflecting similarities between concepts based on multiple dimensions).

In this thesis, I used both a categorical and a semantic ratings approach in Chapter 3 and in Chapter 4.

1.3 Brain bases of abstract concepts

In this section, I will review existing literature on the neural bases of abstract concepts across neuropsychological, neuroimaging and neurostimulation evidence. The first part will focus on the neural correlates of abstract concepts contrasted with concrete concepts as two unitary domains.

Concrete and abstract concepts have been opposed for a long time as a dichotomy; however, theoretical, behavioural, neuroimaging, neurostimulation and neuropsychological studies also suggest that the picture is more complex and that to reach a thorough understanding of abstract concepts, a differentiation of the abstract domain is needed.

Therefore, the second part of this section will examine the evidence regarding the neural bases of distinct categories of abstract concepts, namely emotion, social and magnitude concepts.

1.3.1 Abstract > concrete concepts

Experimental studies as well as meta-analyses comparing the neural representation of concrete and abstract words as two opposite monolithic domains consistently show that abstract words recruit the left inferior frontal gyrus (IFG) and the middle temporal gyrus (MTG) more than concrete ones, regions central in the left-lateralized language system (Binder et al., 2009; Bucur & Papagno, 2021; Del Maschio et al., 2022; Hoffman & Bair, 2025; Papagno, Fogliata, et al., 2009; J. Wang et al., 2010).

The higher involvement of left IFG for abstract words has been interpreted in different ways. First, it has been argued, based on the notion that abstract concepts are based exclusively on a verbal representation, that they would engage the semantic-verbal system during their processing compared to concrete concepts, thus recruiting linguistic regions to a higher degree, namely regions such as the left IFG (J. Wang et al., 2010). This explanation aligns with the Dual-Coding theory of concrete and abstract concepts, where abstract concepts are exclusively linguistically encoded.

Another hypothesis is that abstract concepts, compared to concrete ones, require greater semantic control, i.e., the ability to flexibly access and select the correct or relevant semantic information based on task demands (Jackson, 2021), as their meaning is more ambiguous and their contexts more difficult to retrieve (Schwanenflugel & Shoben, 1983) and more diverse (Hoffman, Lambon Ralph, et al., 2013). Indeed, IFG is more active in situations of greater difficulty of semantic selection, when we correctly select the right word (Moss et al., 2005; Snyder et al., 2011), or the right meaning of a word from a pool of possible alternatives (Grindrod et al., 2008). Its role is primarily in semantic control, more than in executive domain-general control (S. Martin et al., 2025). Abstract words are more difficult in this sense, as they appear in a wider variety of contexts (Hoffman, Lambon Ralph, et al., 2013) and therefore their meaning is more malleable and vaster compared to concrete concepts. This explanation is also supported by Hoffman and Bair's (Hoffman & Bair, 2025) recent meta-analysis, in which the authors found IFG as one of the main regions more activated for abstract single words than for concrete single words, but not for abstract sentences compared to concrete sentences. This result is consistent with the context-availability theory's claim that the contexts of abstract concepts are more difficult to retrieve, especially when they are presented in isolation (i.e., as single words), thus requiring a higher engagement of semantic control regions, whereas the same abstract concepts embedded in a sentence would not pose the same demands, as the context would already constrain their meaning (Hoffman & Bair, 2025).

A study by Della Rosa and colleagues (Della Rosa et al., 2018) suggests that both explanations are possibly true: their analysis shows that the left IFG differentiated between abstract and concrete words, and also showed higher activation for less imageable words, and words with lower context availability. However, connectivity analysis showed that the other regions associated with lower imageability and functionally connected to left IFG were mostly left-lateralized, while other regions associated with lower context availability are more right-lateralized, consistent with the notion that the right hemisphere is more active when we make sense of words in unusual or inconsistent scenarios, like metaphors (Faust & Kenett, 2014).

The left middle temporal gyrus (MTG) is also an area involved in language tasks. It is engaged during lexical-semantic retrieval (Acheson et al., 2011), word-production (Sugimoto et al., 2023), phonetic discrimination (Ashtari et al., 2004), resolution of syntactic ambiguity (Acheson & Hagoort, 2013), semantic judgement tasks (Q. Zhang et al., 2019) and even iconic gestures (Papeo et al., 2019). Its decreased activity has also been found to be associated with the severity of chronic aphasia (J. Li et al., 2017). The higher activation of MTG for abstract compared to concrete words is thus compatible with the idea that abstract concepts require more activation in the verbal semantic system to be processed.

In contrast, three meta-analyses (Bucur & Papagno, 2021; Del Maschio et al., 2022; J. Wang et al., 2010) found more posterior temporo-parietal activations for concrete concepts, namely in left fusiform gyrus, left parahippocampal and lingual gyri, bilateral angular and supramarginal gyri and precuneus, and bilateral posterior cingulate. The higher activity in these regions has been interpreted as a greater recruitment of a perceptual/mental imagery system for concrete compared to abstract concepts. Del Maschio et al. also found an increased activation in the premotor areas (Del Maschio et al., 2022), which suggests that motor activations are also more relevant for concrete compared to abstract concepts.

Together with the findings for the abstract > concrete concepts, these results on abstract concepts considered as a unitary whole align with the claim that abstract concepts are predominantly linguistic, whereas concrete concepts involve a heightened recruitment of the sensorimotor system. However, Del Maschio and colleagues also found common activations related to both concrete and abstract concepts in a set of frontal motor, parietal and temporal regions (motor and premotor cortex, right supramarginal gyrus, and inferior temporal gyri), suggesting that even though they do it to a lesser degree, abstract concepts too recruit the sensorimotor imagery system.

Finally, Anterior Temporal Lobes (ATLs) have been a matter of debate in the concrete vs abstract neural bases literature. ATLs are the centre of the hub-and-spokes model (Patterson & Lambon Ralph, 2015), whereby conceptual representations are based both on modality-specific reactivations in the so-called ‘spokes’, or sensory-motor areas, and on amodal, conceptual representations, localised in a ‘hub’ where similarities between concepts are stored. Based on the observation of semantic memory loss in the semantic variant of Primary Progressive Aphasia (svPPA), or semantic dementia, this theory localises the hub in the bilateral anterior temporal lobes (ATLs) (Hoffman et al., 2012; Hoffman & Ralph, 2011; Patterson & Lambon

Ralph, 2015). However, more recent investigations of these patients suggest a functional specialisation of the left and right ATL, with left ATL atrophy leading to linguistic semantic deficits, and right ATL atrophy leading to non-linguistic socioemotional semantic deficits (Borghesani et al., 2022; Younes et al., 2022).

It was argued that, if abstract concepts mostly rely on a linguistic, amodal representation, then deterioration of ATL should lead to a higher degree of concreteness effect, as abstract concepts, differently from concrete ones, would not be supported by multimodal activations outside the amodal hub (Hoffman & Ralph, 2011). An enhanced concreteness effect indeed has been shown in previous literature with svPPA patients and neurostimulation paradigms (Hoffman, Jones, et al., 2013; Hoffman & Ralph, 2011; Pobric et al., 2009). However, the reversal of the concreteness effect was also observed in patients with svPPA (Breedin et al., 1994; Macoir, 2009; Papagno, Capasso, et al., 2009; Yi et al., 2007). Recent MEG studies also found mixed results, where in one study, left ATL preferentially responded to abstract compared to concrete concepts (Farahibozorg et al., 2022), while another study did not find any greater activation for abstract concepts, and bilateral ATL reflected both abstract and concrete semantic components (Vignali et al., 2023).

This apparent inconsistency, however, might be caused by a graded representation of concreteness within the anterior temporal lobes, where dorsolateral regions of ATL, such as the superior temporal gyrus, respond more strongly to abstract words, while ventromedial regions, such as the parahippocampal gyrus, respond better to concrete items (Hoffman et al., 2015). This is supported by connectivity studies, which found that ventromedial regions of the ATL are more connected to sensory-motor areas, while more dorsolateral regions are connected to prefrontal linguistic areas (Binney et al., 2012; Rice et al., 2015). A recent fMRI study investigating different types of abstract verbs varying in their level of embodiment, valence and association to mental states also found that while vATL responded equally to all classes of verbs, other ATL subregions discriminated different types of abstract verbs (Muraki et al., 2025). These studies suggest that ATL does not function as a monolithic, amodal hub, but rather acts as a Graded Semantic Hub, thus reflecting a graded representation of concepts which depends on their level of association to sensory, motor and emotional properties (Patterson & Lambon Ralph, 2015; Rice et al., 2015).

1.3.2 Categories of abstract concepts

In this section, we will review the existing literature investigating the neural bases of different categories of abstract concepts. The choice of the categories to discuss is based on the main clusters that emerged during empirical investigations on the dimensionality of abstract concepts (Persichetti et al., 2024; Troche et al., 2017; Villani et al., 2019) and the extent to which the neural bases of each category have been investigated in previous literature. We will therefore discuss the neural bases of emotion concepts, social concepts, and magnitude concepts.

1.3.2.1 Emotion concepts

Emotion concepts are one of the main categories investigated in the literature on the neural bases of abstract concepts (Arioli et al., 2021; Conca et al., 2021; Desai et al., 2018), and emotion as a dimension has been given the central role in explaining the peculiarity of the grounding of abstract concepts in the Affective Embodiment account (Kousta et al., 2011; Lenci et al., 2018; Newcombe et al., 2012; Vigliocco et al., 2014) and has been recognised as one of the main experiential grounding ingredients by other embodied approaches to abstract concepts (Barsalou et al., 2018; Borghi et al., 2019; Villani et al., 2019). Words' degree of emotionality, indeed, has been shown in a variety of behavioural paradigms to influence how words are processed, namely, inducing a facilitatory effect whereby emotion words are processed faster (Kousta et al., 2011; Newcombe et al., 2012; Siakaluk et al., 2016; Vinson et al., 2014) and acquired earlier in life (Ponari et al., 2018) than neutral abstract words. In some cases, emotion words have not even been considered a class of abstract words, but a third domain, differing from both concrete and abstract words (Altarriba et al., 1999; Altarriba & Bauer, 2004), even though emotional words are perceived as equally abstract as non-emotional abstract words (González-Arias & Aracena, 2022).

Emotional words are identified with different methods. According to the most used model in the study of emotional words, the circumplex model (Posner et al., 2005), the affective value of words is defined in terms of valence and arousal, whereby words with higher arousal and more positive/more negative valence are considered more emotional. Another important distinction to make is between emotion-label and emotion-laden words. While emotion-label words directly refer, or label, an affective state (e.g., 'happiness', 'sadness'), emotion-laden words do not refer to an affective state but to concepts that carry emotional value (e.g., 'death', 'breakup') (Wu & Zhang, 2025). There is evidence that these two types of emotional words are processed differently and differentially influence other cognitive processes (W. Li et al., 2022; Tang et al., 2023; J. Zhang et al., 2019). However, the literature often does not explicitly make this distinction, either not specifying the type of emotion words used or collapsing the two types together, making it difficult to characterise the differences between the processing of these two types of emotion words.

Both Conca's and Desai's reviews included studies which contrasted the activations of emotional vs abstract non-emotional or concrete words. In Desai's review, emotional words were defined as high-arousal words; in Conca's review, studies using emotion-label and emotion-laden words were both included. The neural activations found considering fMRI and PET of emotion concepts comprise a set of fronto-temporal areas, specifically the inferior frontal gyrus and precentral gyrus, in some cases localised in motor and premotor areas (Dreyer & Pulvermüller, 2018), right orbitofrontal cortex and anterior insula, dorsomedial prefrontal cortex, the bilateral temporal pole, as well as the middle and superior portions of ATL, and the left anterior cingulate cortex, amygdala, hippocampus and precuneus (Desai et al., 2018). Arioli et al.'s meta-analyses (Arioli et al., 2021) found activations of the vmPFC, left amygdala and posterior superior temporal sulcus when contrasting emotional stimuli with neutral words, and only left amygdala contrasting emotional with social stimuli.

Collectively, emotion words activated the same regions responsible for emotion processing and experience (Dixon et al., 2017; Etkin et al., 2011; Gasquoine, 2014; Lindquist et al., 2012; Rolls, 2023; J. X. Zhang et al., 2025). While vmPFC has been associated with general affect-coding and self-referential and automatic emotional appraisal, dmPFC is more engaged in effortful reappraisal and negative emotions, in concert with ACC (Zhou & Becker, 2025). The orbitofrontal cortex and ACC have been linked to the perception of reward or value (Rolls, 2023), with pregenual ACC specifically involved in the appraisal of visceral-internal signals (Dixon et al., 2017). The lateral prefrontal cortex has been connected with emotion regulation (Dixon et al., 2017; Grecucci et al., 2013), while the anterior insula has been linked to emotional awareness (Gu et al., 2013).

This overlap is compatible with an embodied cognition framework, where emotion concepts preferentially activate the same areas involved in emotion experience.

Moreover, activations in motor and insular cortices directly relate emotional concepts processing with sensorimotor and internal experience. Emotional words were found to activate the motor face and hand areas (Dreyer & Pulvermüller, 2018; R. Moseley et al., 2012). Another study suggests that motor areas might have a causal role in determining emotional word understanding: a patient with a focal lesion of the left supplementary motor area showed a specific impairment of emotional abstract words (Dreyer et al., 2015). Another study comparing neurotypicals and participants with autism spectrum disorders found a decreased activation of motor areas for emotional words in the latter group, consistent with the higher levels of alexithymia in that population (R. L. Moseley et al., 2015). Activations in the motor areas for emotional words suggest the importance of motor knowledge for emotional conceptualisation, as emotions are associated with facial expressions and movements of different body parts.

Insula involvement is consistent with the assigned role of interoception for subjective, emotional experience (Duerden et al., 2013; Gasquoine, 2014; Gu et al., 2013; Nguyen et al., 2016). Indeed, emotions are associated with changes in our physiological state, involving feedback from our internal milieu, such as heart rate, breathing, changes in temperature, and gastrointestinal reactions. Consistently, behavioural ratings studies also suggest that emotional concepts are experienced through interoception (Connell et al., 2018; Repetto et al., 2023), solidifying the evidence in favour of a connection between emotional concepts and interoceptive experience.

1.3.2.2 Social concepts

Socialness, or the degree to which concepts refer to "*a social characteristic of a person or group of people, a social behaviour or interaction, a social role, a social space, a social institution or system, a social value or ideology*" (Diveica et al., 2023), is another important feature in the abstract conceptual semantic space. Theoretical approaches underscore the centrality of the social context to learn abstract concepts (Barsalou et al., 2018; Borghi et al., 2019), and semantic ratings studies show how socialness organises the semantic space of abstract concepts (Harpaintner et al., 2018; Persichetti et al., 2024; Troche et al., 2014; Villani et al., 2019), where concepts with high socialness are clustered together in the category of social concepts. Moreover, socialness also influences the behavioural performance to abstract concepts, so that more social concepts are processed more efficiently (faster reaction times and higher accuracy) in lexical decision and word knowledge tasks (Diveica et al., 2023). The importance of socialness for abstract concepts generally has also been supported by Hoffman's recent meta-analyses, which found that abstract concepts, compared to concrete ones, preferentially activate the social network (Hoffman & Bair, 2025).

Conca et al.'s review included social concepts among the investigated categories (Conca et al., 2021). The review reports neuroimaging and neurostimulation studies contrasting social concepts with concrete concepts, or with non-social abstract concepts or quantity-related abstract concepts. The vast majority of studies found an involvement of the superior anterior temporal lobes (sATL), with either a right, left or bilateral involvement. Additionally, an involvement of the ventral/lateral temporal cortex or fusiform gyrus, inferior frontal gyrus, posterior middle/superior temporal gyrus, inferior parietal lobule and occipital lobe has also been found. Studies with patients also confirmed the role of the sATL (Pobric et al., 2016; Zahn et al., 2009, 2017), particularly the right sATL (Pobric et al., 2016), a result confirmed by a recent MEG study with social verbs (Amoruso et al., 2025). Arioli et al.'s meta-analyses (Arioli et al., 2021), that included a contrast between social and non-social verbal stimuli (written words or sentences), and a contrast between social and emotional concepts, also found activations, in both contrasts, of the ATL, as well as the middle temporal gyrus, posterior superior temporal gyrus and temporo-parietal junction bilaterally.

ATL is a central area for social cognition and mentalizing processes, such as attributing mental states, person memory, and moral judgements (Anzellotti, 2017; Olson et al., 2013; Ross & Olson, 2010; Rouse et al., 2024). ATL atrophy is a central feature of fronto-temporal dementia (FTD), and patients affected by it have been reported to show both social behaviour deficits and impairments in social conceptual knowledge (Borghesani et al., 2022; Mancano & Papagno, 2023; Rouse et al., 2024; Younes et al., 2022; Zahn et al., 2009), even though dissociations between social cognition and social conceptual knowledge have also been found (Zahn et al., 2017).

Moreover, the posterior middle/superior temporal gyrus extending into TPJ has also been implicated in storing social perceptual signals such as gaze directions and facial expressions (Engell & Haxby, 2007; Said et al., 2010), body postures and gestures (Redcay et al., 2016; Wurm & Schubotz, 2018).

Overall, these overlaps are consistent with an embodied cognition framework, as social concepts are supported by the same areas involved in social cognition.

1.3.2.3 Magnitude concepts

Quantity or magnitude concepts refer to numbers and operations, scope (quantity), timing, order, duration (time), and to a place, position, or direction (space) (Conca et al., 2021; Troche et al., 2017; Villani et al., 2019). Magnitude is one of the main dimensions in the semantic organisation of abstract concepts, together with emotion, sociality, and sensorimotor associations (Persichetti et al., 2024; Troche et al., 2014; Villani et al., 2019). Space, time and quantity cluster together to create a distinct class of abstract words, namely, magnitude concepts. This type represents a special case of abstract concepts, as they do not refer to specific entities in the external world, but are nonetheless fundamentally grounded in our sensory-motor experience with the external world (Fischer & Shaki, 2018; Villani et al., 2019). They are characterised by higher body-object-interaction according to subject ratings (Villani et al., 2019), and indeed, behavioural studies show that both numbers and numerical operations are rooted in our spatial bodily interactions with the world (Fischer & Shaki, 2018; Lugli et al., 2013, 2018). Small numbers are typically associated with left space and higher numbers with right space, an effect known as the spatial-numerical association (SNL) (Dehaene et al., 1993; Fischer & Shaki, 2018), and different types of numerical operations, addition and subtraction, benefit from a congruent ascending/descending and clockwise/counterclockwise motion (Lugli et al., 2013, 2018).

Compared to emotion or social concepts, however, magnitude concepts have been rarely investigated with neuroimaging or neuropsychological methods. The few studies that did explore their neural bases found that these concepts, contrasted with other categories of abstract concepts such as emotions and social, preferentially involve the intraparietal sulcus (Catricalà et al., 2020; Eger et al., 2003; Wilson-Mendenhall et al., 2013) and the middle and superior prefrontal gyri (Huth et al., 2016; Wilson-Mendenhall et al., 2013). Activations in the same areas and in the ventral temporal cortex have also been found for mathematical sentences vs non-mathematical sentences (Amalric & Dehaene, 2016).

The bilateral inferior frontal sulcus (IPS) is involved during numerosity and quantity processing, as shown by both neuroimaging and neurostimulation studies (Bugden et al., 2012; Cappelletti et al., 2009; Göbel et al., 2006; Y. Li et al., 2013; Nakai & Sakai, 2014; Piazza et al., 2007; Roell et al., 2021; Salillas et al., 2019; Sandrini et al., 2004; Schel & Klingberg, 2017; Tablante et al., 2023). TMS targeting IPS affects quantity judgments on both numerical and non-numerical stimuli (Cappelletti et al., 2009), and an MEG study shows that the duration and numerosity estimation overlap in the intraparietal sulci (Salillas et al., 2019). The parietal cortex, and in particular the IPS, has been proposed to act as a common brain region for the representation of different types of magnitudes (numerosity, time, space) (Bueti & Walsh, 2009; Hubbard et al., 2005).

Moreover, lateral prefrontal activations for magnitude concepts are also consistent with the involvement of prefrontal cortices for number and time representation (Hayashi et al., 2013; Nieder & Dehaene, 2009).

The behavioural and neuroimaging findings on magnitude concepts are also compatible with an embodied cognition account, and their status as a separate class of concepts underscores the heterogeneity of abstract concepts.

1.3.3.4 General remarks on abstract categories

Collectively, different categories of abstract concepts preferentially recruit areas across a wide array of frontal, temporal and parietal lobes, which may belong (e.g., sATL, MTG) or not (e.g., amygdala, IPS) to the linguistic system. In most cases, the same areas are also involved in the processing of the corresponding non-linguistic, experiential counterpart. These results are not aligned with the findings of studies that contrast concrete and abstract as a monolithic whole, and thus conclude that abstract concepts do not have specific activations beyond the linguistic system. As activations for subsets or categories of abstract concepts are distributed across the cortex and differ between categories, they might be smoothed over, and therefore might not emerge, by aggregating them all together (Hoffman & Bair, 2025). The investigations of specific classes of abstract concepts suggest instead that the conceptual representation of different types of abstract concepts is both linguistic and experiential, involving a distributed set of linguistic areas and areas reflecting their semantic features, including their corresponding embodied experiences.

However, further research is needed to understand to what degree the activations of areas outside the language network, reflecting the corresponding non-linguistic experience, are a fundamental part of concept processing, or whether they constitute more of a by-product that does not really impact conceptual representation.

1.4 Outline of the thesis

In the previous section of this introduction, I reviewed (1) current theories for the conceptual representation of abstract words, (2) the use of semantic ratings as a method to investigate the organisation of the abstract semantic space, (3) the neural bases of abstract > concrete concepts, and (4) the neural bases of different categories of abstract concepts. Across these sections, I highlighted the challenges posed by partitioning abstract concepts into distinct categories, and the open questions regarding the importance of sensory, motor and emotional experiences for the brain representation of abstract concepts. In the following chapters, I will present the work that I did during my doctorate to further our understanding of these topics.

In Chapter 2 (Mancano & Papagno, 2023), I will present a review that investigated the concreteness effect, its reversal, and the association with ATL atrophy, as well as dissociations between different categories (emotions, social) of abstract concepts in two clinical populations, namely, svPPA and Alzheimer's disease (AD) patients. In this review, I showed that abstract concepts are often relatively preserved in svPPA patients, and that this reversal of the concreteness effect is associated with the degree of ATL atrophy. Furthermore, we show that emotion and social abstract concepts can be selectively impaired in AD and svPPA patients, suggesting a segregation of the neural bases of these categories.

In Chapter 3 (Mancano & Papagno, 2026), I will present (1) a semantic rating and (2) a TMS study that investigated the role of bilateral Anterior Insula in the processing of emotional and social dimensions of abstract and concrete concepts and in interoception. In this study, results show that right Anterior Insula causally supports both interoception and the emotional and social dimensions of abstract concepts, in line with the behavioural evidence linking interoceptive experience to the representation of abstract concepts.

In Chapter 4, I will present an MEG study that investigated the organisational principles of concrete and abstract concepts, using RSA to compare MEG signals elicited by concrete and abstract concepts to models reflecting distributional, experiential sensorimotor, experiential affective, categorical and concreteness properties. Results show that concrete and abstract concepts are both governed by common distributional organising principles, but concrete concepts also rely on taxonomic information, whereas abstract concepts rely on their sensorimotor properties.

In Chapter 5, I will discuss the theoretical implications of these findings in the context of current theories on the taxonomy and embodiment of abstract concepts.

CHAPTER 2.

CONCRETE AND ABSTRACT CONCEPTS IN THE SEMANTIC VARIANT OF PRIMARY PROGRESSIVE APHASIA AND ALZHEIMER'S DISEASE: A SCOPING REVIEW

This chapter has been published as:

Mancano, M., Papagno, C. (2023) "Concrete and Abstract concepts in the semantic variant of Primary Progressive Aphasia and Alzheimer's Disease: A Scoping Review". Brain Sciences, 13(5)

2.1 Abstract

The concreteness effect (CE), or better performance with concrete compared to abstract concepts, is a constant feature in healthy as well as neurodegenerative patients. However, a reversal of the CE has been reported in patients affected by semantic variant of Primary Progressive Aphasia (svPPA), a neurodegenerative disease characterised by anterior temporal lobe (ATL) atrophy. The present scoping review aims at identifying the extent of evidence regarding the abstract/concrete contrast in Alzheimer's disease (AD) and svPPA, and associated brain atrophy. Five online databases were searched up to January 2023 to identify papers where both concrete and abstract concepts were investigated. Thirty-one papers were selected and showed that while in patients with AD concrete words were better processes than abstract ones, in most svPPA patients there was a reversal of the CE, with five studies correlating the size of this effect with ATL atrophy. However, CE was also reported in svPPA. Furthermore, we found evidence of category-specific impairments, within the concrete (living, non-living) and the abstract (emotion, social) domains.

Future work is needed to disentangle the role of specific portions of ATL in concepts representation, and the duration of disease should be controlled for. Beyond the abstract and concrete dichotomy, selective deficits appeared for social words in svPPA, and facilitation for emotion words in AD.

2.2 Introduction

Concepts (and words) can be classified as concrete or abstract, the difference being that the first are "material" objects that are tangible and can be experienced through our senses (e.g., car, bear), while abstract concepts are not (e.g., happiness, courage). Psycholinguistic studies on healthy participants (C. T. James, 1975; Strain et al., 1995) demonstrated that concrete items are processed faster than abstract ones, and neuropsychological studies (Moss et al., 1995) have shown that in patients with aphasia due to an anterior lesion involving the inferior frontal gyrus, therefore persons with non-fluent aphasia, this advantage, called the concreteness effect (CE), is magnified. However, a subgroup of patients presents with an inversion of this effect, the so-called reversal of the concreteness effect (see (Papagno, 2022) for a review). In general, these patients have bilateral but asymmetric lesions in the anterior part of the temporal lobes, with the left side more damaged than the right. Indeed, most patients described in the literature had suffered from herpes simplex encephalitis (Warrington & Shallice, 1984) or were patients in the early stages of the semantic variant of Primary Progressive Aphasia (svPPA), a subtype of the broader spectrum of Frontotemporal dementia.

Frontotemporal dementia (FTD) is a neurodegenerative disease characterised by temporal and frontal lobar atrophy. It presents with a variety of symptoms, which allows distinguishing three main subtypes (Neary et al., 1998): the behavioural variant of FTD (bvFTD), with primarily behavioural and executive symptoms (Rascovsky et al., 2011), a nonfluent Primary Progressive Aphasia (nfPPA), with primarily language symptoms, and semantic dementia. The latter can start with a predominant left atrophy, which produces a semantic variant of PPA (svPPA). SvPPA's main symptom is the degradation of semantic memory, with difficulties in name retrieval and loss of semantic features of objects. Gorno-Tempini and colleagues (Gorno-Tempini et al., 2011) identified a third form of PPA that was named logopenic variant PPA (lPPA); lPPA more often represents an atypical onset of Alzheimer's disease (AD).

Indeed, AD patients also present with early language and semantic deficits (Adlam et al., 2006; Martínez-Nicolás et al., 2019). BvFTD can also show linguistic deficits, including difficulties with abstract concepts (Ash et al., 2016; Geraudie et al., 2021). Therefore, while a reversal of the concreteness effect has been found in some patients with SD, in bvFTD the concreteness effect seems to increase.

It must be acknowledged, however, that tests for semantic memory, such as the Pyramid and Palm Trees test (Howard & Patterson, 1992), mainly focus on concrete concepts, whereas fewer investigate the contrast between concrete and abstract concepts.

Different theories have been proposed to account for this double dissociation, none of which can explain the reversal of the concreteness effect, as they provide a quantitative difference either in terms of number of available representations, both verbal and sensory-perceptual for concrete concepts, and only verbal for abstract ones (Paivio, 1991) or in terms of larger contextual support for concrete words (Schwanenflugel & Shoben, 1983) or in terms of number of attributes that would be higher in the case of concrete words/concepts than in the case of abstract ones (Jones, 1985; Plaut & Shallice, 1991). To overcome the quantitative explanation, Crutch and Warrington (Crutch & Warrington, 2005) proposed a difference in the organisation, whereby concrete concepts are organised in categories and abstract ones rely on associations with other items, with a different meaning depending on the context. However, abstract concepts can also be referred to categories (Conca et al., 2021). Indeed, emotional words have already been considered apart (Joubert et al., 2017) as social words (Zahn et al., 2007), and quantity-related concepts (Catricalà et al., 2021).

In contrast to the lack of a satisfactory theoretical explanation, what can be taken for granted is the presence of different anatomical correlates for the two types of items. However, there is no agreement on *which* these correlates are. In people with aphasia (PWA), an increase in the concreteness effect has been associated with vascular damage in the territory of the left middle cerebral artery, that involves the prefrontal cortex, while, as already reported, it appears that the large majority of cases with a reversed concreteness effect suffered from an anterior temporal lesion, generally bilateral but more evident on the left side, as it has been confirmed in studies on patients after left or right temporal pole resection (Loiselle et al., 2012), and on patients submitted to direct electrical stimulation during awake surgery (Orena et al., 2019).

Unfortunately, neuroimaging data are not totally in line with the clinical evidence. Indeed, while the role of the left inferior frontal gyrus (IFG) for abstract words is undoubtedly established (Binder et al., 2009), a recent meta-analysis (Bucur & Papagno, 2021) confirmed that concrete and abstract words processing involves at least partially segregated brain areas and that the inferior frontal gyrus is crucial for abstract words, but also demonstrated that more posterior temporoparietal-occipital regions seem to be crucial for processing concrete words. The lack of consistency between neuropsychological and neuroimaging data might be explained by the different populations tested, usually young people in fMRI experiments vs. old people in neuropsychological samples. Another reason could be the frequent overlap of the terms, abstract/concrete, with high-/low-imageability. Concreteness refers to the extent to which a word refers to a tangible referent, whereas imageability refers to the extent to which an item can evoke a mental image (Paivio et al., 1968). It is well-known that the two features operate differently on naming and recall (Boles, 1983; Connell & Lynott, 2012; Richardson, 1975, 1976); and therefore cannot be considered interchangeable.

Another topic of debate is that the reversal of the concreteness effect was initially described in single case reports (Breedin et al., 1994; Macoir, 2009; Papagno, Capasso, et al., 2009; Warrington, 1975), prompting the “negationist” researchers to suggest that these patients were simply outliers with high education. However, subsequent group studies (Bonner et al., 2009; Cho et al., 2021; Cousins et al., 2016, 2017, 2018) confirmed the existence of this effect, especially in patients affected by svPPA, who were contrasted with people affected by the bvFTD who suffered, in turn, an increased concreteness effect. Nonetheless, Jefferies and colleagues’ (Jefferies et al., 2009) group study showed that svPPA patients were more impaired in abstract compared to concrete concepts, and rejected the hypothesis that a reversal of CE is a hallmark of these patients. They further supported these findings with a neurostimulation study (Pobric et al., 2009), where they showed that inhibitory transcranial magnetic stimulation (TMS) targeting anterior temporal regions particularly impaired performance with low-imageability rather than with high-imageability items. On the other hand, no one considered the reversal of the CE a constant feature of the disease, but the point is that when it occurs, it is mainly in patients with svPPA.

To summarize, both a CE and its reversal exist. It is not clear whether a damage of the anterior temporal poles as found in svPPA has a role in producing a selective damage to concrete concepts.

To shed light on the debate concerning the role of the anterior temporal poles in concrete word processing and the occurrence of the reversal of the concreteness effect in svPPA, we analyzed the published cases of neurodegenerative patients in which language was studied with a specific focus on abstract and concrete dissociation to verify whether there is a sharp distinction based on the presence of atrophy in specific regions of the brain. Therefore, we conducted a scoping review to identify and map the available evidence and clarify which is the volume of the literature on this topic, namely the dissociation between abstract and concrete concepts/words and associated brain atrophy.

2.3 Methods

2.3.1 Protocol

We followed a previously developed protocol to create and report scoping reviews, using the Preferred Reporting Items for Systematic Reviews and Meta-analyses extension for Scoping Reviews (PRISMA-ScR) Checklist (Tricco et al., 2018).

2.3.2 Eligibility criteria

Title, abstract, and full-text articles were screened for eligibility based on the inclusion criteria: (1) both concrete and abstract concepts were investigated within the same group/patients, (2) tested patients with a probable diagnosis of either Alzheimer's disease or Primary Progressive Aphasia (the three variants: namely semantic variant of Primary Progressive aphasia (svPPA), nonfluent variant of primary progressive aphasia (nfPPA), logopenic variant of primary progressive aphasia (lPPA) and/or behavioural variant of Frontotemporal Dementia (bvFTD), (3) original studies, (4) written in English and (5) peer-reviewed.

2.3.3 Information sources

The following online bibliographic databases were searched up to January 2023: MEDLINE (accessed by PubMed, https://www.ncbi.nlm.nih.gov/pubmed), PsycARTICLES (via EBSCOHost, https://search.ebscohost.com), PsycINFO (via EBSCOHost), Scopus (https://www.scopus.com, accessed via University of Trento) and Web of Science (https://webofknowledge.com/). For one included paper (Stockbridge et al., 2022), we contacted the first author to obtain the full text. Papers including only abstract, or only concrete (and not both) categories were excluded; we considered only papers where both abstract and concrete concepts were investigated and compared. We included both group studies and single-case reports.

2.3.4 Search

Search keywords were the following: (1) "dementia", "semantic dementia", "FTD", "Alzheimer" AND (2) "concreteness", "abstract concepts", "concrete concepts", "concrete words", and "abstract words".

2.3.5 Selection of sources of evidence

The references were exported into a text format and uploaded on Rayyan software (Ouzzani et al., 2016). On Rayyan, we removed duplicates after careful detection. To prevent the risk of bias, both authors carried out autonomously (i.e., with Rayyan 'blind on' modality) title and abstract screening. After both authors completed the screening, the resulting conflicts were reviewed and resolved by discussion and consensus. After that, both authors proceeded to the full-text screening of the potentially relevant papers, which were included in accordance with the abovementioned inclusion criteria.

2.3.6 Data charting process

Relevant data were extracted from the included papers by one reviewer, while the other verified the accuracy of the data.

2.3.7 Data items

We abstracted data related to participants' features (sample size, presence of a control group, diagnosis, atrophy extension), methods (tasks, type and the number of stimuli, semantic and grammatical categories investigated) and outcomes (behavioural results and correlation between atrophy site and behavioural results).

2.3.8 Synthesis of results

We grouped the records according to the diagnosis of patients included in the study (only PPA, only AD, both PPA and AD). We summarised the results considering more specifically the contrast between concrete and abstract concepts performance, and, when present, the correlation between imaging and behavioural results, the distinction between different grammatical classes (i.e., nouns, verbs, adjectives), and different categories of concrete (living/non-living) and abstract (social, emotion, etc.) words.

The administered tasks varied, including synonym judgement task, picture naming, naming to definition, elicited speech by means of the Cookie Theft picture description task (Goodglass & Kaplan, 1983), autobiographical memory, and semantic priming paradigms.

When considering the contrast between concrete and abstract domains, we collapsed results across comprehension, production, and priming paradigms.

2.4 Results

2.4.1 Selection of sources of evidence

The literature search identified 2148 articles, including 1541 from PubMed, 481 from Web of Science, 110 from PsychInfo, 6 from PsychArticles, and 45 from Scopus. Of these, 252 were removed as duplicates. After title, abstract screening, and full-text articles assessment, 31 papers survived the final selection and were included in the analysis. Figure 1 shows the search and selection process.

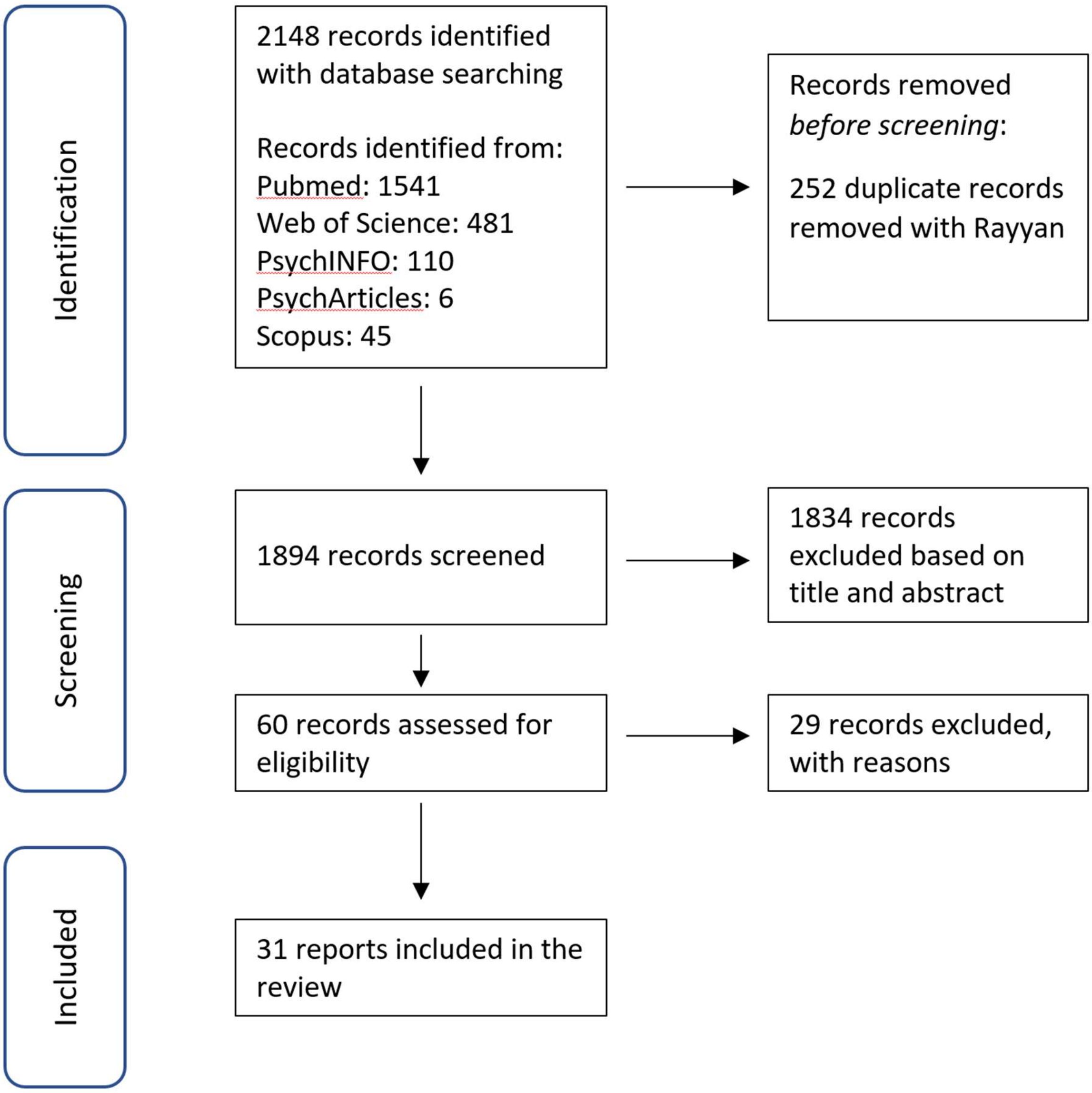


Figure 1. Flow diagram of study selection and inclusion.

2.4.2 Characteristics of sources of evidence

Among the 31 included records, 19 were experimental studies investigating semantic representation in Primary Progressive Aphasia patients. Three of them were case reports, two were case series, and the remaining were all group studies.

Among the group studies, six records investigated semantic representations in AD patients, while the other six were group studies investigating semantic representations in both PPA and AD patients.

For reasons of coherence, we reported all studies referring to "Semantic Dementia" and "svPPA" under one label, "svPPA".

2.4.3 Results of individual sources of evidence

Results are shown in Table S1, Table S2, and Table S3 in Appendix 1.

2.4.4 Synthesis of results

2.4.4.1 Participants

PPA records included 163 bvFTD and 492 PPA patients: 63 nfPPA, 113 lPPA, 40 unclassified, and 276 svPPA.

AD records included 214 patients.

2.4.4.2 Contrast concrete/abstract

In this section, we present the results of the contrast between concrete and abstract concepts, without distinguishing for grammatical class (nouns, verbs) and categories (e.g., animals, emotions). The results based on these variables are discussed in sections 18.4 and 18.5.

2.4.4.2.1 Semantic variant Primary Progressive Aphasia (svPPA)

Out of the 24 studies on svPPA patients, 14 (58.3%, 147 patients) showed a better performance with abstract compared to concrete concepts (Bonner et al., 2009; Breedin et al., 1994; Catricalà et al., 2014; Cho et al., 2021; Cousins et al., 2016, 2017, 2018; Hoffman et al., 2014; Joubert et al., 2017; Macoir, 2009; Papagno, Capasso, et al., 2009; Reilly et al., 2007; Woollams, 2015; Yi et al., 2007). Six studies (25%, 99 patients) found better performance with concrete compared to abstract concepts (Catricalà et al., 2021; Hoffman, Jones, et al., 2013; Hoffman & Ralph, 2011; Jefferies et al., 2009; Pobric et al., 2016; Stockbridge et al., 2022). Finally, four studies (16.6%, 30 patients) found no significant difference in performance between abstract and concrete concepts (Crutch & Warrington, 2006; Hsieh et al., 2012; Macoir et al., 2015; Poos et al., 2022).

2.4.4.2.2 Behavioural variant Frontotemporal Dementia (BvFTD)

Three studies (66 patients) found better performance with concrete than abstract concepts in bvFTD patients (Cousins et al., 2016, 2017; Poos et al., 2022). Two studies (82 patients) found a similar performance between the two domains (Cho et al., 2021; Hsieh et al., 2012).

2.4.4.2.3 Logopenic variant Primary Progressive Aphasia (lPPA)

Both the two studies which included lPPA patients found better performance with concrete compared to abstract concepts (Poos et al., 2022; Stockbridge et al., 2022).

2.4.4.2.4 Nonfluent Primary Progressive Aphasia (nfPPA)

The three studies which included nfPPA patients found better performance with concrete compared to abstract concepts (Cho et al., 2021; Poos et al., 2022; Stockbridge et al., 2022).

2.4.4.2.5 Alzheimer's disease (AD)

Out of the 12 studies on AD patients, five (41.6%, 106 patients) found better performance with concrete compared to abstract concepts (Bushell & Martin, 1997; Giffard et al., 2015; Peters et al., 2009; Rissenberg & Glanzer, 1987; Yi et al., 2007), while four studies (33.33%, 58 patients) found no difference (Catricalà et al., 2014; Crutch & Warrington, 2006; Hsieh et al., 2012; Joubert et al., 2017). Two studies (16.66%, 39 patients) found better performance with abstract compared to concrete concepts (Fleming et al., 2003; A. Martin & Fedio, 1983), and the remaining study was unclassifiable (Westbury et al., 2002). In this study, the authors tested both concrete and abstract concepts but did not contrast them directly.

Results are summarised in Table 1 and Figure 2.

	SvPPA	BvFTD	NfPPA	LPPA	AD
C>A	6 records, 99 patients	3 records, 66 patients	3 records, 63 patients	2 records, 113 patients	5 records, 106 patients
A>C	14 records, 147 patients	/	/	/	2 records, 39 patients
C=A	4 records, 30 patients	2 records, 82 patients	/	/	4 records, 58 patients

Table 1. Results of concrete/abstract contrast for each disease. C>A: Concreteness effect, A>C: Reversal of concreteness effect, C=A: no difference between concrete and abstract concepts

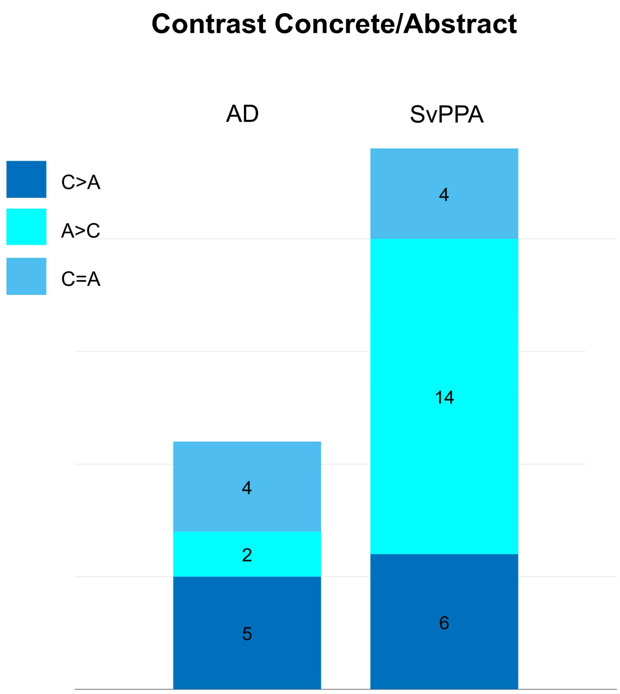


Figure 2. Synthesis of results on concreteness effect for svPPA and AD patients. Numbers inside the stacked bar chart indicate the number of studies that found the effect corresponding to each colour. C>A: Concreteness effect, A>C: Reversal of concreteness effect, C=A: no difference between concrete and abstract concepts

2.4.4.3 Correlation between semantic representations and site of atrophy in PPA

Among the included records, only a portion of PPA studies (N=13) reported imaging data of patients' atrophy (Bonner et al., 2009; Breedin et al., 1994; Cho et al., 2021; Cousins et al., 2016, 2017, 2018; Hoffman & Ralph, 2011; Hsieh et al., 2012; Macoir, 2009; Macoir et al., 2015; Papagno, Capasso, et al., 2009; Pobric et al., 2016; Stockbridge et al., 2022), while another study only reported the correlation between svPPA patients' performance and atrophy sites (Joubert et al., 2017).

2.4.4.3.1 Site of atrophy

As regards the svPPA patients, the majority of these studies reported atrophy in the Anterior Temporal Lobe (ATL), bilaterally (Bonner et al., 2009; Cousins et al., 2018; Macoir et al., 2015), bilateral with a predominance on the left side (Bonner et al., 2009; Breedin et al., 1994; Cho et al., 2021; Cousins et al., 2016; Hoffman & Ralph, 2011; Hsieh et al., 2012; Macoir, 2009; Pobric et al., 2016; Stockbridge et al., 2022), limited to the left side (Papagno, Capasso, et al., 2009). The specific parts of ATL involved in the atrophy were specified as inferolateral (Bonner et al., 2009; Macoir, 2009), medial temporal cortex (Papagno, Capasso, et al., 2009), bilateral Inferior Temporal Gyrus (ITG) and left Fusiform Gyrus (FG) (Cousins et al., 2017), medial and lateral (Cousins et al., 2018), inferior (Stockbridge et al., 2022).

A minority of them also reported significant atrophy in some frontal regions: left Inferior Frontal Gyrus (IFG) and orbitofrontal cortex, particularly on the left side (Cho et al., 2021). Atrophy of the insula was also reported (Cousins et al., 2016, 2018).

As regards the bvFTD patients, the reported sites of atrophy are frontal (Hsieh et al., 2012), frontal lobe regions, modest right temporal lobe atrophy (Cousins et al., 2016), bilateral IFG, orbitofrontal cortex, superior temporal gyrus (Cousins et al., 2017), bilateral frontal and temporal lobes (Cho et al., 2021).

Two studies reported sites of atrophy for nfPPA: left middle frontal, inferior temporal and middle temporal regions (Cho et al., 2021), and asymmetric frontal atrophy (Stockbridge et al., 2022).

One study (Stockbridge et al., 2022) also reported left temporoparietal atrophy for their lPPA cohort.

There was no data regarding atrophy in AD patients.

2.4.4.3.2. Correlation between atrophy and reversal of concreteness effect

Some of these studies analysed the relationship between the svPPA patients' semantic performance and cortical atrophy. Five group studies reported a positive correlation between the size of reversal of CE (better performance with abstract compared to concrete concepts) and atrophy in anterior temporal regions: right anterolateral temporal cortex (Bonner et al., 2009), left anterior temporal cortex (Cousins et al., 2016), parahippocampal gyrus and portions of left ATL (Cousins et al., 2017), left ATL, medial and lateral (Joubert et al., 2017), right ventral and left superior temporal regions (Cousins et al., 2018), left ATL (Cho et al., 2021).

In one of these studies (Cousins et al., 2017), the authors also observed that decreased abstractness of speech in bvFTD was related to atrophy in the left IFG, left superior frontal gyrus, left anterior cingulate, and bilateral caudate.

2.4.4.4 Different semantic effects across grammatical classes: nouns, verbs, adjectives

2.4.4.4.1 Nouns

Seven studies assessed semantic performance on nouns (Catricalà et al., 2021; Cho et al., 2021; Cousins et al., 2016, 2017, 2018; Macoir, 2009; Papagno, Capasso, et al., 2009).

In their svPPA case report, Papagno and colleagues (Papagno, Capasso, et al., 2009) tested the patient's performance on different categories of concrete nouns, and on concrete contrasted to abstract nouns. In the different categories of concrete nouns, the patient revealed a better performance with inanimate nouns compared to biological ones; in the picture naming, verbal fluency on phonemic cue and word-definition tasks, the patient performed better with abstract than with concrete nouns.

In his longitudinal svPPA case report, Macoir (Macoir, 2009) reported a better performance on the similarity judgement of the abstract compared to the concrete meaning of homophones in a semantic similarity task in the first testing session, which disappeared in the following two with the progression of the disease.

Cousins and colleagues (Cousins et al., 2016), in a similar way, found higher accuracy in svPPA patients for abstract noun triads compared to concrete ones in a similarity judgement task, whereas bvFTD patients demonstrated the opposite pattern and controls showed no effect of concreteness.

Three studies (Cho et al., 2021; Cousins et al., 2017, 2018) used the Cookie Theft Picture description task (Goodglass et al., 1983), and the elicited descriptions were transcribed; in particular, they measured the abstractness of produced nouns. In one of these studies (Cousins et al., 2017), the authors found that svPPA patients produced significantly more abstract nouns than bvFTD patients, and the degree of abstractness of produced nouns positively correlated with other measures of semantic impairment. In a longitudinal study (Cousins et al., 2018), the authors found that svPPA produced fewer concrete nouns than bvFTD at baseline, and a longitudinal decrease in the concreteness of produced nouns only in the first group, so that there was a positive relationship between the duration of disease and the abstractness of speech. Similarly, in another study (Cho et al., 2021), the authors found that svPPA, compared to bvFTD, nfPPA and controls produced more abstract nouns in their descriptions.

In their case series, Catricalà and colleagues (Catricalà et al., 2021) observed semantic priming in a lexical decision task with pairs of different categories of concrete and abstract nouns. They found priming for all categories in controls and abolished priming in their svPPA patients only for one abstract category of pairs, namely social pairs.

2.4.4.4.2 Verbs and Nouns

Seven studies investigated the dissociation in the semantic representation of nouns and verbs across different tasks (Breedin et al., 1994; Bushell & Martin, 1997; Hoffman, Jones, et al., 2013; Hoffman & Ralph, 2011; Papagno, Capasso, et al., 2009; Reilly et al., 2007; Yi et al., 2007).

One study found no difference between performance on nouns and verbs (Hoffman, Jones, et al., 2013). The authors found a similar increased CE across nouns and verbs triplets in svPPA patients compared to controls in a synonym matching task, with a better comprehension of more imageable than less imageable items regardless of their grammatical class. In a verb-picture naming task with svPPA, lPPA and unclassified PPA patients, Stockbridge and colleagues (Stockbridge et al., 2022) also found the presence of a concreteness effect for verbs, with increased concreteness related to better performance. Another study (Breedin et al., 1994), instead, in a synonym judgement task where the patient was asked to choose the less related word, found better performance with verbs than with nouns. However, in a following test, they investigated three types of verb triplets: non-relational triplets (distractor verb opposite in meaning to the probe), manner triplets (distractor verb that expresses the same action, but executed in a different way), and relational triplets (distractor verb expresses the same event but assigns thematic roles differently). The patient's performance was significantly impaired only with manner verbs, for which the sensorimotor (or concrete) component is relevant.

Other studies found different effects of concreteness depending on the word class of the tested stimuli. In a study on semantic priming in AD patients (Bushell & Martin, 1997), the authors found different priming effects depending on the word class and concreteness: neither controls nor AD showed priming for abstract nouns and non-motion verbs, but controls showed priming for both motion verbs and concrete nouns, AD patients only for concrete nouns.

Yi and colleagues (Yi et al., 2007), using a naming-to-description task, with concrete and abstract nouns, and motion and cognitive verbs, found the presence of a concreteness effect for nouns in AD patients, but not with verbs, and of a reversal of CE in svPPA patients, with better performance on cognition compared to motion verbs, but no difference in performance between abstract and concrete nouns.

Similarly, Reilly and colleagues (Reilly et al., 2007), in a concreteness judgement task (a task where patients are asked to answer whether the stimulus was concrete or abstract) which included nouns and verbs, found that svPPA patients were prone to misclassifying long concrete words as abstract, but this effect was apparent only with verbs. Another study (Bonner et al., 2009) included only verbs and found that svPPA patients were better at similarity judgement of abstract compared to concrete verbs (reversal of CE), opposite to controls' performance.

This reversal CE was not replicated by (Hoffman & Ralph, 2011) on svPPA patients using the same tasks used in two other studies (Bonner et al., 2009; Yi et al., 2007); instead, they found no significant difference between abstract and concrete verbs.

Papagno and colleagues (Papagno, Capasso, et al., 2009) also did not find any concreteness effect (nor reversal) for verbs in a svPPA patient: in synonymy and word-definition tasks, the patient was indistinguishable from controls with verbs; however, the same subject was impaired in concrete, but not in abstract nouns in those tasks, i.e., a reversal of concreteness effect specific to nouns.

2.4.4.4.3 Adjectives

No effect of concreteness with adjectives was found by (Papagno, Capasso, et al., 2009), as well as in (Macoir et al., 2015), who found a similar performance across concreteness levels, with no significant difference between concrete (colour, dimension, physical property) and abstract (human propensity, value) performance in synonymy judgement and adjective-to-noun matching tasks.

Other studies did not provide information regarding the grammatical class of the stimuli used.

2.4.4.5 Abstract and concrete categories

Beyond the dichotomous abstract vs concrete concepts distinction, 12 studies investigated the dissociation between different categories within concrete, abstract, or both concrete and abstract domains (Breedin et al., 1994; Catricalà et al., 2014, 2021; Fleming et al., 2003; Giffard et al., 2015; Hsieh et al., 2012; Joubert et al., 2017; Macoir, 2009; Macoir et al., 2015; A.

Martin & Fedio, 1983; Papagno, Capasso, et al., 2009; Pobric et al., 2016). Two studies also investigated emotion as a dimension rather than a category (Giffard et al., 2015; A. Martin & Fedio, 1983).

2.4.4.5.1 Concrete domain: the distinction between living and non-living entities

Five studies investigated the distinction between living and non-living concepts processing (Breedin et al., 1994; Catricalà et al., 2014, 2021; Macoir, 2009; Papagno, Capasso, et al., 2009).

Breedin and colleagues (Breedin et al., 1994), in their svPPA report, found a worse performance in answering questions on perceptual compared to non-perceptual features, and better performance with living (animals) than with non-living (tools) concepts in a synonymy judgement task.

Macoir (Macoir, 2009), in his longitudinal svPPA case report, found no difference in performance between living and non-living items, observed across a variety of different tasks (semantic similarity judgement, word-to-picture matching, word definition, word spelling to dictation, picture naming and naming to definition). Papagno and colleagues' (Papagno, Capasso, et al., 2009) svPPA patient, in a similar picture naming task, showed a significant difference in the naming of living and non-living entities, and a semantic memory questionnaire revealed a ceiling performance for inanimate and a selective loss of conceptual knowledge of living entities. Subsequent tests probing knowledge of visual features also confirmed preserved knowledge for non-living, and a selective impairment for living entities.

Catricalà and colleagues (Catricalà et al., 2014), in their study on AD and svPPA patients' groups, consistently found a similar performance in living and non-living in a picture naming task. They only observed a dissociation in naming by description, where AD performed better on inanimate entities than biological ones. In a following svPPA case (Catricalà et al., 2021), the authors tested for priming effects across several concrete (animals, tools) and abstract categories. They observed a hyperpriming effect (increased priming) only for animal (living) word pairs.

2.4.4.5.2 Abstract domain: the role of emotion and social concepts

Nine studies investigated emotion and/or social abstract concepts categories (Breedin et al., 1994; Catricalà et al., 2014, 2021; Fleming et al., 2003; Hsieh et al., 2012; Joubert et al., 2017;

A. Martin & Fedio, 1983; Papagno, Capasso, et al., 2009; Pobric et al., 2016). Two studies considered emotion also as a dimension (Giffard et al., 2015; A. Martin & Fedio, 1983).

Martin and Fedio (A. Martin & Fedio, 1983) asked AD patients and controls to read aloud words belonging to four categories and select which of four drawing best represented it (symbol referent test); they found that patients were impaired in objects (e.g. '*chair*'), actions (e.g. '*sit*'), and modifiers (e.g., '*strong*'), but not in emotion (e.g. '*love')* words.

They also asked patients to provide pleasantness ratings for neutral, positive (pleasant) and negative (unpleasant) words and found they did not differ from controls in this task.

In another study (Fleming et al., 2003), AD patients performed better on immediate recall of emotional abstract (positive and negative valence, e.g., *friend, hate*) than neutral word (e.g., *thermometer*) lists, and better with negative than with positive words. Giffard and colleagues (Giffard et al., 2015) tested four types of semantic priming, manipulating the word concreteness and type of relationship, that could be either emotional (negative) or neutral: concrete neutral (*table-chair*), concrete emotional (*viper-cobra*), abstract neutral (*motive-reason*), abstract emotional (*grief-sadness*). AD patients showed signs of CE only in the neutral concrete and abstract priming conditions, whereas in the emotional conditions, they showed equivalent priming for concrete and abstract words: the authors suggested that emotion could be one of the main components that bind semantically close concepts together in AD.

Hsieh and colleagues (Hsieh et al., 2012) tested AD, svPPA and bvFTD patients and controls on concrete, abstract neutral and emotional words. AD did not differ from controls in any of these categories, while the other two patient groups fared significantly worse: svPPA were significantly more impaired than all other groups with concrete and abstract neutral words, and both svPPA and bvFTD were impaired with emotion words. No groups showed any difference between performance on positive and negative emotion words.

In another study (Catricalà et al., 2014), svPPA and AD patients were tested with the same tests for abstract concepts, from the DeCAbs battery (Anthony et al., 2014), where stimuli belonged to five abstract categories, namely emotions, cognitions, traits, social relations, and human actions. While they were impaired in all the other categories, AD showed normal performance on two out of three tests with emotions (association task and sentence completion), while svPPA patients were selectively impaired in social relations concepts.

In another study testing both svPPA and AD (Joubert et al., 2017), a similar performance was observed in AD patients for concrete, emotional abstract, and non-emotional abstract triplets in a similarity judgement task. SvPPA were better with abstract non-emotional than with concrete, while performance on emotion triplets was intermediate.

Breedin and colleagues (Breedin et al., 1994) svPPA case report, using a word-picture matching task showed a non-significant improvement in a word-picture matching of abstract non-emotional compared to concrete and emotion abstract words, a pattern opposite to that of matched controls. In verbal fluency of abstract words, a svPPA patient (Papagno, Capasso, et al., 2009) produced positive and negative feelings (emotion), producing the same number of words as controls, while she was impaired in concrete categories. Pobric and colleagues (Pobric et al., 2016) compared the performance of two controls with two svPPA with bilateral ATL atrophy, with respectively a predominant left or right atrophy, on a synonym judgement task on social concepts (abstract) and non-social concepts (properties of animals). Both controls were significantly impaired in both conditions, while the right ATL patient was significantly more impaired than the left on social concepts. Catricalà and colleagues' (Catricalà et al., 2021) svPPA patient also showed a similar specific impairment for social concepts, compared to emotion and quantity concepts (abstract categories), animals and tools (concrete categories) on a lexical decision task: the patient showed abolished priming only for social concepts, while controls were primed in all conditions.

An overall summary of the results are provided in Table 2.

Reference ID	**Patients Type**	**Site of Atrophy**	**Semantic Categories**	**Grammatical Class**	**Short Results**
(Joubert et al., 2017)	AD, svPPA, controls	n.a.	Concrete, Abstract: emotion, non-emotion	n.s.	AD: C = A svPPA: A non-emotion > C controls: A emotion >C
(Catricalà et al., 2021)	CBS, svPPA, controls	n.a.	Concrete: living, non-living Abstract: emotion, social, quantity	Nouns	CBS: C > A quantity svPPA: C > A quantity controls: C = A
(Breedin et al., 1994)	svPPA, controls	ATL, particularly left ATL	Concrete: living, non-living Abstract: non-emotion, emotion	Nouns, Verbs	svPPA: A > C controls: C > A

(Papagno, Capasso, et al., 2009)	svPPA, controls	Left ATL	Concrete: living, non-living Abstract: non-emotion, emotion	Nouns, Verbs, Adjectives	svPPA: A > C Non-living > living controls: C = A
(Macoir, 2009)	svPPA, Controls	ATL, particularly left ATL	Concrete: living, non-living	n.s.	svPPA: A > C
(Cousins et al., 2016)	bvFTD, svPPA, controls	svPPA: ATL, particularly left ATL bvFTD: frontal lobes	Concrete, Abstract	Nouns	svPPA: A > C bvFTD: C > A controls: C = A
(Cousins et al., 2017)	bvFTD, svPPA, controls	svPPA: left IFG, left FG, right ITG bvFTD: frontal lobes	Concrete, Abstract	Nouns	svPPA: A > C bvFTD: C > A
(Cousins et al., 2018)	bvFTD, svPPA, controls	SvPPA: medial and lateral temporal regions	Concrete, Abstract	Nouns	svPPA: A > C bvFTD: C > A
(Cho et al., 2021)	bvFTD, nfPPA, svPPA, controls	SvPPA: ATL and orbitofrontal cortex NfPPA: left middle frontal, inferior and middle temporal regions BvFTD: frontal and temporal	Concrete, Abstract	Nouns	svPPA: A > C BvFTD, nfPPA, controls: C > A
(Bonner et al., 2009)	svPPA, controls	ATL	Concrete, Abstract	Verbs	svPPA: A > C controls: C > A
(Jefferies et al., 2009)	svPPA, controls	n.a.	Concrete, Abstract	n.s.	svPPA: C > A controls: C > A
(Stockbridge et al., 2022)	lPPA, nfPPA, svPPA, uPPA	svPPA: left anterior and inferior temporal lPPA: left temporo-parietal	Concrete, Abstract	Verbs	lPPA, nfPPA, svPPA, uPPA: C > A

		nfPPA: asymmetric frontal			
(Reilly et al., 2007)	svPPA	ATL, particularly left ATL	Concrete, Abstract	Nouns, Verbs	svPPA: A > C
(Hoffman et al., 2014)	svPPA, controls	n.a.	Concrete, Abstract	n.s.	svPPA: A > C controls: C > A
(Woollams, 2015)	svPPA, controls	n.a.	Concrete, Abstract	n.s.	svPPA: A > C controls: C > A
(Yi et al., 2007)	AD, svPPA, controls	n.a.	Concrete, Abstract	Nouns, Verbs	AD: C > A (specific to nouns) svPPA: A > C (specific to verbs)
(Catricalà et al., 2014)	AD, svPPA, controls	n.a.	Concrete: living, non-living Abstract: Emotions, Cognitions, Traits, Social relations, Human actions	n.s.	AD: C = A svPPA: A > C
(Hoffman & Ralph, 2011)	svPPA	ATL	Concrete, Abstract	Nouns, Verbs	svPPA: C > A
(Hoffman, Jones, et al., 2013)	svPPA, controls	n.a.	Concrete, Abstract	Nouns, Verbs	svPPA: C > A
(Pobric et al., 2016)	svPPA, controls	ATL, predominantly on the left or right side	Concrete: properties of animals Abstract: social	n.s.	svPPA: C > A
(Macoir et al., 2015)	svPPA, controls	ATL	Concrete: colour, dimension, physical properties Abstract: human propensity, value	Adjectives	svPPA: C = A
(Poos et al., 2022)	bvFTD, lPPA, nfPPA, svPPA, controls	n.a.	Concrete, Abstract	n.s.	bvFTD, lPPA, nfPPA: C > A svPPA: C = A
(Crutch & Warrington, 2006)	AD, svPPA, controls	n.a.	Concrete, Abstract	n.s.	AD: C = A svPPA: C = A

(Hsieh et al., 2012)	AD, bvFTD, svPPA, controls	svPPA: ATL predominantly on the left bvFTD: frontal regions	Concrete, Abstract: emotion, non-emotion	n.s.	AD: C = A svPPA: C = A controls: C = A
(Rissenberg & Glanzer, 1987)	AD, controls	n.a.	Concrete, Abstract	n.s.	AD: C > A, controls: C > A
(Bushell & Martin, 1997)	AD, old controls, young controls	n.a.	Concrete, Abstract	Nouns, Verbs	AD: C > A young controls: C > A old controls: C = A
(Peters et al., 2009)	AD, old controls, young controls	n.a.	Concrete, Abstract	n.s.	AD: C > A old controls: C > A young controls: C > A
(Giffard et al., 2015)	AD, controls	n.a.	Concrete: emotion and neutral Abstract: emotion and neutral	n.s.	AD: C neutral >A neutral
(A. Martin & Fedio, 1983)	AD, controls	n.a.	Concrete, Abstract: emotion	n.s.	AD: A > C
(Fleming et al., 2003)	AD, old controls, young controls	n.a.	Concrete, Abstract: emotion negative, emotion positive	n.s.	AD: A emotion negative >C and emotion positive Old, young controls: A emotion negative = A emotion positive
(Westbury et al., 2002)	AD, PPA	n.a.	Concrete, Abstract	n.s.	Unclassifiable

Table 2. Summary of the 31 studies included in this review. Abbreviations: IFG: Inferior frontal gyrus, FG: fusiform gyrus, ITG: inferior temporal gyrus, ATL: anterior temporal lobes, n.a.: not available, n.s.: not specified, AD: Alzheimer's disease, PPA: Primary Progressive Aphasia, SvPPA: semantic variant of Primary Progressive Aphasia, nfPPA: nonfluent variant of Primary Progressive Aphasia, lPPA: logopenic variant Primary Progressive Aphasia, uPPA: unclassified Primary Progressive Aphasia bvFTD: behavioural-variant Frontotemporal Dementia, CBS: Cortico-Basal Syndrome, C > A: Concreteness effect, A > C: Reversal of concreteness effect, C = A: no significant difference between concrete and abstract concepts.

2.5 Discussion

2.5.1 Summary of evidence

In this scoping review, we aimed at identifying the extent of evidence regarding abstract and concrete concepts knowledge in FTD (with a specific focus on svPPA) and AD patients, and the related sites of atrophy. We also analysed the difference concerning grammatical classes and, when available, semantic categories.

2.5.1.1 Abstract/Concrete concepts contrast and related site of atrophy

According to the collected evidence, the reversal of the concreteness effect (A>C) appears as the most frequent pattern in svPPA patients. Most studies (14 out of 24) reported better performance with abstract compared to concrete concepts in svPPA, showing that in the majority of svPPA patients, the reversal of CE is present. This pattern differs from that of bvFTD patients, whose performance suggests an increase of the concreteness effect. It also deviates from that of AD, who, like bvFTD patients, showed more frequently a better performance with concrete over abstract concepts, with a significant deviation from this pattern when emotion concepts were included in the study.

However, not all svPPA patients show the reversal of the concreteness effect: six records reported the opposite trend, with a better performance with concrete concepts, and other four found a similar performance between abstract and concrete concepts. Taken together, these results are inconsistent and leave open the question as to why this reversal of concreteness effect appears. We will discuss possible explanations below, but this discussion first requires some information about the neural substrates.

Some of the svPPA studies reported the site of atrophy, which was in the ATL, predominantly on the left side. Inside the ATL, the reported areas of atrophy are heterogeneous, including both ventral and superior portions of the ATL, as well as medial and lateral. These patients, whose cortical atrophy was evaluated, performed better on abstract concepts (Bonner et al., 2009; Breedin et al., 1994; Cho et al., 2021; Cousins et al., 2016, 2017, 2018; Macoir, 2009; Papagno, Capasso, et al., 2009), better on concrete (Hoffman & Ralph, 2011; Pobric et al., 2016; Stockbridge et al., 2022), or similarly on concrete and abstract concepts (Hsieh et al., 2012; Macoir et al., 2015). Five of these studies also reported a positive correlation between

ATL atrophy and the reversal of the concreteness effect (Bonner et al., 2009; Cho et al., 2021; Cousins et al., 2016, 2017, 2018; Joubert et al., 2017).

Different theories have been proposed to account for both patterns of performance in svPPA (A>C and C>A), ascribing both opposing roles to the same cortical region, namely the ATL.

According to the hub-and-spoke model, ATL represents a central, amodal hub where all conceptual knowledge is stored and represented. This hub receives inputs from different, modality-specific regions (the spokes), and combines them to create a unitary, coherent multi-modal conceptual representation (Lambon Ralph et al., 2010; Patterson et al., 2007). According to this view, concepts are represented by means of the multi-modal representations (spokes) throughout the brain, and by the central hub (ATL) that receives inputs from all of them. This theory has been put forward to explain svPPA cases that perform better on concrete than on abstract items (C>A). Since abstract concepts do not benefit from the same rich multisensory representation that supports concrete concepts (Plaut & Shallice, 1993), in the case of ATL atrophy, they shall be the first to decay, whereas concrete concepts would still be supported by their richer representation. This theory is further supported by TMS evidence (Pobric et al., 2009): in this study, inhibitory stimulation on healthy subjects targeting ATL significantly slowed subjects' semantic processing, particularly for less imageable (abstract) items. Neuroimaging studies (Binney et al., 2010; Visser et al., 2012) also highlight ventral and middle lateral ATL as the core regions for semantic processing.

To explain the reversal of the concreteness effect in svPPA (A>C), others observed how the ventral ATL (inferior temporal gyrus, fusiform gyrus, parahippocampal gyrus), the main target of svPPA atrophy (Gorno-Tempini et al., 2004), corresponds to high-level visual association areas (Bonner et al., 2016; J. Wang et al., 2010). Since these regions are specifically involved in concrete concepts (objects, animals) representation, concrete concepts would be primarily impaired, leading to the reversal of the concreteness effect observed in svPPA patients. In this review, five studies (see above) directly correlated the size of the reversal of the concreteness effect in svPPA patients to ATL atrophy. This connection is also supported by studies that found svPPA cases more impaired in living than in inanimate concepts (Lambon Ralph et al., 2003; Merck et al., 2014; Papagno, Capasso, et al., 2009), and more impaired in perceptual than functional features knowledge (Breedin et al., 1994; Macoir, 2009). Indeed, according to the Sensory/Functional theory of category-specific disorders (Farah & McClelland, 1991; Warrington & Shallice, 1984), living entities are defined mostly by their perceptual (visual) attributes, whereas inanimate ones are distinguished by both perceptual and non-perceptual (functional) features.

However, the ATL is not a unitary region: neuroimaging (Hoffman et al., 2015; Zahn et al., 2007, 2009) and TMS (Pobric et al., 2016) evidence showed how different portions of ATL are preferentially weighted towards the processing of abstract or concrete knowledge.

Hoffman and colleagues (Hoffman et al., 2015), in an fMRI study, showed that there is a gradual specialization in ATL from dorsolateral to medial-ventral ATL: while the inferior temporal gyrus responds similarly to concrete and abstract concepts, superior and middle temporal gyri (dorsolateral) show a greater response to abstract, and fusiform and parahippocampal gyri (ventromedial) to concrete concepts. Zahn and colleagues (Zahn et al., 2007), in a fMRI study on healthy participants, showed that bilateral superior ATLs are more strongly activated by social than animal concepts, and both types activate similarly middle ATL regions. In a following study on FTD and Cortico-basal syndrome patients (Zahn et al., 2009), the authors corroborated these results: patients with right superior ATL hypometabolism showed a selective impairment to social contrasted to animal concepts. Pobric and colleagues (Pobric et al., 2016), with the same stimuli used by (Zahn et al., 2009), used repetitive TMS to inhibit right and left superior ATL: right superior ATL stimulation selectively impaired social concepts performance, while left stimulation impaired both social and animal concepts.

The gradual specialisation of ATL might explain the seemingly controversial results in svPPA patients: the extent and precise location of grey matter atrophy are heterogeneous across patients included in this review, and this might explain the opposite C>A and A>C patterns found in patients affected by the same disease. ATLs might preserve their central role as the semantic hub in the brain (Lambon Ralph et al., 2010), while maintaining a graded specificity, whereby dorsolateral regions are preferentially involved in abstract concepts processing, and ventromedial regions, corresponding to high-level visual association areas, are responsible for concrete concepts processing (Hoffman et al., 2015; J. Wang et al., 2010).

Another potential factor that could account for variability in svPPA semantic performance is the duration of the disease: the extent of atrophy increases with the progression of the disease, and so does the patients' semantic impairment. Initial atrophy in svPPA is usually located in the left ATL, whereas a minority of patients present right ATL degradation first (Brambati et al., 2009; Kumfor et al., 2016). From that region, atrophy spreads posteriorly across the temporal lobe, involving visual association areas important for concrete concept representation, and temporarily sparing inferior frontal regions more important for abstract concepts (Bright et al., 2008).

Patients tested at different time points from the beginning of the disease would consequently show different patterns of impairment of abstract/concrete concepts. However, there are very few studies that investigated the longitudinal progression of semantic impairment in svPPA patients (Cousins et al., 2018; Hoffman et al., 2012; Macoir, 2009), and only one (Cousins et al., 2018) directly assessed the connection between longitudinal changes in grey matter atrophy and semantic impairment.

Hoffman and colleagues (Hoffman et al., 2012) found that concrete concepts strongly associated with visual experiences in svPPA patients become more impaired with the progression of the disease. In Macoir's (Macoir, 2009) longitudinal case report, the patient was tested on both concrete and abstract concepts at three time points: the patient showed an early reversal of the concreteness effect, which decreased with the progression of the disease.

Cousins and colleagues (Cousins et al., 2018) tested a group of svPPA in the Cookie Theft picture description task (Goodglass et al., 1983) at two time points. They found a decrease in the concreteness of produced nouns with the progression of the disease, and this effect correlated with progressive grey matter atrophy in the left superior temporal gyrus and right ventral temporal regions. They also tested another group of bvFTD patients, which did not show any longitudinal effect of the concreteness of produced nouns.

Five records also included bvFTD patients, and all reported better performance with concrete or similar performance with concrete and abstract concepts.

Four of them reported the related site of atrophy, which always included predominantly inferior frontal lobe regions, and to a lesser extent, temporal regions (Cho et al., 2021; Cousins et al., 2016, 2017; Hsieh et al., 2012). This is consistent with the typical extent of atrophy in this disease, which includes the dorsolateral, inferior, and orbital regions of the frontal lobe (Cousins et al., 2016). Cousins and colleagues (Cousins et al., 2016) also found that bilateral inferior frontal and insula atrophy correlated with the degree of concreteness effect in these patients. Taken together, this evidence is in line with neuroimaging studies showing a preferential involvement of the IFG in abstract concepts processing (Bucur & Papagno, 2021; J. Wang et al., 2010).

Another aspect that emerged in this review is the distinction among grammatical classes.

2.5.1.2 Grammatical classes: nouns, verbs, adjectives

Two grammatical classes were investigated: nouns and verbs. A third class, adjectives, was evaluated only in two studies (Macoir et al., 2015; Papagno, Capasso, et al., 2009), and no difference between concrete and abstract items was revealed. The effect of concreteness across grammatical classes is once again inconsistent. Some studies that tested the same patients in both classes reported an effect of concreteness only in nouns but not in verbs (i.e., effect of concreteness specific to nouns, see for example (Papagno, Capasso, et al., 2009) AD patients in (Yi et al., 2007)), only in verbs but not in nouns (i.e., effect of concreteness specific to verbs, see svPPA patients in (Reilly et al., 2007; Yi et al., 2007). Other studies instead found no difference between grammatical classes (Hoffman, Jones, et al., 2013). There are no specific data on the atrophy in these patients. We can only refer to neuroimaging studies on healthy subjects, showing that motion and cognition verbs are represented in distinct regions (Grossman et al., 2002; Rodríguez-Ferreiro et al., 2011). In one of these studies (Grossman et al., 2002), motion verbs activated more anterior, prefrontal regions, and the temporal-occipital cortex, while cognition verbs recruited left posterior portions of the temporal cortex. Motion verbs impairment was also correlated to bilateral prefrontal and motor association cortex atrophy in patients affected by amyotrophic lateral sclerosis (York et al., 2014). The other fMRI study (Rodríguez-Ferreiro et al., 2011), instead, contrasted concrete (motion) and abstract (including emotion, e.g., '*love*') verbs: they found that the abstract verbs elicited higher activity in the bilateral inferior frontal gyrus and anterior middle temporal lobe.

Given the discrepancies in the effect of concreteness across nouns and verbs material, and the likely differences in nouns and verbs' cortical representation, future studies should investigate the effect separately for each grammatical class.

Finally, in studies showing a reversal of the concreteness effect, an association with a disproportionate impairment of living things has been described, and different results were found when considering different types of abstract concepts.

2.5.1.3 Semantic categories

2.5.1.3.1 Living/Non-living

Among the five studies that distinguished the living (biological)/non-living (inanimate) concrete categories in svPPA, two (Breedin et al., 1994; Macoir, 2009) found better processing of functional over perceptual concepts' features, and two (Breedin et al., 1994; Papagno, Capasso, et al., 2009) found better knowledge for non-living compared to living entities; in all these works, these effects occurred together with a reversal of the concreteness effect. The other two records (Catricalà et al., 2014, 2021), did not find evidence of category or features specific effects in svPPA; only one (Catricalà et al., 2014) found better processing of non-living concepts in AD patients.

2.5.1.3.2 Abstract categories

The included studies revealed a selective sparing of emotion concepts in AD patients and a selective impairment of social concepts in svPPA patients.

Despite the AD patients' performance most frequently reflects the concreteness effect found also in healthy subjects, when the abstract material consists of emotion words contrasted with concrete (Catricalà et al., 2014; Fleming et al., 2003; Hsieh et al., 2012; Joubert et al., 2017; A. Martin & Fedio, 1983), or the relationship between concepts is emotional rather than neutral (Giffard et al., 2015), the advantage shifts toward emotion concepts, resulting in no difference or in a reversal of the concreteness effect. These results are in line with the notion that affective processes are relatively preserved in the initial stages of AD and can thus facilitate the processing of emotion concepts (Martínez-Nicolás et al., 2019).

In svPPA, the pattern with emotion words is more heterogenous, with reports of worse performance in emotion compared to other abstract concepts (Breedin et al., 1994), similar performance between emotion and non-emotion abstract concepts (Hsieh et al., 2012; Joubert et al., 2017), or preservation of emotion words over other categories of abstract concepts, like social ones (Catricalà et al., 2014). In a neuroimaging and behavioural study (Bertoux et al., 2020), the authors also found impaired emotion concepts knowledge in svPPA patients, which was significantly correlated with emotion recognition; in turn, both measures correlated with grey matter atrophy in ventral frontal, temporal and insular regions.

Social concepts are found to be consistently more impaired when compared to other categories of abstract words in svPPA (Catricalà et al., 2014, 2021; Pobric et al., 2016) or to concrete words (Pobric et al., 2016; Zahn et al., 2009).

Recent works suggested that, like the concrete, the abstract domain can be distinguished into different semantic categories, namely emotion, social, quantity and theory of mind concepts. In line with an embodied view of abstract concepts cognition, these categories are grounded in the same distinct neural basis representing the corresponding experiences (Conca et al., 2021; Desai et al., 2018). Likewise, multidimensional scaling studies showed that the concrete/abstract distinction is too simplified, and different dimensions/experiences organize the semantic space (Troche et al., 2014), into different concrete and abstract categories (Villani et al., 2021).

Taken together, the included studies also support the existence of different categories of abstract concepts, that can be selectively impaired in patients affected by AD and svPPA dementias.

2.5.2 Limitations

This scoping review has some limitations.

First, we analysed together studies that used both concreteness and imageability ratings to classify a word as either concrete/abstract, without distinguishing results based on the dimension used. However, it is known that emotion words are rated as more imageable than other abstract concepts, but less concrete (Altarriba et al., 1999; Altarriba & Bauer, 2004). Even though the two measures are highly correlated (Paivio et al., 1968), they are not synonymous and affect semantic performance differently (Boles, 1983; Connell & Lynott, 2012; Richardson, 1975, 1976).

Second, we did not distinguish results based on the type of task. We included studies using comprehension (mostly synonym judgement tasks) but also production (picture naming, oral descriptions of pictures) and semantic priming tasks. We cannot exclude that the effect of concreteness might vary depending on the modality of the task used.

Third, we also included studies without a control group. In these studies, it is impossible to determine whether the difference in patients' performance between abstract and concrete concepts reflects the same or different trend and/or to the same degree that a control healthy group would show.

2.6 Conclusions

In this scoping review, the main aim was to assess the contrast between concrete and abstract concepts in the semantic variant of primary progressive Aphasia and Alzheimer's disease patients to shed light on the anatomical correlates of the reversed CE.

As regards AD, the most frequent pattern was a better performance with concrete compared to abstract concepts. These patients also showed selective preservation of emotion abstract concepts, which were processed better than concrete and abstract neutral concepts.

Most svPPA showed a reversal of the concreteness effect but a few studies also found the opposite trend, or no difference between concrete and abstract. All svPPA patients presented with ATL atrophy, which in some cases also correlated with the size of the reversal of concreteness effect. We argue that to account for the discrepancies in svPPA performance across the concrete and abstract domain two main factors must be considered. First, the ATL is not homogeneous, whereby the dorsolateral region responds more strongly to abstract, and the ventromedial region more to concrete concepts. Differences in size and location of atrophy in svPPA patients would consequentially give rise to opposite effects. Second, and related to the first point, the duration of the disease is a factor to control for, as longitudinal studies found the degree of reversal of the concreteness effect to change with the progression of the disease, along with the spread of the atrophy over the temporal lobe.

We also found that grammatical class influences the effects of concreteness, although in an inconsistent way, with effects specific to nouns, specific to verbs, or generalized across the two.

Finally, beyond the distinction of concepts across the concreteness spectrum, different semantic categories (emotion, social concepts for the abstract, living, non-living for the concrete domain) appear to be selectively impaired in svPPA and AD patients, suggesting that the concrete/abstract distinction is insufficient and a finer, multidimensional method is needed to characterize the neurodegenerative patients' semantic impairment.

CHAPTER 3.

EMOTIONAL AND SOCIAL DIMENSION OF ABSTRACT CONCEPTS MEET WITH INTEROCEPTION IN RIGHT ANTERIOR INSULA

This chapter has been published as:

Mancano M., Papagno C. (2026) Emotional and Social Dimension of Abstract Concepts Meet with Interoception in Right Anterior Insula. The Journal of Neuroscience 46(2):e0238252025

3.1 Abstract

According to the embodied cognition theory, which claims that concepts' representation is grounded in sensory and motor components, abstract concepts are grounded in interoception, which is processed in the Anterior Insula (AIns). However, it is not clear whether interoception and abstract concepts share common anatomical substrates, and if yes, whether AIns is one candidate. In this study, we used repetitive Transcranial Magnetic Stimulation (rTMS) on healthy human participants (N=25, 19 females) to examine whether left and right AIns play a role in both abstract concepts and interoception. The heartbeat counting task served as a measure of interoceptive accuracy, and the semantic similarity judgment of semantic performance. Concepts were characterized according to both a categorical approach, contrasting three categories of concepts, namely social and emotion (abstract categories), and objects (concrete category), and a dimensional approach, collecting semantic ratings on the emotion and social dimensions of abstract and concrete concepts. TMS site, and TMS-induced electric field inside the AIns ROI were used to predict interoceptive and semantic behavioural responses. Both TMS site and E-field AIns ROI analyses confirmed the right Ain's role in

supporting interoception and the emotion and social dimensions of abstract concepts. This aligns with an embodied cognition framework, where AIns is involved in both the non-linguistic and linguistic processing of emotional and social dimensions. Together, these results support the evidence of a relation between interoception and socio-emotional semantics, and of the convergence of these two processes on the right AIns.

3.2 Significance statement

Humans' awareness of their internal, physiological states enables them to perceive their emotions and navigate the social environment successfully. However, little is still known on how the meaning of words we use to refer to emotions and social events is rooted in our bodily awareness. In the present study, we show that the right Anterior Insula, a crucial region for interoception, causally supports the representation of the emotional and social dimensions of abstract words as well. These results demonstrate that there is a common region in the brain involved in both processes, stress the connection between Anterior Insula and emotional processing, and deepen our understanding of the connection between body and language.

3.3 Introduction

Concrete concepts refer to external entities (e.g., *car, dog*); abstract concepts to complex, introspective ideas (e.g., *fear, problem*).

Concrete concepts are usually processed significantly faster than abstract concepts, i.e., the so-called concreteness effect (Paivio et al., 1994). The Dual-coding theory (Paivio, 1991) explains it claiming that abstract concepts are represented in a linguistic format only, while concrete concepts have both a linguistic and a perceptual representation.

Conversely, the Embodied Cognition claims that both concrete (Barsalou, 2008) and abstract concepts (Barsalou et al., 2018; Desai et al., 2018) are represented in the sensory and motor brain areas activated by the corresponding experiences.

While concrete concepts can be clearly divided in categories (Warrington & Shallice, 1984), only recently, a distinction in categories (e.g., social: "democracy", quantity: "zero") has been confirmed for abstract concepts, in healthy (Conca et al., 2021; Desai et al., 2018) and clinical populations (Mancano & Papagno, 2023).

The abovementioned research highlights Emotion as one important dimension of abstract concepts (Vigliocco et al., 2014). Abstract words are more emotionally valenced than concrete ones (Kousta et al., 2011), and emotionality facilitates processing of abstract more than of concrete words (Moffat et al., 2015; Newcombe et al., 2012; Siakaluk et al., 2016).

The experience of emotions is associated with physiological responses (e.g., heartbeat, visceral and breathing) (W. James, 1884) that we perceive through interoception, i.e., perception of the internal states (Craig, 2003; Critchley & Harrison, 2013). Interoception is processed in the bilateral Insula (AIns), whereas interoceptive and salient stimuli are integrated into a unified representation of the bodily emotional state in the Anterior Insula (Craig, 2009; Critchley et al., 2004).

Interoceptive strength, i.e., how much a concept is experienced through interoception, is higher for abstract than concrete concepts, and for emotional compared to neutral abstract concepts (Connell et al., 2018; Repetto et al., 2023). Words with low concreteness, or abstract words, elicit a higher change in heart rate (Vergallito et al., 2019). The difference in perceived difficulty between abstract and concrete words was larger when participants were at the same time monitoring their heartbeat rather than performing other non-interoceptive tasks, especially for emotional and social concepts (Villani et al., 2021).Convergent results from recent studies strengthen the association between interoception and abstract emotional word (Barca et al., n.d.; Ferré et al., 2024).

AIns is also involved in the representation of abstract concepts (Cousins et al., 2016; Papagno et al., 2013), particularly emotion concepts (Conca et al., 2021; Desai et al., 2018; Ziegler et al., 2018). However, we are not aware of studies investigating AIns in relation to both emotion words and interoception at the same time. Even though emotion and social have been distinguished as two different categories (Conca et al., 2021; Mancano & Papagno, 2023), they have been seldom directly contrasted.

To address these points, we performed a behavioural study to obtain semantic ratings on the Emotion and Social dimensions of concepts (Figure 1). Then, we used repetitive Transcranial Magnetic Stimulation (rTMS) to investigate the role of bilateral AIns in the representation of concrete and abstract concepts and interoception (Figure 2).

We considered Objects, Emotion and Social categories based on a categorical approach. We also adopted a dimensional approach (Crutch et al., 2013; Troche et al., 2017), considering both the Emotional and Social dimensions of concepts.

We predicted an interference on interoception after stimulation of right AIns, but not left AIns (Critchley et al., 2004; Mai et al., 2019; Pollatos et al., 2016; Pollatos, Gramann, et al., 2007).

For the semantic results, although "linguistic" regions are typically left-lateralized (Binder et al., 2009), emotional language deficits follow right brain damage (Sheppard et al., 2022; Sidtis & Sidtis, 2018). Based on the literature linking interoception and emotion concepts (Connell et al., 2018; Villani et al., 2021), and their partial overlap with social ones, we expected an effect either (a) restricted to the Emotion or (b) extended to both the Emotion and the Social features.

3.4 Methods

All Extended Data are provided in Appendix 2.

3.4.1 Experiment 1 – Semantic ratings

Abstract concepts are not as easily classifiable into distinct categories as concepts referring to concrete, tangible entities. They can evoke multiple meanings and are more difficult to characterise.

Therefore, in the first preliminary behavioural study, we asked participants to provide semantic ratings of the emotion and social dimension of experience on the abstract stimuli in our dataset. In a second data collection phase, we obtained ratings on the same emotion and social dimensions on concrete stimuli as a control.

3.4.1.1 Participants

Twenty-one participants (10 males and 11 females, mean age: 25.23 years, SD = 2.94, range = 19-30) took part in the first data collection phase. All participants were right-handed, Italian native speakers. One was removed from the analysis due to performance in the experimental task >2 SD below the group mean in all conditions. Thus, the final sample comprised 20 people (10 males and 10 females, mean age: 25.27 years, SD = 2.88, range = 19-30). Twenty participants (14 females, mean age: 27.95 years, SD: 3.44, range: 22-35) took part in the second data collection phase, all right-handed Italian native speakers. All participants gave their written informed consent before starting the experiment. The experiment was approved by the Research Ethics Committee of the University of Trento.

3.4.1.2 Methods

Our set of linguistic stimuli comprised triplets categorised as either objects (concrete triplets), emotion or social concepts (abstract triplets) (see ‘Semantic similarity task’ for a full description of linguistic stimuli. We collected these emotion and social ratings on the Social and Emotion triplets because, despite their categorisation based on the concepts they referred to, the distinction was sometimes fuzzy as words belonging to one of the two categories (i.e., social concepts, e.g.: ‘friendship’), often displayed a certain degree of features from the other category (e.g., ‘friendship’ having an emotional connotation). We also collected ratings on the Object triplets as a control. Since we included mostly everyday objects that should not consistently elicit an emotional response or be associated with a social interaction, we did not expect these items to present with significant scores on these dimensions.

In each trial, subjects were required to rate on a 7-point Likert scale the meaning of the triplets’ words on two dimensions: the Emotion scale, i.e., how much a concept refers to/evokes an affective state, and the Social scale, i.e., how much a concept refers/is associated to relationships between people or social constructs. Participants were instructed to read all three words before expressing their judgement, which should refer to the whole triplet. Triplets appeared in the centre of the screen, and the two scales on the bottom half of the screen, one on top of the other. All triplets were rated on both scales by all participants. They were instructed to press the numerical keyboard button corresponding to their rating on the first scale, and then the numerical keyboard button corresponding to their rating on the second scale. Participants were given no time limit to make their choice. The order of the scales in each trial was randomised. Each trial began with a fixation cross at the centre of the screen (1500 milliseconds), followed by the presentation of the triplet for 1000 milliseconds, after which the two scales appeared (no time limit) (Figure 1).

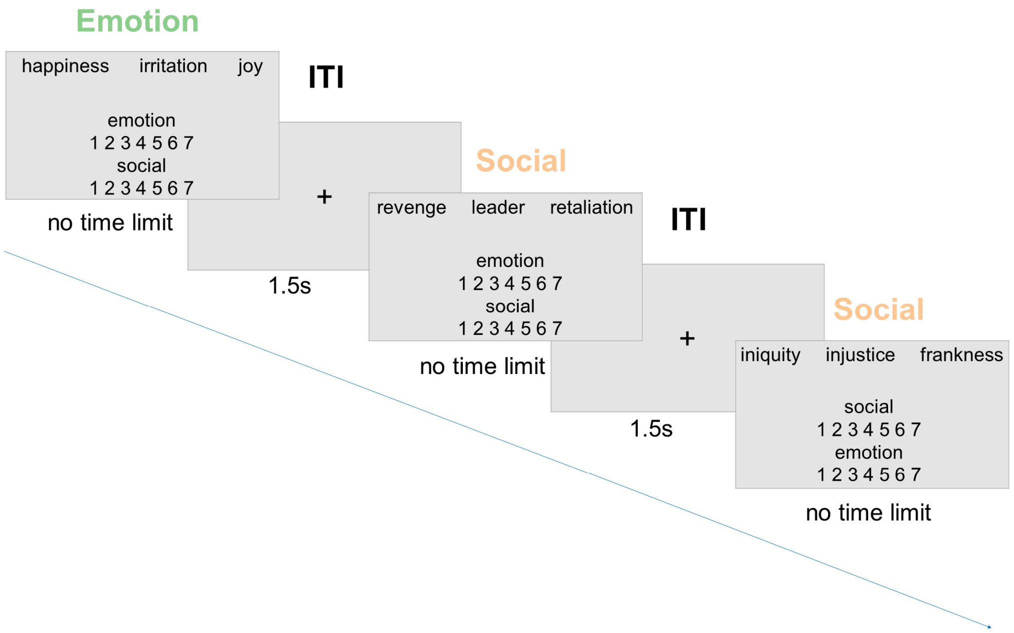


Figure 1. Semantic ratings study. Experimental procedure. Subjects were presented with triplets of words. In each trial, they were asked to evaluate how strongly, on a Likert scale ranging from 1 to 7, the meaning of the triplet words was associated to the emotion and social scales. They were asked to read all the three words before making their choice. Emotion scale was defined as how much a concept is used to express/evokes an affective state or an internal state that you can perceive. Social scale was defined as how much a concept is used to describe/is associated to an interpersonal relationship, an institution or a social construct.

3.4.1.3 Analyses

We analysed mean category and by-triplet Social and Emotion ratings. Analyses were performed on MATLAB 2021b.

We first calculated the average Emotion and Social ratings for each triplet. For each triplet, we eliminated outliers above or below two SD from each triplet's average rating on the respective scale (0.047% of ratings on the social dimension and 0.044% of ratings on the emotion dimension), and then re-calculated mean category Emotion and Social ratings without outliers. One-way ANOVAs and post-hoc tests were performed to test whether mean emotion and social scores differed between triplets categorised as either Emotion, Social or Objects concepts.

For abstract concepts, we also checked for triplets with ambiguous features, i.e., rated below 4.5 on the corresponding scale or above 4 on the other category scale (e.g., an Emotion triplet that scores below 4.5 average rating on the Emotion scale, or above 4 average rating on the

Social scale, and vice versa). We found 14 triplets with ambiguous features and replaced them with other items, which we did not include in the semantic ratings analysis of abstract concepts.

3.4.2 Experiment 2 – TMS experiment

In our main TMS experiment, we used repetitive TMS to disrupt activity in right and left AIns, to test its role in semantic processing and interoception. After 15 minutes of real (inhibitory) or sham rTMS, participants performed two tasks in counterbalanced order: a heartbeat counting task, to test their interoceptive accuracy, and a semantic similarity task, to test their semantic performance (Figure 2).

3.4.2.1 Participants

Twenty-six healthy Italian participants (7 males, 19 females, mean age 23.15 years, range 20-30, SD 3.00) took part in the TMS experiment. Inclusion criteria were the following: right-handed, Italian native speakers, and no history of psychiatric, neurological, or developmental disorders. No subject who participated in the semantic ratings experiment took part in the TMS experiment. We excluded one participant due to technical problems, so the final sample comprised 25 subjects (6 males, 19 females, mean age 23 years, range 20-30, SD 2.95). We recruited, through advertisement at the University of Trento, Italy, participants whose magnetic resonance (MRI) had already been acquired at CIMeC, University of Trento. They received a token of 60 €. All participants gave their written informed consent before starting the experiment. The experiment was approved by the Research Ethics Committee of the University of Trento.

3.4.2.2 Methods

The experiment consisted of two sessions, in which the right and left AIns were targeted (Figure 2). In each session, we administered both a real and a sham stimulation, separated by a wash-out period of 60 minutes. We used a repeated measures design where all participants underwent all stimulations and the sequence of sessions was counterbalanced across participants (4 possible sequences: (1) day 1: Left Insula Real- Left Insula Sham; day 2: Right Insula Sham – Right Insula Real, (2) day 1: Left Insula Sham – Left Insula Real; day 2: Right Insula Real – Right Insula Sham, (3) day 1: Right Insula Real – Right Insula Sham; day 2: Left Insula Sham

– Left Insula Real, (4) day 1: Right Insula Sham – Right Insula Real; day 2: Left Insula Real – Left Insula Sham).

At the beginning of each session, participants performed a first heartbeat counting task (baseline). After that, there was a short training phase for the semantic similarity task, where participants made semantic decisions on a set of training triplets. We did not explain to participants that triplets belonged to three categories either in the training phase or in the experiment. Subsequently, in the first session, the resting motor threshold was acquired, whereas in the second session, we started directly with the 15-minute rTMS stimulation. Subjects performed two tasks immediately after rTMS: the heartbeat counting and the semantic similarity task. The order of the tasks was counterbalanced across participants and sessions. The completion of both tasks took about 10 minutes. After concluding the second task, there was a break of about 50 minutes (60 minutes of washout minus the 10 minutes of tasks), before starting the second stimulation condition (real or sham). After this second stimulation of each day, participants performed the same two tasks, in the same order as after the first stimulation (i.e., if participants had started with the semantic task in the first stimulation of the day, they would start with the semantic task also in the second one). In the following session, after two weeks, they performed the two tasks in the opposite order (i.e., if they had started with the semantic task the first day, they would start with the heartbeat counting task on the second day, and vice versa).

The first session lasted approximately two hours and 20 minutes, and the second one lasted two hours.

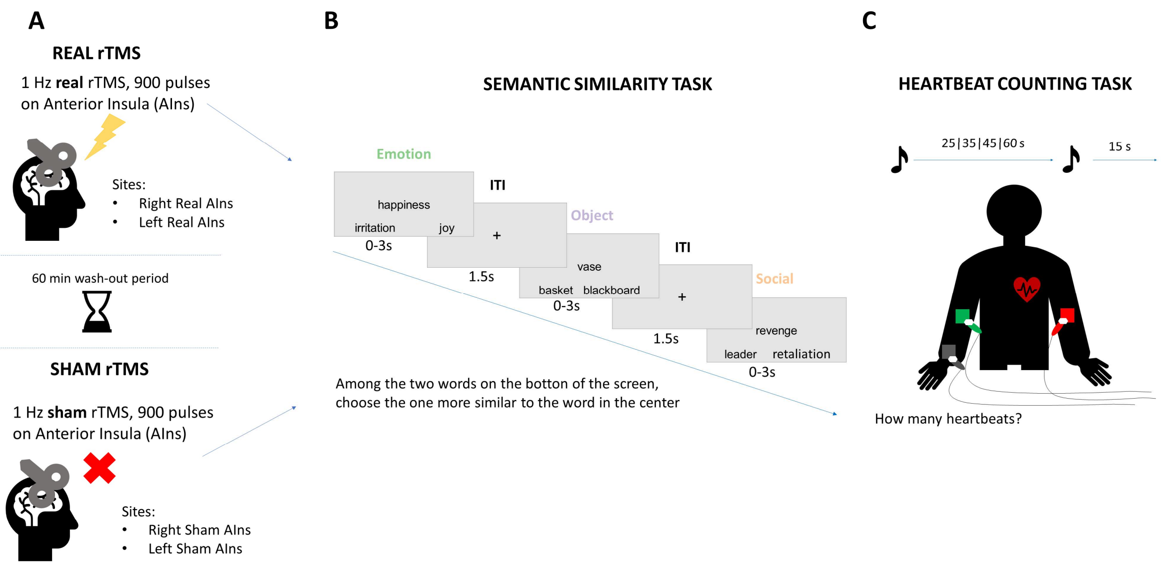


Figure 2. TMS experiment. Experimental procedure. Schematic representation of one TMS session. A, TMS. Participants were first submitted to a 15 min (900 pulses) neuronavigated repetitive TMS (rTMS) session, consisting of one of the four experimental conditions: Right Real AIns, Right Sham AIns, Left Real AIns, Left Sham AIns. During sham conditions, a wooden eight-shaped block was placed between the coil and the scalp. The order of TMS conditions was counterbalanced across participants. Two tasks followed the stimulation: B, Semantic similarity task. In this task, participants were presented with triplets of words. In each trial, they were asked to identify, among the two words at the bottom of the screen, the more similar word in meaning ("target") to the word presented in the center ("probe"), by pressing respectively "A" and "L" on the keyboard, if the target word appeared on the left or the right side. C, Heartbeat counting task. During the electrocardiogram (ECG) recording, subjects were asked to start silently counting their heartbeats at a signal sound and report how many heartbeats they perceived until they heard a second sound. Participants performed four blocks of variable duration in randomised order (25, 35, 45, and 60 s). The order of the tasks was counterbalanced across participants and sessions.

3.4.2.2.1 TMS paradigm

Neuronavigated rTMS was delivered using a MagPro X100 with MagOption connected to a MagVenture MCF-B65 coil, using the Softaxic navigator system software (SofTaxic, EMS, Bologna, Italy).

Participants underwent rTMS on two different days, separated by two weeks (mean: 14 days, SD: 1.26). In each session, two 15-minute rTMS at 1 Hz (900 pulses) were applied over one of two sites: right AIns or left AIns. Placement of the coil on the target area was accomplished through neuronavigation on each participant's individual MR T1.

Each day, the TMS conditions were a real and a sham stimulation, in counterbalanced order. In the sham stimulation, an 8-shaped wooden block, 3 cm thick, was placed between the coil and the scalp, to prevent the induced electric current from reaching the brain. Real and sham stimulations were separated by a wash-out period of 60 minutes (counted from the end of the first stimulation to the beginning of the second). In the following session, participants would start with the other condition (e.g., day 1: left real-left sham, day 2: right sham-right real).

The stimulation intensity was set at 90% of the previously determined resting motor threshold (RMT), which corresponded on average to 58.9% (SD = 9.89%) of maximum stimulator output (MSO). To determine the RMT, we first localised the left motor hand area delivering TMS pulses and inspecting for visible muscle twitches in the contralateral hand. We acquired the position of the coil that reliably elicited muscle twitches. With the coil placed in that position, to identify the RMT, we used the software TMS Motor Threshold Assessment Tool, MTAT

2.1, with the option set to 'without a priori information'. A trial was considered successful when a visible muscle twitch was induced in the index finger of the contralateral hand.
For each participant, we manually selected the target area in the dorsal-rostral part of the first gyrus of the anterior insula, corresponding approximately to [(-)36, 18, 0] MNI coordinates. We positioned the coil on the participant's head based on online navigated TMS and stabilised it with mechanical support.

3.4.2.2.2 Heartbeat counting task

The heartbeat counting task consisted of four counting phases that lasted 25, 35, 45, or 60 seconds, in randomised order, with a fixed interval of 15 seconds between sessions. A sound signalled the beginning (1200 Hz) and the end (300 Hz) of each session. With their eyes closed, subjects were asked to silently count their heartbeats during the sessions and to verbally report at the end of each counting session how many heartbeats they had felt.
Meanwhile, the ECG was recorded with electrodes placed on the right (negative) and left (positive) upper forearm, and ground on the right wrist, connected to an EKG sensor (https://www.vernier.com/product/ekg-sensor/) and SensorDAQ data-acquisition interface (https://www.vernier.com/product/sensordaq/). We used MATLAB Support Package for Vernier SensorDAQ to access and store data. ECG data were recorded with a sampling rate of 250 Hz. The presentation of the task was governed through Psychophysics Toolbox Version 3 (PTB-3) (Kleiner et al., 2007) in MATLAB.

During the task, participants were comfortably sitting on a chair, with their palms facing up and their forearms resting on the table.
The first time that they performed the task in each session (pre-TMS or baseline), they were presented with the instructions, where they were explicitly told to report only heartbeats that they felt, without trying to guess their heart rate. This could mean reporting all heartbeats, some heartbeats, or no heartbeats at all. We formulated the instructions following Desmedt and colleagues (Desmedt et al., 2020) study, to minimise the risk that participants based the number of reported heartbeats on time estimates. We added these baselines to the heartbeat counting task in both sessions (baseline day 1, baseline day 2) to familiarise participants with the task and prevent possible confounding practice effects (Sagliano et al., 2019). When they performed the tasks after TMS administration, instructions were not repeated.

3.4.2.2.3 Semantic similarity task

In this task, subjects were presented with triplets of nouns (180 triplets, 540 words). Each trial consisted of one triplet: a probe word appeared in the centre of the screen (e.g., “crime”), and two other semantically related words at the bottom right and bottom left: one was the target word (semantically similar to the probe, e.g., “offence”) and the other a semantically distant word (semantically distant from the probe word, e.g., “friendship”).

The side of the target and the distant word were randomised. In each trial, subjects were required to select the target word.

Triplets belonged to three semantic categories: Emotion, Social (i.e., the abstract categories), and Objects (i.e., the concrete category), with 60 triplets for each category.

For Object concepts, we selected words referring to man-made objects, mostly manipulable objects (e.g., “forbici”, scissors; “scopa”, broom), but also a few non-manipulable objects were included (e.g., “armadio”, closet).

For Emotion concepts, we selected words directly referring to an emotional state/internal feeling (e.g., “euforia”, euphoria; “timore”, fear).

For Social concepts, we selected words referring to interpersonal relationships/actions (e.g., “amicizia”, friendship, “aggression”, aggression) and societal/cultural concepts (e.g., “penalità”, penalty).

The abstract categories were also rated on both the emotion and the social dimensions (see Experiment 1 - Semantic ratings section), so that an emotion triplet (made of emotion-referring words) had a score on both the emotion and the social continuous dimensions, and a social triplet (made of social-referring words) had a score on both dimensions as well.

Words were initially drawn from Villani et al. (2019), Montefinese et al. (2014) and Della Rosa et al. (2010) datasets, but new words were used to achieve the necessary number of stimuli and balance across categories. All stimuli are available on the Open Science Framework (OSF) project page associated with this study (https://osf.io/cavsy/).

The main task was preceded by a short training phase before TMS, during which participants were presented with 12 different triplets (4 triplets for each category) to familiarise themselves with the task.

The order of triplet presentation was randomised, and triplets belonging to the different categories (Emotions, Social concepts, Objects) were interleaved. Words were balanced across categories in terms of Subtlex-it log frequency (https://osf.io/zg7sc/) ($F(2, 537) = 1.86$, $p = 0.157$) and controlled for length ($F(2, 537) = 10.04$, $p = <.001$). We could not balance for

length, in that objects were significantly shorter than both abstract categories (Objects-Emotions: T=-4.19, p = <.0001, Objects-Social: T=-3.467, p = 0.001).
We used Word-Embeddings Italian Semantic Space (Marelli, 2017), a Word2Vec model trained on Italian text corpora, to extract cosine similarity between pairs of words in our dataset. Stimuli were balanced for semantic similarity between probe-target words ("semantic similarity similar") (F(2, 177) = 2.09, p = 0.126) and semantic similarity between probe-distant words ("semantic similarity distant") (F(2, 177) = 2.33, p = 0.1) across categories.
The presentation of task stimuli was performed using Psychophysics Toolbox Version 3 (PTB-3) (Kleiner et al., 2007) on MATLAB.
Each trial began with a fixation cross at the centre of the screen (1500 milliseconds), followed by the triplet presentation. Subjects had a time limit of 3 seconds to respond. They were instructed to press the "A" keyboard button when the target word was presented on the left side and the "L" button when it appeared on the right side. After they responded to the stimulus, the script automatically moved to the next trial. If no answer was provided, after the maximum time (3 seconds), the next trial appeared. Reaction times (RTs) and accuracy were recorded.
In each session, half of the stimuli (90 triplets, 30 per category) were presented after the first stimulation and the other half after the second stimulation. The splitting of the dataset was randomised for each session and each participant, balancing for probe frequency and length, target frequency and length, distant frequency and length, semantic similarity similar, and semantic similarity distant between the two halves (all p>0.06).

3.4.2.3 Analyses

3.4.2.3.1 Heartbeat counting task

In the ECG data, R-wave peaks of recorded heartbeats were detected using 'findpeaks' MATLAB function. Interoceptive accuracy was calculated with the following formula: ¼ ∑ (1- (|recorded heartbeats - counted heartbeats|) / recorded heartbeats), whereby scores range continuously between 0 and 1, with higher scores indicating better performance (i.e., higher accuracy). We also computed the average Heart Rate during the counting sessions.
The following analyses were conducted using R-Studio (Version 4.3.1). Outliers detected using the 'boxplot.stats' function were excluded from the analysis (3 observations above the third quantile+(1.5*IQR)).
Interoceptive accuracy was analysed with generalised linear mixed models (GLMMs), fitting a model with beta family and link function logit, computed using the 'glmmTMB' package

(Magnusson et al., 2017) and 'lmerTest' package (Kuznetsova et al., 2017) for p-values. Beta distribution is a distribution used to analyse continuous proportional data ranging in the interval 0-1. An approach based on GLMMs was used to account for the effects of repeated measures within subjects. Even though it is recommended to use the maximal random effect structure (Barr et al., 2013), adding the random by-subjects slopes led to convergence issues, so we used a random intercept model.

Interoceptive accuracy was modelled with TMS session (6 levels: Baseline 1, Baseline 2, Left Insula Real, Left Insula Sham, Right Insula Real, Right Insula Sham) as fixed effect, Heart Rate as control covariate, and by-subject random intercept as a random effect. The model formula (R syntax) was the following:

accuracy ~ TMS_session + Heart_Rate_overall + (1 | ID_subject)

In this and all the following models, continuous predictors and covariates were always centred. Model assumptions were tested with 'DHARMa' package (Hartig & Hartig, 2017) and did not reveal any significant problems.

Estimated marginal means (EMMs) were calculated with the 'emmeans' package (Lenth & Lenth, 2018). We applied planned comparisons to test for contrasts of interest; specifically, we tested for differences in interoceptive accuracy between Left Insula Real-Left Insula Sham, and differences between Right Insula Real-Right Insula Sham. The results were adjusted for multiple comparisons using the 'holm' method.

3.4.2.3.2 Semantic similarity judgement

Analyses were conducted using R-Studio (Version 4.3.1). Single-trial RTs and accuracy were analysed with linear mixed models (LMMs) and generalised linear mixed models (GLMMs). Mixed models were chosen to account for the effects of repeated measures within subjects and trials. Adding the random slopes led to convergence problems, therefore we only included by-subjects and by-triplet random intercepts.

3.4.2.3.2.1 Category

In this first analysis, we adopted a categorical approach, which aimed to investigate the effect of the interaction between TMS site and semantic categories in predicting semantic processing.

3.4.2.3.2.1.1 RTs

The histogram of raw RTs and QQ-Plot suggested that RTs were not normally distributed, and presented a right-skewed distribution. Therefore, we run all the following analyses with log-transformed RTs as the dependent variable. RTs faster than 300 milliseconds and RTs for incorrect trials were excluded from the analysis (646 incorrect trials, 7,17%)

Log RTs were analysed with linear mixed models (LMMs), computed using the 'lme4' package (Bates, Mächler, et al., 2015) for modelling and 'lmerTest' package for p-values (Kuznetsova et al., 2017).

Log RTs were modelled with TMS site (4 levels: Left Insula Real, Left Insula Sham, Right Insula Real, Right Insula Sham), category (3 levels: Emotions, Objects, Social), and their interaction, as fixed factors; semantic similarity similar, semantic similarity distant and triplet length as control covariates; by-subject and by-triplet random intercepts as random effects. The model formula (R syntax) was the following:

log(RTs) ~ TMS_session * category + semanticSimilaritySimilar + semanticSimilarityDistant + triplet length + (1 | ID_subject) + (1 | IDTriplet)

Triplet length was calculated as the sum of the letters of all three words in the triplet.
Model assumptions were visually inspected with the plot_model function from 'sjPlot' package (M. D. Lüdecke, 2023) and did not reveal any large deviation from normality or homoscedasticity.
Estimated marginal means (EMMs) were calculated with the 'emmeans' package (Günther et al., 2015). We applied planned comparisons to test for contrasts of interest, namely the following 6 TMS * category comparisons: Emotions Left Insula Real-Left Insula Sham, Social Left Insula Real-Left Insula Sham, Objects Left Insula Real-Left Insula Sham, Emotions Right Insula Real-Right Insula Sham, Social Right Insula Real-Right Insula Sham, Objects Right Insula Real-Right Insula Sham. The results were adjusted for multiple comparisons using the 'holm' method.

3.4.2.3.2.1.2 Accuracy

Accuracy was analysed with generalized linear mixed models (GLMMs), with family binomial and link function logit, using 'lme4' package (Bates, Maechler, et al., 2015) for modelling and 'lmer-test' package (Kuznetsova et al., 2017) for p-values.

Accuracy was modelled with the same fixed and random effects specified for RTs. The model formula (R syntax) was the following:

Accuracy ~ TMS_session * category + semanticSimilaritySimilar + semanticSimilarityDistant + triplet length + (1 | ID_subject) + (1 | IDTriplet)

Model assumptions were tested with 'DHARMa' package (Hartig & Hartig, 2017) and did not reveal any significant problems.

Estimated marginal means (EMMs) were calculated with the 'emmeans' package (Lenth & Lenth, 2018). We applied planned comparisons to test for contrasts of interest, specifically, we tested for the same TMS*category comparisons described for RTs.

3.4.2.3.2.2 Semantic ratings

In a second analysis, we adopted a dimensional approach, using the semantic ratings collected in the first behavioural experiment (see Experiment 1 – Semantic ratings). Due to a substitution of triplets with ambiguous features, ratings were available for 106 out of the 120 abstract triplets. As our main analysis, we tested the interaction between TMS site and the Emotion and Social scale ratings on abstract triplets. As a control, we repeated the same analysis on concrete triplets. If the effects of ratings and TMS targeting AIns are specific to the abstract concepts, we should find significant results in the first analysis with abstract triplets, whereas with concrete triplets we should not observe significant results.

3.4.2.3.2.2.1 RTs

Log RTs were modelled with TMS site (4 levels: Left Insula Real, Left Insula Sham, Right Insula Real, Right Insula Sham), Social rating and Emotion rating, the interaction between TMS and Social rating, and between TMS and Emotion rating, as fixed effects; semantic similarity similar, semantic similarity distant, and triplet length as control covariates; and by-subject and by-triplet random intercepts as random effects. The model formula (R syntax) was the following:

log(RTs) ~ (Emotion_rating + Social_rating) * TMS_session + semanticSimilaritySimilar + semanticSimilarityDistant + triplet length + (1|ID_subject) + (1|IDTriplet)

Model assumptions were visually inspected with the plot_model function from 'sjPlot' package (M. D. Lüdecke, 2023) and did not reveal any large deviation from normality or homoscedasticity.
Estimated marginal means of linear trends were calculated with 'emmeans' package (Lenth & Lenth, 2018) for TMS site-Emotion rating and TMS site-Social rating interaction, to estimate the slope of the effect of the Emotion or Social rating at each TMS level. We applied planned comparisons to test for differences in Social and Emotion rating slopes between Left Insula Real-Left Insula Sham, and between Right Insula Real-Right Insula Sham. The results were adjusted for multiple comparisons using the 'holm' method.

3.4.2.3.2.2.2 Accuracy

The model formula was:

Accuracy ~ (Emotion_rating + Social_rating) * TMS_session + semanticSimilaritySimilar + semanticSimilarityDistant + triplet length + (1|ID_subject) + (1|IDTriplet)

Model assumptions were tested with 'DHARMa' package (Hartig & Hartig, 2017) and did not reveal any significant problems. Estimated marginal means of linear trends and planned comparisons were calculated in the same way described for RTs.

3.4.2.3.3 E-field modelling

Simulations were performed in SimNIBS 4.0 (Thielscher et al., 2015). Individual T1-weighted structural MRI scans were segmented and meshed into tetrahedral head models through the *charm* pipeline (Figure 3). Simulations of the TMS-induced E-field were performed in MATLAB environment. The TMS focus coil position was extracted from the *stmpx* files saved after each session from Softaxic, with the handle pointing towards F8 for stimulation of right AIns and F7 for left AIns. The stimulation intensity was determined using the *dI/dt* (speed of variation of the current through the coil) value displayed directly on the TMS machine screen. E-field values are expressed in volts per meter (V/m). To simulate the TMS-induced E-field in the sham condition, we used the same parameters as in the real condition except for the distance of the coil from the scalp, which was set to 31 mm. The E-field in the sham condition, indeed, has much lower values compared to the real condition, but still it tells us that a very low intensity stimulation reached the brain. Mean E-field MagnE component was evaluated in ROIs defined in the MNI space (Van Hoornweder et al., 2023). Left and right dorsal Anterior Insula MNI coordinates were selected with an independent approach, where peak cluster activations were obtained from NeuroSynth 'anterior insula' association maps (https://neurosynth.org/analyses/terms/anterior%20insula/). The resulting peaks MNI coordinates (right AIns: [40, 18, 2], left AIns: [-34, 22, 0]) were chosen as the centre of spherical grey matter ROIs (r = 10mm). E-field values (mean MagnE) were extracted via the **mni2subject_coords** function within these spheres in individual spaces. Because of technical problems (i.e., the simulation of the E-field in one subject could not be aligned to the MNI space), we removed this participant from this analysis.

To test whether the effects observed for interoceptive accuracy in the Heartbeat Counting task and RTs and accuracy in the semantic similarity task of the previous analyses were ascribable to TMS-induced E-field in AIns, we ran all previous GLMMs analyses, substituting TMS site categorical predictor with subject-level E-field values calculated inside AIns as continuous predictors (E-field value in right AIns, E-field value in left AIns) (S. Martin et al., 2025; B. B. B. Zhang et al., 2022). To make an example, the equivalent of Category*TMS site analysis for RTs model formula (R syntax) was the following:

> log(RTs) ~ E-field MagnE right AIns * category + semanticSimilaritySimilar + semanticSimilarityDistant + triplet length + (1 | ID_subject) + (1 | IDTriplet)

E-field MagnE right AIns in the formula is the mean electric field magnitude induced in the right AIns ROI. For the category analysis, estimated marginal means of linear trends were calculated, and planned comparisons were run to test for specific contrasts between E-field AIns values and category level: Emotion-Social, Emotion-Objects, and Social - Objects.

Since this predictor variable represents the mean intensity of the E-field induced specifically inside AIns, and therefore the level of interference induced in this area by TMS, its predictive value of behavioural responses provides a measure of the relevance of AIns in sustaining those responses.

As a control analysis, we tested whether E-field calculated in an ROI centred around the E-field maximum peak in the brain predicted behavioural responses, and if yes, whether it provided a better fit for the data compared to E-field elicited inside right and left AIns ROI. We also did the same with another ROI, centred inside the parahippocampal gyrus (PHC), an area anatomically distant from the stimulation sites but involved in abstract and concrete concepts' processing (Kafkas et al., 2023; Loiselle et al., 2012; Stochel & Sandberg, 2025; J. Wang et al., 2010) , therefore an area that potentially, if stimulated, would have exerted an effect on the semantic similarity judgement task. We added these two areas to verify the specificity of the effects of the E-field evoked inside AIns on behavioural responses, namely, whether and how much these responses could be predicted by the E-field induced in other areas of the brain potentially involved.

For PHC, the MNI coordinates were ±22, -28, 16.

For E-field maximum peak (MAX E-field), MNI coordinates during right and during left TMS were extracted from single-subject E-field simulations during right and left TMS.

The same procedure used for AIns was also used to create a spherical grey matter ROI centred around the maximum peaks and one centred around PHC coordinates, yielding E-field average value in a sphere centred around the maximum left and the maximum right peak, and a sphere centred around right and left PHC.

Single-subject right and left MAX coordinates are shown in figure 3-1. The average peak in the right hemisphere was located in [57.48 30.56 16] MNI coordinates, the average peak in the left hemisphere in [-51.20, 32.12, 14.92] MNI coordinates, which correspond to pars triangularis of the left and right Inferior Frontal Gyrus.

Then, GLMMs analogous to the ones with AIns E-field were computed using right and left MAX E-field as continuous predictors, to test whether the behavioural responses could be explained by the E-field elicited in the area of its peak intensity. The same was done using right and left PHC E-field.

Only when both models with AIns E-field and MAX E-field and/or PHC E-field presented a significant effect of interest, we compared the fit of the models to the data using the models' log likelihood (loglik) and Akaike information criterion (AIC).

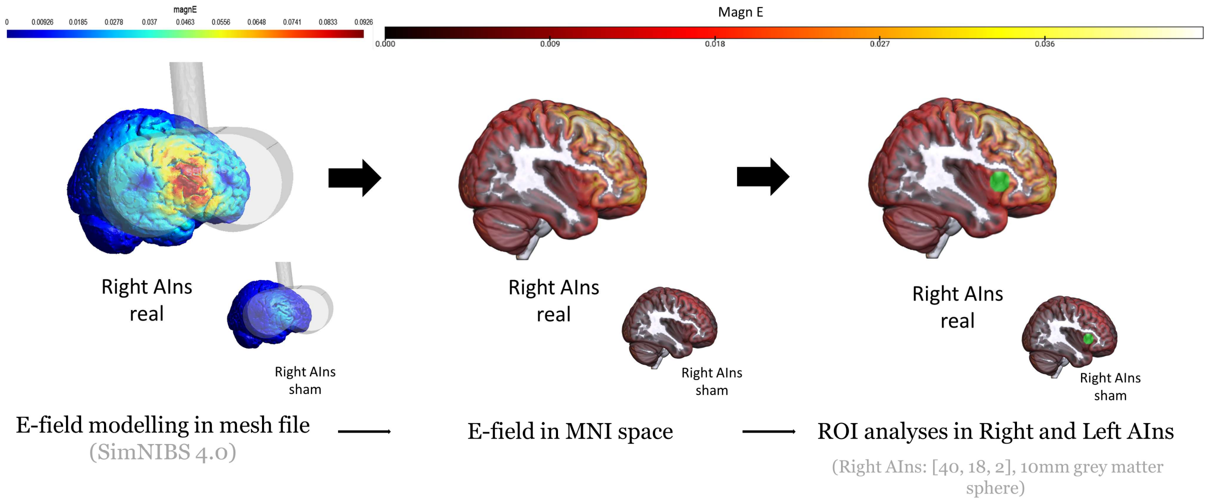


Figure 3. E-field modeling. E-field analysis pipeline. Analyses are conducted in SimNIBS 4.0. E-field is first simulated inside a head mesh model built from individual participants' T1. Based on the focus of the coil coordinates, and the stimulation intensity, a propagation of the TMS-induced electric field in the brain is modeled for each subject in each TMS condition. These simulations are then interpolated to standard MNI space, where spherical, gray matter ROI centred around left and right AIns, left and right E-field maximum peak, and left and right PHC are created. E-field values from inside these ROI are then averaged to obtain the mean intensity (MagnE) of the E-field inside that specific area. These latter will be used in GLLMs to predict participants' behavioural responses. See Extended Data Figure 3-1 for single-subject and average MNI coordinates of left and right maximum E-field peaks.

3.5 Results

3.5.1 Experiment 1 - Semantic ratings

For Emotion triplets, mean Emotion and Social ratings (±SD) were: Emotion ratings, 5.92±0.73, Social ratings, 2.73±0.86. For Social triplets, mean Emotion and Social ratings (±SD) were: Emotion ratings, 2.91±1.03, Social ratings, 6.00±0.82. For Objects triplets, mean Emotion and Social ratings (±SD) were: Emotion ratings, 2.46±0.93, Social ratings, 2.12±0.75. Emotion, Social and Objects triplets differed significantly in their Emotion ratings (Objects-Emotions: $t(177) = -20.971$, $p < 0.001$, Social-Emotions: $t(177) = -18.218$, $p < 0.001$, Social-Objects: $t(177) = 2.753$, $p < 0.018$)and in their Social ratings (Objects-Emotions: $t(177) = -4.114$, $p < 0.001$, Social-Emotions: $t(177) = 22.094$, $p < 0.001$, Social-Objects: $t(177) = 26.208$, $p < 0.001$) (Figure 4).

Lower emotional and social ratings on concrete triplets confirm that these dimensions are not predominant in objects. While the higher average rating in the corresponding scale suggests that the categorical distinction between Emotion and Social concepts is valid, the moderate average rating on the other scale (i.e., social rating for emotion concepts, and vice versa) indicates that a dimensional model captures more fine-grained features of abstract concepts representation.

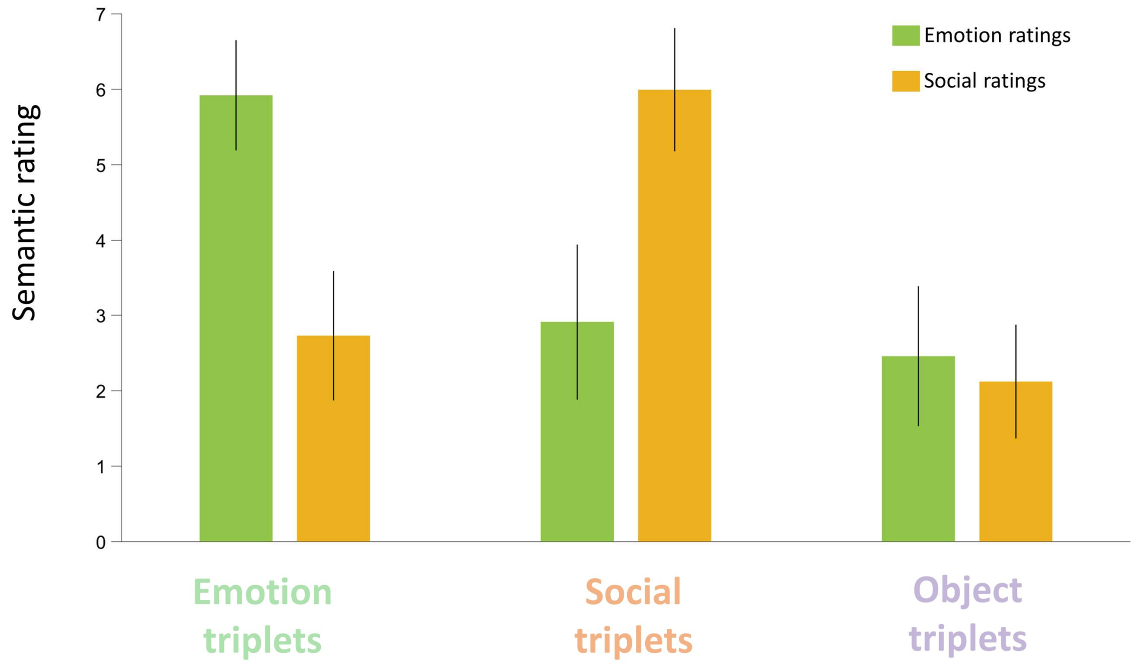


Figure 4. Semantic ratings experiment results. Average emotion (in green) and social (in orange) ratings for emotion triplets and social triplets, respectively. Error bars represent the standard deviation of the mean. Planned comparisons show both emotion and social ratings are significantly different across all three categories.

3.5.2 Experiment 2 - TMS experiment

3.5.2.1 Heartbeat counting task

TMS site (X^2 (5) = 11,350, p = 0.045) significantly affected interoceptive accuracy, as did heart rate control covariate (X^2 (5) = 11,273, p = 0.001), whereby higher heart rate predicted lower interoceptive accuracy.

Planned comparisons revealed a significant effect of the right AIns stimulation (Right Insula Real-Right Insula sham: z value = -2,940, p = 0,007), namely, participants' interoceptive accuracy was lower after real vs sham right insula stimulation. Left insula stimulation, instead, did not significantly affect performance (Figure 5A-B, Table 1).

Crucially, E-field ROI analyses revealed consistent results. E-field values in the right AIns significantly affected interoceptive accuracy (MagnE Right AIns: X^2 =5.896, p = 0.015), namely higher E-field values in right AIns predicted lower interoceptive accuracy. Heart rate also had a significant effect on interoceptive accuracy (X^2 =11.022, p = 0.001), with a higher heart rate predicting lower interoceptive accuracy. In contrast, E-field values in left AIns did not significantly affect interoceptive performance (Figure 5C-D, Table 2, Table 2-1).

E-field values in the right MAX E-field ROI also significantly affected interoceptive accuracy, namely higher E-field values in right MAX predicted lower interoceptive accuracy (X^2 =5.861, p = 0.015). In contrast, E-field values in left MAX did not significantly affect interoceptive performance (X^2 = 0.001, p = 0.970) (Figure 5-1).

The E-field in right PHC does not have a significant effect on Interoceptive accuracy (X^2 = 3.539, p = 0.060). The E-field in left PHC does not predict Interoceptive accuracy either (X^2 = 3.502, p = 0.061) (Figure 5-2).

Since both right MAX and right AIns exerted a significant effect on interoceptive accuracy, we compared the models' fit to the data.

Right MAX ROI model loglik and AIC were respectively 56.992 and -103.985, those of right AIns model were 56.995 and -103.989. The results indicate that right AIns model is a better fit (higher loglik, smaller AIC) than right MAX in explaining interoceptive accuracy data.

In brief, both TMS site and E-field analysis showed that stimulation applied over the right AIns significantly decreased interoceptive performance.

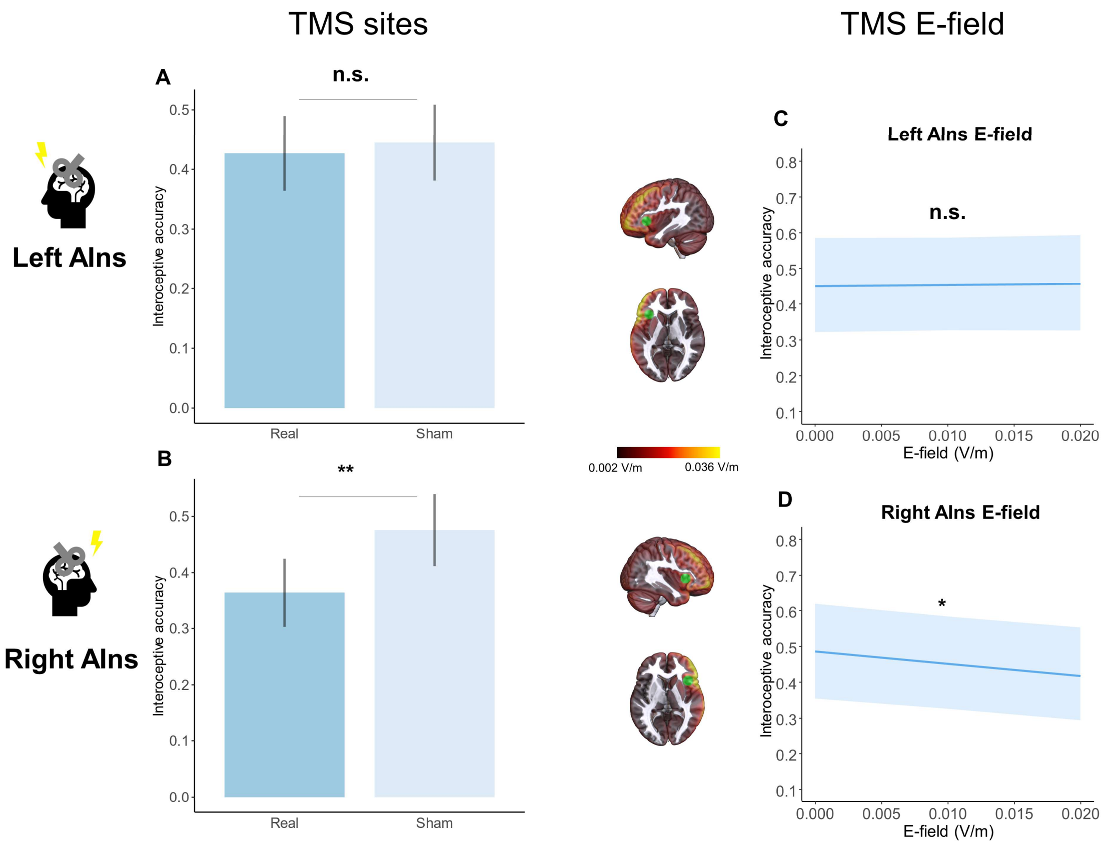


Figure 5. Heartbeat counting task results. AIns, anterior insula; E-field, electric field. **A**, Estimated marginal means of interoceptive accuracy following left TMS conditions, converted from logit to the response scale. The comparison between left real-left sham is not significant. **B**, Estimated marginal means of interoceptive accuracy following right TMS conditions, converted from logit to the response scale. The comparison between right real-right sham is significant: right real stimulation led to a decrease in performance, namely, to lower interoceptive accuracy. **C**, Adjusted predictions of the effect of the E-field induced in left AIns on interoceptive accuracy. The effect of left AIns E-field is not significant. See **A** of Extended Data Figures 5-1 and 5-2 for the analysis with, respectively, left MAX E-field and left PHC E-field. **D**, Adjusted predictions of the effect of the E-field induced in right AIns on interoceptive accuracy. The degree of right AIns E-field significantly lowers interoceptive accuracy: higher E-field values in right AIns lead to lower interoceptive accuracy. See **B** of Extended Data Figures 5-1 and 5-2 for the analysis with, respectively, right MAX E-field and right PHC E-field. **A, B**, Error bars represent standard errors of the marginal means (SEM). **C, D,** Error bars represent 95% confidence intervals (CI) of the adjusted predictions. **A, B**, p values of the planned comparisons were corrected for multiple comparisons using Holm correction. Tests are performed on the logit scale. $^{**}p < 0.01$, $^{*}p < 0.05$, n.s., $p > 0.05$.

Model results

	Chisq	*Df*	*p-value*
(Intercept)	0.984	1	0.321
TMS site	**11.350**	**5**	**0.045**
Heart rate	**11.273**	**1**	**0.001**

Planned comparisons

contrast	*odds.ratio*	*SE*	*z.ratio*	*p-value*
Left Real - Left Sham	0.929	0.139	-0.491	0.624
Right Real - Right Sham	**0.630**	**0.099**	**-2.940**	**0.007**

Table 1. TMS site as predictor of Interoceptive accuracy. Mixed-effect model results of TMS site predicting interoceptive accuracy and planned comparisons between ipsilateral real and sham stimulations, showing that right real stimulation significantly affected interoceptive accuracy compared to right sham stimulation. Significant results are written in bold. Chisq: Chi-squared statistic, Df: degrees of freedom, SE: standard error, z.ratio: test statistic

Model results

	Chisq	*Df*	*p-value*
(Intercept)	0.506	1	0.477
Right AIns MagnE E-field	**5.896**	**1**	**0.015**
Heart rate	**11.022**	**1**	**0.001**

Table 2. E-field in right Anterior Insula as predictor of Interoceptive accuracy. Mixed-effects regression model results of TMS E-field in right AIns predicting interoceptive accuracy, showing that the magnitude of E-field inside right AIns significantly affected interoceptive accuracy. Significant effects are written in bold. See table 2-1 for the analysis with left AIns E-field as predictor of Interoceptive accuracy. Chisq: Chi-squared statistic, Df: degrees of freedom

3.5.2.2 Semantic similarity task

3.5.2.2.1 Category

The main effect of TMS site ($F = 6{,}994$, $p < 0.0001$) and category ($F = 9.817$, $p < 0.0001$) were significant. The effects of the covariates semantic similarity similar ($F = 10.294$, $p = 0.002$) and triplet length ($F = 5.745$, $p = 0.018$) were also significant, whereas those of semantic similarity distant and the interaction between TMS and category were not significant. Planned comparisons were not significant (all $p > 0.05$) (Figure 6A-B, figure 6-1).

E-field analyses with right AIns also revealed a significant effect of category ($F = 9.865$, $p < 0.001$), while the effect of MagnE was not significant. Again, we found a significant effect of covariate semantic similarity similar ($F = 9.797$, $p = 0.002$) and triplet length ($F = 5.642$, $p = 0.019$). The interaction between E-field in right AIns and category was not significant. Planned comparisons were not significant (all $p > 0.05$) (Figure 6D, figure 6-3).

On the contrary, in the E-field analysis on the left AIns, the effect of MagnE was significant (magnE Left AIns: $F=7.352$, $p=0.007$), as was the effect of category ($F = 9.858$, $p<0.001$), and the effects of semantic similarity similar ($F = 9.649$, $p = 0.002$) and triplet length ($F = 5.649$, $p = 0.019$). The interaction between category and MagnE left AIns was not significant. Planned comparisons were non-significant (all $p > 0.05$). (Figure 6C, figure 6-2).

Likewise, E-field analyses with right MAX and with left MAX did not present any significant comparisons (all $p > 0.05$) (Figure 6-4). E-field analysis with right PHC and left PHC E-field did not result in any significant comparisons either (all $p > 0.05$) (Figure 6-5).

The analysis of semantic accuracy did not reveal any significant interaction between category and TMS site or E-field in any ROI either (figure 6-6 to figure 6-11).

In brief, neither TMS nor E-field in either left or right AIns interacted with category. E-field induced in left AIns had a nonspecific effect, whereby the higher the E-field, the slower the RT.

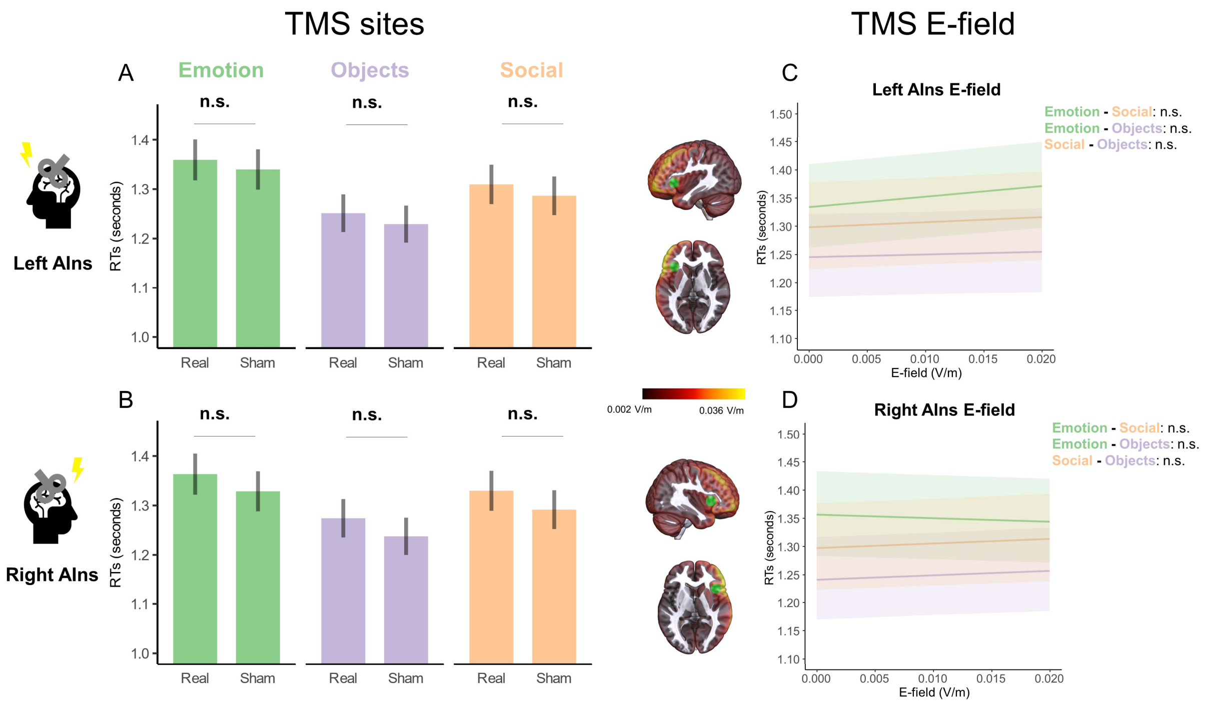


Figure 6. Semantic similarity task. Category results. RTs. AIns, anterior insula; E-field, electric field. **A, B,** Estimated marginal means of reaction times (RTs) following left (A) and right (B) TMS conditions, back-transformed from log to the response scale. Planned comparisons were nonsignificant (Extended Data Fig. 6-1). **C**, Adjusted predictions of the interaction between the electric field (E-field) induced in left anterior insula (AIns) and category on RTs. Planned comparisons were nonsignificant (Extended Data Fig. 6-2). See **A** of Extended Data Figures 6-4 and 6-5 for the analysis with, respectively, left MAX E-field and left PHC E-field. **D,** Adjusted predictions of the interaction between the electric field (E-field) induced in right anterior insula (AIns) and category on RTs. Planned comparisons were nonsignificant (Extended Data Fig. 6-3). See **B** of Extended Data Figures 6-4 and 6-5 for the analysis with, respectively, right MAX E-field and right PHC E-field. **A, B**, Error bars represent standard errors of the marginal means. **C, D**, Error bars represent 95% confidence interval (CI) of the adjusted predictions. All p values were corrected for multiple comparisons using Holm correction. n.s. $p > 0.05$. See Extended Data Figures 6-6–6-11 for the respective analysis with category and E-field in AIns, MAX and PHC as predictors of accuracy.

3.5.2.2.2 Semantic ratings

3.5.2.2.2.1 Abstract triplets

According to the dimensional approach, we also tested the interaction between TMS and semantic ratings on the Emotion and Social dimension of abstract triplets. The main effect of TMS site (F= 5,313, p=0,001), Social rating (F= 5,212, p=0,024), TMS and Social rating interaction (F=4.304, p=0.005), TMS and Emotion rating interaction (F=3.678, p=0.012) were all significant. Only the main effect of Emotion rating did not reach significance (F = -1.92, p = 0.055). Both Social and Emotion showed a similar, negative trend: the higher the triplet rating on Social and/or Emotion scale, the faster the response. Semantic similarity similar (F= 5.877, p = 0.017) and triplet length (F= 12.762, p = 0.001) also showed significant effects, whereas semantic similarity distant did not.

Planned comparisons tested whether the slope of Emotion and Social rating differed depending on TMS site. We found a significant difference in the slopes of Social rating effect between Right Insula real-Right Insula sham stimulation (T = 2,420, p=0,031), and in the slope of Emotion rating effect between Right Insula real-Right Insula sham stimulation (T=2.306, p=0.042) (Figure 7A-D). In both cases, the real Right Insula stimulation slowed responses to triplets with higher Social and Emotion ratings. The interaction with Left Insula stimulation was not significant in either case (all p > 0.05) (Figure 7A-D, Table 3).

In the E-field analysis with right AIns, the main effect of Social rating (F=5.473, p =0.021), MagnE Right AIns and Social rating interaction (F=10.028, p = 0.002), MagnE Right AIns and Emotion rating interaction (F =6.828, p =0.009) were significant. The main effect of Emotion rating and MagnE Right AIns did not reach significance. Semantic similarity similar (F= 5.589, p = 0.020) and triplet length (F= 12.924, p = < 0.001) also showed significant effects, whereas semantic similarity distant did not. The interaction between MagnE right AIns and Social and Emotion ratings revealed a positive trend, whereby higher MagnE values in Right Insula determined slower RTs to triplets with higher Social and Emotion ratings (Figure 7C-F, Table 4).

In the E-field analysis with left AIns, the main effect of MagnE was significant (F=5.602, p =0.018), as Social rating (F=5.281, p =0.024), and the interaction between Social rating and E-field (F= 4.450, 0.035), whereas all other effects were not significant (Figure 7B-E, Table 4-1). Semantic similarity similar (F= 5.427, p = 0.022) and triplet length (F= 12.989, p < 0.001) also showed significant effects, whereas semantic similarity distant did not.

In the E-field analysis with right MAX, the interaction between MagnE right MAX and Social and Emotion ratings were also significant and revealed a positive trend (right MAX E-field*Emotion rating: F = 5.168, p = 0.023, right MAX E-field*Social rating: F = 7.913, p = 0.005), whereby higher MagnE values in Right MAX determined slower RTs to triplets with higher Social and Emotion ratings (Figure 7-1 B, D). In the E-field analysis with left MAX, the two interactions were not significant (left MAX E-field*Emotion rating: F = 2.551, p = 0.110, left MAX E-field*Social rating: F = 2.746, p = 0.098) (Figure 7-1 A, C).

In the E-field analysis with right PHC, the interaction between the E-field in right PHC and social or emotion ratings is not significant (right PHC*Emotion rating: F value= 0.281, p = 0.596, right PHC*Social rating: F value= 0.844, p = 0.358). In the E-field analysis with left PHC, the interactions with left PHC are not significant either (left PHC*Emotion rating: F value= 1.146, p = 0.284, left PHC*Social rating: F value= 1.163, p = 0.281) (Figure 7-2).

Since both right AIns and right MAX models presented significant interactions with Emotion and Social semantic ratings, we compared the fit of the models.

Right MAX ROI model loglik and AIC were respectively -170.145 and 364.289, those of right AIns model were -169.950 and 363.899. The results indicate that right AIns model is a better fit (higher loglik, smaller AIC) than right MAX in explaining semantic RTs data.

To summarise, both TMS and E-field analysis revealed a significant interaction between right AIns and social and emotion scale, whereby triplets with higher Social and Emotion ratings were particularly affected by stimulation. We also found a significant interaction between E-field in the left insula and the social scale, whereby triplets with higher Social ratings were facilitated by higher E-field in left AIns.

E-field analysis of accuracy revealed a consistent pattern, namely the higher the E-field induced in right AIns, the lower the probability of responding correctly to triplets with higher Social and Emotion ratings (figure 7-3 to 7-6). In other words, the higher E-field in right AIns interfered with participants' ability to make correct semantic decisions on highly Emotional and Social triplets.

E-field in right PHC did not interact with semantic ratings in predicting semantic accuracy (right PHC *Emotion rating: $X^2 = 1.806$, p = 0.179, right PHC*Social rating: $X^2 = 1.336$, p = 0.248) (figure 7-8). E-field in left PHC did not interact either (left PHC*Emotion rating: $X^2 = 2.179$, p = 0.140, left PHC*Social rating: $X^2 = 1.431$, p = 0.232) (figure 7-8). Left MAX E-field did not interact with semantic ratings in predicting accuracy either (left MAX*Emotion rating: $X^2 = 0.054$, p = 0.815, left MAX*Social rating: $X^2 = 0.008$, p = 0.927) (figure 7-7). The right MAX E-field significantly interacted with Emotion rating only ($X^2 = 4.850$, p = 0.028), whereas the interaction with social rating was not significant ($X^2 = 3.084$, p = 0.079) (figure 7-7). We compared the right AIns and right MAX models, and similarly to the models predicting semantic RTs, right AIns model provided a better fit to the semantic accuracy data compared to the right MAX model (loglik and AIC were respectively -1259.762 and 2541.523 for right AINs, and -1260.101 and 2542.202 for right MAX model).

Given the high proportion of female participants in this study (19/25), and that there are known sex differences in the neural bases of emotion processing (Filkowski et al., 2017), we performed the right and left AINs E-field analyses of both RTs and accuracy, adding sex as a covariate, and its three-way interaction with E-field in AIns and emotion and social ratings. The interaction was never significant in any of these models, suggesting that sex did not influence the observed effect (Table 8.1-8.4). Future studies, including a more balanced sample of participants, could further investigate this point.

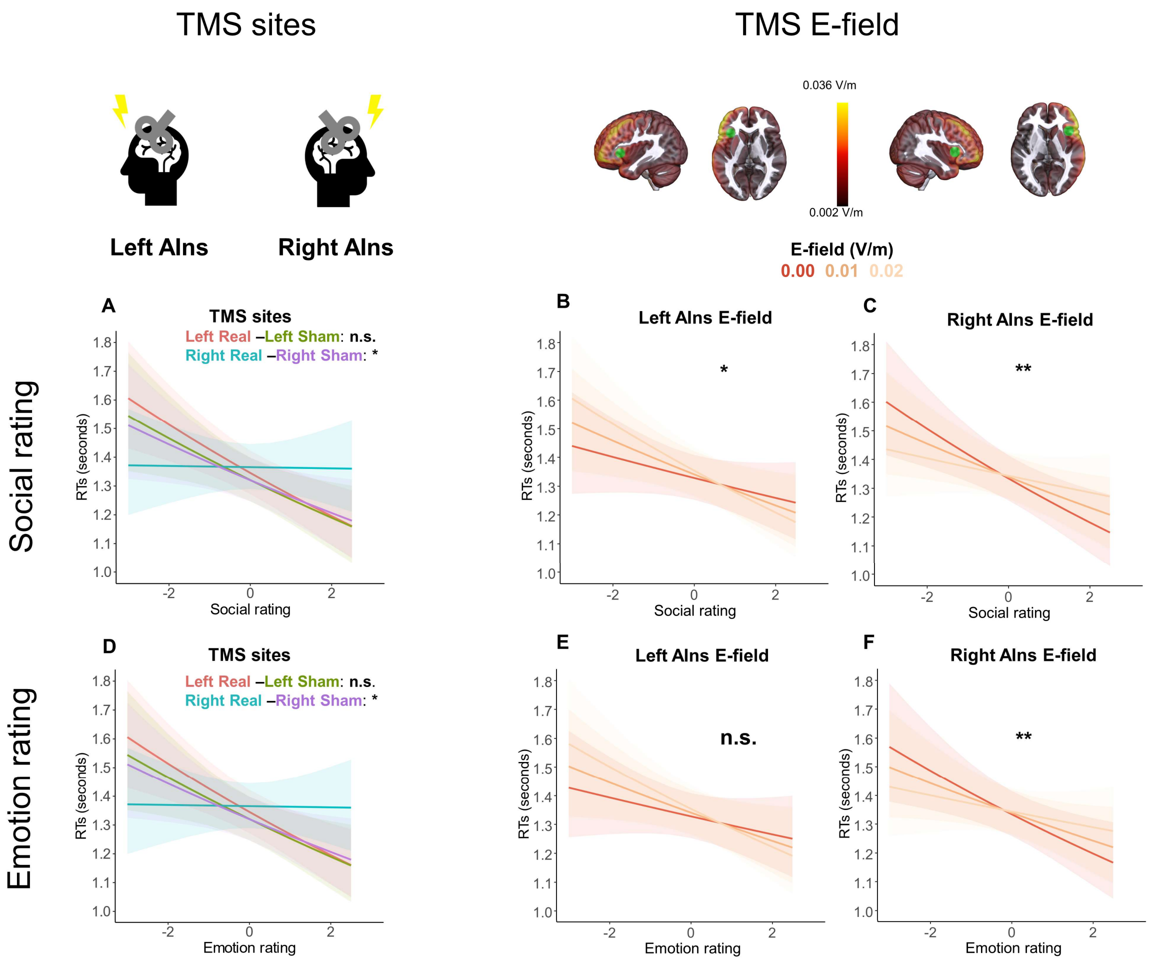


Figure 7. Semantic similarity task. Semantic ratings results with abstract triplets. RTs. AIns, anterior insula; E-field, electric field. Results are shown on the centred Social and Emotion rating. **A, D**, Adjusted predictions of reaction times (RTs) following each TMS condition, shown in the response scale. The comparisons between left real-left sham were not significant. In contrast, right real

stimulation significantly hindered semantic processing, interfering with both the social (A) and the emotion (D) dimensions: subjects were no longer faster in responding to abstract triplets with higher social and emotion scores after right real compared with right sham stimulations. p values of the planned comparisons were corrected for multiple comparisons using Holm correction. **B, E**, Adjusted predictions of the interaction between the E-field induced in left AIns on Social (B) and Emotion (E) rating. The interaction with Social rating is significant and shows a negative trend. See **A** of Extended Data Figures 7-1 and 7-2 for the analysis with, respectively, left MAX E-field and left PHC E-field. **C, F**, Adjusted predictions of the interaction between the E-field induced in right AIns on Social (C) and Emotion (F) rating. Both interactions are significant and show a positive trend, whereby the facilitatory effect of the Emotion and Social rating is reduced in the presence of a higher E-field in the right AIns. See **B** of Extended Data Figures 7-1 and 7-2 for the analysis with, respectively, right MAX E-field and right PHC E-field. Error bars represent 95% confidence intervals (CI) of the adjusted predictions. $^{**}p < 0.01$, $^{*}p < 0.05$, n.s., $p > 0.05$. See Extended Data Figures 7-3–7-8 for the respective analysis with semantic ratings and E-field in AIns, MAX and PHC as predictors of accuracy for abstract triplets. See Extended Data Figures 7-9 to 7-16 for the analysis with semantic ratings and E-field in AIns as predictors of RTs and accuracy for concrete triplets.

Model results

	Sum.Sq	*Mean.Sq*	*NumDF*	*DenDF*	*F.value*	*p-value*
Emotion rating	0.217	0.217	1	103.339	3.676	0.058
Social rating	**0.308**	**0.308**	**1**	**103.423**	**5.212**	**0.024**
TMS site	**0.941**	**0.314**	**3**	**4707.745**	**5.313**	**0.001**
semantic similarity similars	**0.347**	**0.347**	**1**	**103.588**	**5.877**	**0.017**
semantic similarity distants	0.003	0.003	1	104.638	0.048	0.827
triplet length	**0.754**	**0.754**	**1**	**103.084**	**12.762**	**0.001**
Emotion rating:TMS site	**0.651**	**0.217**	**3**	**4707.231**	**3.678**	**0.012**
Social rating:TMS site	**0.762**	**0.254**	**3**	**4707.033**	**4.304**	**0.005**

Planned comparisons

Emotion rating and TMS site

contrast	*estimate*	*SE*	*df*	*t.ratio*	*p.value*

Left Real – Left Sham	-0.009	0.019	4727.923	-0.448	0.654
Right Real – Right Sham	**0.043**	**0.019**	**4715.815**	**2.306**	**0.042**

<u>*Social rating and TMS site*</u>

contrast	*estimate*	*SE*	*df*	*t.ratio*	*p.value*
Left Real – Left Sham	-0.007	0.018	4726.225	-0.376	0.707
Right Real – Right Sham	**0.044**	**0.018**	**4716.928**	**2.420**	**0.031**

Table 3. Interaction between semantic ratings and TMS site as predictors of Reaction times of Abstract triplets. Mixed-effects regression model results of TMS site and semantic ratings predicting (log-transformed) reaction times, and planned comparisons between ipsilateral real and sham stimulations, showing the difference in the average slope of emotion and social scores effect between right real and right sham TMS conditions, and between left real and left sham TMS conditions. In the right real compared to the right sham condition, the stimulation significantly interacted with both social and emotion scores, interfering with their facilitatory effect on RTs. Significant results are written in bold. Sum.Sq: Sum of squares, Mean.Sq: Sum of squares / degrees of freedom, NumDF, df: Degrees of freedom, DenDF: Denominator degrees of Freedom, estimate: estimated value of the contrast, SE: standard error, t.ratio: test statistics

<u>*Model results*</u>

	Sum.Sq	*Mean.Sq*	*NumDF*	*DenDF*	*F.value*	*p-value*
Right AIns E-field	0.057	0.057	1	4518.688	0.962	0.327
Emotion_rating	0.229	0.229	1	103.432	3.874	0.052
Social_rating	**0.323**	**0.323**	**1**	**103.524**	**5.473**	**0.021**
semantic similarity similars	**0.330**	**0.330**	**1**	**103.614**	**5.589**	**0.020**
semantic similarity distants	0.000	0.000	1	104.846	0.001	0.970
triplet length	**0.764**	**0.764**	**1**	**103.150**	**12.924**	**0.000**
Right AIns E-field:Emotion_rating	**0.404**	**0.404**	**1**	**4512.546**	**6.828**	**0.009**
Right AIns E-field:Social_rating	**0.593**	**0.593**	**1**	**4512.586**	**10.028**	**0.002**

Table 4. Interaction between semantic ratings and E-field in right Anterior Insula as predictors of Reaction times of Abstract triplets. Mixed-effect regression model results of TMS E-field in right AIns and semantic ratings predicting (log-transformed) reaction times to abstract triplets, where the last two rows represent the interaction between the magnitude of the E-field inside right AIns and respectively emotion and social rating. Significant effects are written in bold. See table 4-1 for the respective analysis with left AIns E-field and semantic ratings as predictors of RTs. Sum.Sq: Sum of squares, Mean.Sq: Sum of squares / degrees of freedom, NumDF: Degrees of freedom, DenDF: Denominator degrees of Freedom

3.5.2.2.2.2 Concrete triplets

As a control analysis, we tested the interaction between TMS and Emotion and Social ratings on concrete triplets. If our results are specific to the abstract domain, we should not find significant results with this latter analysis.

First, in the TMS site analysis, Emotion ratings and Social ratings did not exert a main effect on RTs to concrete triplets (Emotion rating: F value = 0.898, p = 0.347, Social rating: F value = 0.113, p = 0.738). The planned comparisons testing whether TMS site interacted with the semantic ratings also did not show any significant results, either for Emotion rating (Left Real-Left Sham: t value = 1.009, p = 0.500, Right-Real-Right Sham: t value = 1.151, p = 0.500), or for Social rating (Left Real-Left Sham: t value = -1.161, p = 0.492, Right-Real-Right Sham: t value = -1.009, p = 0.492) (figure 7-9, 7-12).

In the right Anterior Insula (AIns) E-field analysis, neither Social nor Emotion ratings showed a main effect on RTs (Emotion rating: F value = 0.985, p = 0.325, Social rating: F value = 0.068, p = 0.795). The interactions with right AIns are not significant either (right AIns E-field*Emotion rating: F value = 0.021, p = 0.884, right AIns E-field*Social rating: F value = 1.987, p = 0.159) (figure 7-10, 7-12).

In the left AIns E-field analysis, neither Social nor Emotion ratings showed a main effect on RTs either (Emotion rating: F value = 1.000, p = 0.321, Social rating: F value = 0.070, p = 0.792). The interactions with left AIns are not significant either (left AIns E-field*Emotion rating: F value = 1.878, p = 0.171, left AIns E-field*Social rating: F value = 0.010, p = 0.921) (figure 7-11, 7-12).

The analysis of semantic accuracy revealed the same pattern of results: emotion and social ratings did not exert a significant effect of accuracy, and the interactions with TMS site and with right and left AIns E-field are all non -significant either (figure 7-13 to 7-16).

Overall, these results confirm that social and emotion value of concrete triplets did not significantly interfere with semantic judgements, while in abstract triplets, social score significantly facilitated semantic judgements. Moreover, we confirmed, both with the TMS site and the TMS E-field analyses, that the stimulation targeting right and left AIns did not interact with concrete triplets' social and emotional dimensions. Given the high number of observations (N= 2759), we believe this lack of interactions to reflect a true null result, which strengthens the conclusion that the right AIns is involved in processing the emotion of social dimensions of abstract concepts specifically.

3.6 Discussion

TMS on the right AIns significantly interfered with interoceptive accuracy. In the semantic task, the effect was also right-lateralized; it was observed in both the emotion and the social dimensions, and emerged only using a dimensional approach and only with abstract but not with concrete triplets.

3.6.1 Insula in interoception

In the heartbeat counting task, rTMS over the right AIns interfered with interoceptive processing (Figure 5A, 5B). This finding aligns with previous neuroimaging studies, showing that people's ability to detect their heartbeats correlates with activity or grey matter volume in right AIns (Critchley et al., 2004; Pollatos, Schandry, et al., 2007). RTMS studies confirmed this, finding a decrease in interoceptive accuracy after right AIns inhibition (Mai et al., 2019; Pollatos et al., 2016), although in these studies, the left AIns was not stimulated, hence the effect of its inhibition was not tested.

However, concerns have been expressed regarding the plausibility of reaching AIns through non-invasive brain stimulation (NIBS) (Coll et al., 2017). To ensure that our results could be ascribed to the rTMS interference on AIns, we simulated the TMS-induced E-field in left and right AIns, and used it to predict interoceptive accuracy.

If the E-field in the AIns ROI were found to exert a significant effect on interoceptive accuracy it would demonstrate that AIns had a direct role in the observed response. The results of the E-field models confirmed our findings. While E-field in left AIns exerted no effect (Figure 5C), E-field in right AIns interfered with participants' performance, with higher E-field predicting lower interoceptive accuracy (Figure 5D).

Together, these analyses demonstrate the effectiveness of stimulation and align with Craig's theory on the role of right AIns in interoceptive awareness (Craig, 2009).

3.6.2 Insula in emotion

In the semantic similarity task, right AIns stimulation interfered with judgments on abstract triplets with higher scores on the Emotion dimension (Figure 7D).

AIns has a role in emotion experience (Duerden et al., 2013). Its activity supports emotion recognition of facial expressions (Motomura et al., 2019; Papagno et al., 2016) and perceived (un)pleasantness of visual stimuli (Feng et al., 2021; Mai et al., 2019).

Crucially, AIns is involved in the processing of emotional words. While some of these studies employed emotion-referring words (i.e., words referring to internal states, i.e., "fear") (Lebois et al., 2020; R. Moseley et al., 2012; Wilson-Mendenhall et al., 2011), others used 'emotional words', where emotionality is defined in terms of high valence and/or arousal (Citron et al., 2014; Vigliocco et al., 2014). Emotional words refer not only to emotions but also to other types of abstract concepts, such as social ones (e.g., "war", "traitor"). In our stimuli, words belonging to the Emotion category were emotion-referring words, but ratings on the Emotion dimension were obtained for all stimuli.

The results show that right AIns stimulation interacted with Emotion dimension (Figure 7D): after right real stimulation, compared to sham, the higher emotional connotation no longer facilitated decisions on the abstract triplets. Consistently, the higher the E-field induced in right AIns, the lower the facilitation for abstract triplets with higher emotional scores (i.e., slower RTs and lower accuracy) (Figure 7F, Figure 7-6 F).

We did not find any interaction between AIns stimulation and Emotion category (Figure 6). Abstract concepts might be better characterised by a dimensional rather than a categorical approach, because boundaries between categories of abstract concepts are difficult to define (Desai et al., 2018; Harpaintner et al., 2018).

As confirmed by our control analysis, these effects were not present with concrete object triplets, supporting the idea that right AIns is predominantly involved with the emotional content of abstract concepts.

These findings align with an embodied view of the abstract domain, where the emotional content of abstract words is supported by the right AIns, an area engaged in the corresponding non-linguistic emotional experience (Parrinello et al., 2022).

The right AIns role in emotion experience has also been linked with its role in interoception (Adolfi et al., 2017; Nguyen et al., 2016; Zaki et al., 2012). Intriguingly, interoception is an important modality for the perceptual grounding of abstract concepts (Connell et al., 2018; Repetto et al., 2023), and the processing of abstract emotion words and heartbeat interact with each other (Vergallito et al., 2019; Villani et al., 2021). Based on that, we hypothesise that in right AIns, interoceptive feedback may inform semantic judgements by providing a grounded representation of emotional linguistic content.

3.6.3 Insula in social experience

In the semantic similarity task, right AIns stimulation interfered with abstract triplets with higher scores on the Social dimension (Figure 7A).

The right AIns has been related to social processes, such as learning of social structure (T. Lau et al., 2020), social prediction errors (Henco et al., 2020), empathy (Corradi-Dell'Acqua et al., 2016), social connotation of speech and action (Di Cesare et al., 2018), and socially induced emotions (Immordino-Yang et al., 2014).

Social concepts, or social-referring concepts, refer to interpersonal relationships (Troche et al., 2014) , to values or ideologies (Diveica et al., 2023). Even though AIns does not appear among the areas involved in the representation of social concepts (Arioli et al., 2021), studies that investigated the representation of emotional concepts finding activation in AIns (Citron et al., 2014; Vigliocco et al., 2014) included social-referring words as stimuli (e.g., "war", "seduction"). On the other hand, emotion-referring words (such as "jealousy") refer to internal states that are experienced in interpersonal situations. In our stimuli, words belonging to the social category were social-referring words, while ratings on the social dimension were obtained for all stimuli.

We observed a main effect of social dimension, i.e., a negative estimate of the effect of social rating (also observed as a non-significant trend for emotion rating), reflecting participants' tendency to respond faster to triplets the higher their social value. This finding aligns with previous studies in which a word with higher socialness predicts faster RTs on lexical tasks (Diveica et al., 2023).

The facilitatory effect of the social dimension was hindered by right AIns stimulation (Figure 7A): after real right stimulation, compared to sham, the higher social connotation no longer facilitated semantic decisions on the abstract triplets. Consistently, the higher the E-field induced in right AIns, the lower the facilitation caused by higher social scores (i.e., slower RTs and fewer correct responses) (Figure 7C, Figure 7-6 C). The main effect of social dimension makes it unlikely that this interaction is due to the stimulation interfering with cognitive abilities in general: indeed, the triplets with higher social (and emotional) ratings benefit from that facilitatory effect, suggesting that higher scores on these dimensions facilitate semantic processing, and the TMS interferes particularly with these 'easier' triplets.

Again, we only found an interaction with the social dimension, but not with the social category (Figure 6), perhaps because a dimensional model is more fine-grained than a categorical one, therefore more powerful as it captures the overlap between emotional and social features.

The control analysis with concrete triplets did not show any significant results with social ratings either, showing that right AIns is primarily involved in the representation of social content of abstract concepts.

These findings align with an embodied view of the abstract domain (Desai et al., 2018), where the social content of abstract words is supported by the right AIns, which plays an important role in non-linguistic social experience.

Literature supports a connection between social cognition and interoception (Arnold et al., 2019; Arslanova et al., 2022; Feldman et al., 2023; Gao et al., 2019; Mattarozzi et al., 2019; Oldroyd et al., 2019; Pollatos et al., 2015), whereby higher interoceptive abilities predict a more adaptive sociality. Together with the results from the heartbeat counting task, our findings support a convergence of interoceptive and social and emotional processes in the right AIns (Adolfi et al., 2017; Garfinkel & Critchley, 2013), wherein we hypothesize that interoceptive feedback informs semantic judgements providing a grounded representation of the social value of abstract concepts.

3.6.4 Limitations

Although we reached AIns with the TMS, we certainly could not restrict the stimulation to this area (see MAX and PHC E-field analysis in the Results section), and we inevitably stimulated other brain regions that have contributed to the observed responses. AIns might also have been indirectly influenced by the other connected regions that were reached by rTMS.

Moreover, while our results suggest that there are neural resources inside AIns dedicated to the social and emotional components of language and to interoception, with our NIBS methods we do not know whether these resources consist of the same populations of neurons performing computations for both tasks, or to different populations of neurons, therefore other methods, such as intracranial recordings, might clarify this.

To further clarify the relationship between interoception and emotional and social ratings, future studies should also include ratings on how much concepts are experienced through interoception, or interoceptive ratings (Connell et al., 2018; Repetto et al., 2023), and their associations with social and emotional ratings.

Finally, our results were obtained using emotion and social-referring abstract concepts, and also in the light of critics expressed on the affective embodiment account (Winter, 2023), future studies are needed to clarify how much the importance of the emotion and social dimensions generalizes to other categories of abstract concepts, such as quantities or cognitive concepts (Persichetti et al., 2024; Villani et al., 2019).

3.7 Conclusions

According to the embodied cognition theory, abstract concepts are perceptually grounded in interoception. This study investigated whether abstract concepts and interoception processing overlap in the Anterior Insula, leveraging the causal inference provided by TMS and E-field ROI analysis. Our findings revealed that the right AIns stimulation interfered with both interoception and social and emotional dimensions of abstract concepts. Our interoception findings confirm the role of the right AIns in cardiac interoceptive awareness. The semantic results provide evidence for the role of the right AIns in the processing of socio-emotional content of abstract concepts, in line with an embodied theory where abstract concepts engage areas representing the corresponding experience, challenging the dual coding theory claim that abstract concepts only rely on a linguistic format. Together, these results suggest that interoceptive and semantic processes converge on the right AIns, where we hypothesise that interoceptive states are integrated into semantic judgements and provide a perceptual, internal signature for emotional and social content.

3.7 Code accessibility

Data, stimulus words and code have been deposited at the OSF repository (https://osf.io/cavsy/). The original MRI and the mesh files of the E-field simulations cannot be deposited in a public repository for privacy reasons.

3.8 Conflict of interest statement

The authors declare no competing interests.

3.9 Acknowledgements

This project was funded by the Next Generation EU - European Union - PNRR – M4 – C2 – INV1.1 – PRIN – Project title "The insula between interoception and abstract thinking" – project identification code: P20228X7R5 – CUP E53D23019510001 – fund UNITN 40104640 - PAPAGNO PRIN PNRR 2022 – Next Generation EU.

We thank Jesse Sagoe for his contribution to the data collection. We thank Luigi Cattaneo and Daniele Romano for helpful discussions and support, and Marco Marelli for sharing the distributional semantics model data.

CHAPTER 4.

NEURAL DYNAMICS AND REPRESENTATIONAL CONTENT ACROSS ABSTRACT AND CONCRETE CONCEPTS

A preregistration of this study is available on OSF (https://osf.io/p5b2c/overview).

4.1 Introduction

The nature of the semantic representation of concepts remains a matter of debate, and this is particularly relevant for concepts lower on the concreteness spectrum, or abstract concepts. While some authors advocate for a purely linguistic representation (Clark & Paivio, 1987; Paivio, 1991), where abstract concept meaning is only acquired through language and does not recruit any additional resources compared to concrete concepts, embodied cognition supports a grounded representation, where concept representation relies on sensorimotor and internal information (Barsalou, 2008; Barsalou et al., 2018; Borghi et al., 2019; Vigliocco et al., 2014). Another debated question regarding the nature of abstract concepts concerns the applicability of categorical distinctions between them. While concrete concepts are successfully divided into categories based on taxonomic information or shared features (Mirman et al., 2017) the same process does not apply with equal success to abstract words. For this reason, other approaches have been developed to characterise the organisation of the abstract semantic space, often based on the collection of explicit human ratings on designated multimodal properties and following clustering procedures based on the distribution of these properties (Troche et al., 2014; Villani et al., 2019). One way to advance our knowledge on these issues and discover the organisational principles driving the representation of linguistic concepts is to leverage semantic similarity models.

In these models, the semantic distance between words is calculated based on different kinds of information (Bruffaerts et al., 2019). In distributional models, lexical corpora are exploited, and pairs of words that appear in similar linguistic contexts are rated as more similar (i.e., less distant) than pairs of words that appear in different contexts. In taxonomic models, words are divided into different categories, which are interconnected according to hyper/hyponym relations, i.e., a taxonomic network (e.g., 'dog' being a hyponym of 'canine', 'canine' being a hyponym of 'mammal', etc.), wherein closer words are rated as more similar. The most widely used way to create these models is WordNet (Fellbaum, 2010), a lexical database available in different languages which stores hierarchical relationships among concepts. Experiential models usually rely on human behavioural ratings, where participants are asked how much they experience concepts through multimodal dimensions related to the senses, the body, or emotional and social features (Harpaintner et al., 2018; Troche et al., 2017; Villani et al., 2019), and distances are calculated based on the word's rating on these dimensions.

Each of these types of models relies on a different source of information (purely linguistic, categorical, or experiential) to encode the similarity structure of concepts. Using Representation Similarity Analysis (RSA, Kriegeskorte et al., 2008), it is possible to evaluate to what extent the information encoded in each model reflects the observable neural representational structure of the same concepts.

Recent studies employing fMRI have used these models and RSA to characterise the semantic representation of concrete (Carota et al., 2017; Liuzzi et al., 2015, 2017) or abstract concepts (Kaiser et al., 2022; X. Wang, Wu, et al., 2018). In these studies, concepts are presented one by one, and their brain responses are compared to their respective model's representation. Overall, this literature showed that different models are reflected in brain patterns, and that the organisational principles vary across the brain regions under examination. However, these fMRI studies do not provide information on the temporal unfolding of concept representation, i.e., when and in which order different kinds of semantic information are used during concept processing. Moreover, only a few of them directly compared models' performance between concrete and abstract concepts in the same paradigm (Meersmans et al., 2020; Montefinese et al., 2021).

Montefinese and colleagues (Montefinese et al., 2021) used fNIRS to test the correlation between a distributional and an emotional similarity model with neural signals in the Inferior Parietal Lobule (IPL) separately on concrete and abstract concepts. They found that neural patterns in bilateral IPL correlated with the distributional model for concrete concepts, and in left IPL with the emotional model for abstract concepts. These results showed that the same region works according to different principles depending on the concepts' concreteness. However, they limited their investigation to the IPL.

In Meersmans and colleagues' (Meersmans et al., 2020) fMRI experiment, the authors captured semantic and affective similarities derived from distributional and associative properties and compared their performance separately on concrete and abstract concepts in a set of ROIs. They found a significant correlation for the associative semantic model only with abstract concepts. Moreover, in line with the Affective Embodiment Account, which states that abstract concepts rely more on emotional information than concrete ones (Kousta et al., 2011; Vigliocco et al., 2014), associative and distributional affective models correlated only with abstract words.

While these two studies suggest that word representation principles in the brain vary according to their level of concreteness, they do not provide information regarding their temporal unfolding and whether they differ between abstract and concrete concepts.

We filled these gaps by comparing concrete and abstract concepts with RSA on a set of semantic models, leveraging the high temporal resolution of MEG.

We used MEG to record neural responses during written word comprehension, and RSA to correlate a set of semantic models separately on concrete and abstract word-to-word MEG responses. We investigated: (i) which information (i.e., which model) is encoded during concept comprehension, and (ii) when the information is encoded, doing that separately on concrete and abstract concepts.

The models we used reflect linguistic (two distributional models), experiential (one sensorimotor and one affective model), taxonomic (one categorical model) and concreteness information.

RSA results will inform us about (i) which models correlate with the neural activity, and (ii) the temporal course of these correlations.

We expected: (1) significant correlations between MEG data and the distributional model, both for abstract and concrete concepts (Hultén et al., 2021; Sassenhagen & Fiebach, 2020; Vinaya et al., 2025); (1a) distributional correlations temporally preceding correlations with the experiential models (Vignali et al., 2023); (2) significant correlations between MEG data and the sensorimotor experiential model for concrete concepts (Vignali et al., 2023; Vinaya et al., 2025). (3) significant correlations between MEG data and the affective experiential model for abstract concepts (Meersmans et al., 2020; Montefinese et al., 2021; Vigliocco et al., 2014), in line with the Affective Embodiment account (Kousta et al., 2011; Vigliocco et al., 2014) (4) the taxonomic categorical model to correlate with MEG data elicited by concrete concepts (Carota et al., 2021), while no correlations are expected with the MEG data of abstract concepts (Fernandino et al., 2022).

4.2 Methods

4.2.1 Participants

Based on previous literature, we recruited 28 young healthy participants (20 self-identified as female, 8 self-identified as male, mean age: 24.57 years, SD: 4.79, range: 19-39 years), considering the possibility of excluding participants due to high noise levels or dropout. Inclusion criteria were: Italian native-speakers, aged 18-40 years, right-handed, with no neurological, developmental or psychiatric disease. Following preprocessing of MEG data, one participant was excluded from the analyses due to a high-noise level in the MEG signal. All the analyses were performed on the remaining 27 participants. All participants gave their written informed consent before starting the experiment. The experiment was approved by the Research Ethics Committee of the University of Trento (protocol 2022-051).

4.2.2 Stimuli

Stimuli consist of 80 Italian nouns (3-10 letters), taken from Repetto and colleagues' dataset (Repetto et al., 2023). We selected words from this dataset as it provided ratings on psycholinguistic variables, as well as sensory, motor, and affective variables, which were used to build the experiential models (see section 'Model'). All stimuli are listed in Table 1.

Words were selected with a semi-automated approach, and the procedure was implemented in a Python environment, using the Natural Language Toolkit (NLTK 3.4.5; https://www.nltk.org). The process was developed to optimise categorical distinctiveness based on WordNet taxonomy, and the variability of kinds of concrete and abstract concepts included. In WordNet (Fellbaum, 2010), concepts are organised according to taxonomic relations, with a hypernyms and hyponyms hierarchical structure. First, noun words in Repetto's dataset were divided into abstract and concrete based on their ratings on the concreteness scale, which was defined as "*the extent to which a word denotes something that can be perceived directly by the* *senses*" (Repetto et al., 2023), and ranged from 1 (very abstract) to 9 (very concrete). Thresholds were >7 concreteness rating for concrete words and <5.5 concreteness rating for abstract words. These thresholds were selected as they guaranteed a balance between a separation in terms of concreteness between concepts considered concrete and those considered as abstract, and also a sufficient number and variability of nouns in both domains, as a more extreme threshold would have significantly reduced the number of possible concepts to select. Secondly, we computed the most common hypernyms of all words respecting the selected threshold within Repetto's dataset. Then, four categories for the concrete (animal, person, device, structure) and four categories for the abstract domain (acts, quality, cognition, feeling) were selected among the most common and intuitively distinct hypernyms in each domain. Therefore, each of these hypernyms comprised a set of words from the dataset. At this point, words that did not properly fit the hypernym label and composite words were excluded from the lists. Categories were chosen to maximise the variability of abstract and concrete concepts included in the stimuli (e.g., animate concrete concepts like person and animals, inanimate concepts like devices and structures; more grounded abstract concepts like feelings, and more neutral ones like cognition), and the distinctiveness of categories. In this line, we also checked that no words were shared between any possible pair of hypernyms. Then, ten words for each category were sampled from the pool of words belonging to each of these hypernyms until balancing on a set of psycholinguistic variables was achieved. In this way, we obtained 10 exemplars for each of the 8 hypernyms or categories, which were balanced according to the Kruskal-Wallis test on: Colfis log frequency, Repubblica log frequency, word length (i.e., number of letters), number of orthographic neighbours and mean frequency of orthographic neighbours (Table 2). A Mann-Whitney test confirmed that the two domains, concrete and abstract, differed significantly in terms of concreteness ($u = 1600$, $p < 0.001$) and on imageability ($u = 1596$, $p < 0.001$). Concreteness ratings for the 40 abstract words were: avg = 4.228, std = 0.628, and for the 40 concrete words were: avg = 8.091, std = 0.444.

concreteness	***category***	***Ita_Word***	***Eng_Word***	***Ita_associate_1***	***Eng_associate_1***	***Ita_associate_2***	***Eng_associate_2***
concrete	animal	elefante	*Elephant*	proboscide	*trunk*	africa	*Africa*
concrete	animal	agnello	*Lamb*	pecora	*sheep*	pasqua	*Easter*
concrete	animal	maiale	*Pig*	porcile	*pigsty*	grugnito	*grunt*
concrete	animal	ragno	*Spider*	tela	*canvas*	veleno	*poison*
concrete	animal	rana	*Frog*	stagno	*pond*	girino	*tadpole*
concrete	animal	cane	*Dog*	guardia	*guard*	abbaio	*bark*
concrete	animal	cavallo	*Horse*	redini	*reins*	maneggio	*riding school*

concrete	animal	scimmia	*Monkey*	banana	*banana*	nocciolina	*peanut*
concrete	animal	tigre	*Tiger*	strisce	*stripes*	zanne	*fangs*
concrete	animal	scorpione	*Scorpion*	pungiglione	*sting*	deserto	*desert*
concrete	person	prete	*Priest*	parrocchia	*parish*	tonaca	*cassock*
concrete	person	ginnasta	*Gymnast*	atletica	*athletics*	olimpiadi	*Olympics*
concrete	person	fratello	*Brother*	sorella	*sister*	mamma	*mother*
concrete	person	ragazza	*Girl*	adolescente	*teenager*	femmina	*female*
concrete	person	lesbica	*Lesbian*	sessualità	*sexuality*	fidanzata	*girlfriend*
concrete	person	sposa	*Bride*	anello	*ring*	abito	*dress*
concrete	person	ladro	*Thief*	cassaforte	*safe*	furto	*theft*
concrete	person	tuffatore	*Diver*	trampolino	*trampoline*	piscina	*swimming pool*
concrete	person	amico	*Friend*	confidente	*confidant*	compare	*friend*
concrete	person	bebè	*Baby*	neonato	*newborn*	ciuccio	*pacifier*
concrete	device	violino	*Violin*	flauto	*flute*	orchestra	*orchestra*
concrete	device	pistola	*Gun*	polizia	*police*	proiettile	*bullet*
concrete	device	pugnale	*Dagger*	assassinio	*murder*	lama	*blade*
concrete	device	stampella	*Crutch*	bastone	*stick*	zoppo	*lame*
concrete	device	forcina	*Hairpin*	capelli	*hair*	elastico	*elastic*
concrete	device	tromba	*Trumpet*	banda	*gang*	squillo	*ring*
concrete	device	computer	*Computer*	schermo	*screen*	tastiera	*keyboard*
concrete	device	righello	*Ruler*	scuola	*school*	centimetro	*centimeter*
concrete	device	specchio	*Mirror*	riflesso	*reflection*	bagno	*bathroom*
concrete	device	luce	*Light*	giorno	*day*	sole	*sun*
concrete	structure	villetta	*small house*	giardino	*garden*	schiera	*row*
concrete	structure	cantina	*Cellar*	umidità	*humidity*	taverna	*tavern*
concrete	structure	hotel	*Hotel*	turismo	*tourism*	vacanza	*vacation*
concrete	structure	prigione	*Prison*	sbarre	*bars*	detenuto	*prisoner*
concrete	structure	chiesa	*Church*	campanile	*bell tower*	rosario	*rosary*
concrete	structure	terrazzo	*Terrace*	altezza	*height*	panorama	*panorama*
concrete	structure	palazzo	*Palace*	nobiltà	*nobility*	sovrano	*sovereign*
concrete	structure	ospedale	*Hospital*	malati	*sick people*	infermiere	*nurse*
concrete	structure	muro	*Wall*	sostegno	*support*	mattoni	*bricks*
concrete	structure	camera	*Room*	letto	*bed*	comodino	*bedside table*
abstract	act	ricatto	*Blackmail*	minaccia	*threat*	estorsione	*extortion*
abstract	act	rifiuto	*Refusal*	rigetto	*rejection*	respinta	*rejection*
abstract	act	massacro	*Massacre*	morte	*death*	genocidio	*genocide*
abstract	act	vista	*Sight*	occhi	*eyes*	percezione	*perception*
abstract	act	avventur a	*Adventure*	eroe	*hero*	mistero	*mystery*
abstract	act	colpa	*Guilt*	sentenza	*sentence*	tribunale	*court*
abstract	act	debito	*Debt*	soldi	*money*	povertà	*poverty*
abstract	act	inganno	*Deception*	bugia	*lie*	menzogna	*lie*
abstract	act	lussuria	*Lust*	peccato	*sin*	sesso	*sex*
abstract	act	dispetto	*Spite*	ripicca	*revenge*	cattiveria	*malice*
abstract	quality	accordo	*Agreement*	patto	*pact*	intesa	*understanding*

abstract	quality	gloria	*Glory*	militare	*military*	vittoria	*victory*
abstract	quality	fascino	*Charm*	attrattiva	*attractiveness*	seduzione	*seduction*
abstract	quality	ignoranz a	*Ignorance*	illetterato	*illiterate*	analfabeta	*illiterate*
abstract	quality	potenza	*Power*	forza	*strength*	potere	*power*
abstract	quality	fase	*Phase*	stadio	*stadium*	periodo	*period*
abstract	quality	onore	*Honor*	rispetto	*respect*	dignità	*dignity*
abstract	quality	bellezza	*Beauty*	meraviglia	*wonder*	splendore	*splendor*
abstract	quality	virtù	*Virtue*	bontà	*kindness*	bene	*good*
abstract	quality	pietà	*Pity*	cristianesimo	*Christianity*	clemenza	*clemency*
abstract	cognition	fama	*Fame*	attore	*actor*	reputazione	*reputation*
abstract	cognition	delizia	*Delight*	squisitezza	*exquisiteness*	dolce	*sweet*
abstract	cognition	dio	*God*	trinità	*trinity*	monoteismo	*monotheism*
abstract	cognition	leggenda	*Legend*	storia	*history*	narrazione	*narrative*
abstract	cognition	idea	*Idea*	nozione	*notion*	invenzione	*invention*
abstract	cognition	incubo	*Nightmare*	sogno	*dream*	spavento	*fear*
abstract	cognition	inferno	*Hell*	aldilà	*afterlife*	demone	*demon*
abstract	cognition	mente	*Mind*	cervello	*brain*	razionalità	*rationality*
abstract	cognition	fastidio	*Annoyance*	seccatura	*nuisance*	scocciatura	*annoyance*
abstract	cognition	fragranza	*Fragrance*	aroma	*aroma*	essenza	*essence*
abstract	feeling	estasi	*Ecstasy*	misticismo	*mysticism*	buddismo	*Buddhism*
abstract	feeling	disprezzo	*Contempt*	disdegno	*contempt*	superbia	*pride*
abstract	feeling	panico	Panic	paura	fear	terrore	*terror*
abstract	feeling	ottimism o	Optimism	speranza	hope	futuro	*future*
abstract	feeling	orgoglio	Pride	fierezza	pride	vanità	*vanity*
abstract	feeling	odio	Hatred	antipatia	antipathy	inimicizia	*enmity*
abstract	feeling	collera	Anger	violenza	violence	rabbia	*anger*
abstract	feeling	ira	Rage	furia	fury	impeto	*impetus*
abstract	feeling	astio	Resentment	avversione	aversion	ostilità	*hostility*
abstract	feeling	agonia	Agony	angoscia	anguish	dolore	*pain*

Table 1. Stimuli. Complete list of stimuli presented in this study. Associate 1 and associate 2 are the pair of words associated to the Ita_Word in the correct catch trials (see section "Semantic relatedness task").

Variable	**Statistic**	**P-Value**
Let_ITA	3.656	0.818
Ln_Colfis	12.663	0.081
Ln_FreqRep	12.965	0.073
N_OrtNeig	4.4296	0.729
MeanFreq_Neig	8.671	0.277

Table 2. Psycholinguistic variables balance across categories. Results of Kruskal-Wallis test across the 8 categories on psycholinguistic variables. Let_ITA: Number of letters, Ln_Colfis: The natural logarithm of Colfis frequency, Ln_FreqRep: The natural logarithm of Repubblica frequency, N_OrtNeig: Number of ortographic neighbours, MeanFreq_Neig: The mean frequency of ortographic neighbours

4.2.3 Experiential features: Concrete vs Abstract words

We verified the profile of concrete vs abstract words, namely, whether and how concrete and abstract words differed on a series of experiential, embodied variables.

Mann-Whitney tests showed that concrete and abstract words differed significantly on the affective variables centred valence ($u = 393$, $p = 0.0001$), arousal ($u = 446.5$, $p = 0.0007$), but they did not differ on dominance ratings ($u = 769$, $p = 0.769$). Abstract words were more intensely valenced (concrete: mean = 1.417, std = 0.913, abstract: mean = 2.215, 0.760) and more arousing (concrete: mean = 5.436, std = 0.818, abstract: mean = 6.042, std = 0.686) than concrete words.

Concrete and abstract words also differed significantly on the sensory variables, namely vision ($u = 1479$, $p < 0.0001$), audition ($u = 1028$, $p = 0.0286$), touch ($u = 1359.5$, $p < 0.0001$), smell ($u = 1036$, $p = 0.0226$), taste ($u = 578$, $p = 0.0265$), and interoception ($u = 69.5$, $p < 0.0001$). Results largely reflect what found by Banks and Connell in their study of the distribution of ratings on the same dimensions in English (Banks & Connell, 2023). Namely, concrete words, compared to abstract ones, were rated as more strongly experienced through vision (concrete: mean = 4.178, std = 0.527, abstract: mean = 2.117, std = 1.100), touch (concrete: mean = 2.418, std = 1.177, abstract: mean = 0.945, std = 0.888), smell (concrete: mean = 1.068, std = 1.057, abstract: mean = 0.626, std = 0.984) and audition (concrete: mean = 2.213, std = 1.341, abstract: mean = 1.577, std = 0.861). Abstract words, on the other hand, were more strongly grounded in interoception (concrete: mean = 1.279, std = 0.834, abstract: mean = 3.445, std = 0.860), and taste (concrete: mean = 0.260, std = 0.641, abstract: mean = 0.476, std = 0.823).

Concrete and abstract words also differed significantly in their association to body parts: head ($u = 360$, $p < 0.0001$), hand/arm ($u = 1293.5$, $p < 0.0001$), mouth/throat ($u = 448.5$, $p = 0.0007$). They did not differ in association with foot/leg ($u= 990.5$, $p = 0.0673$) and torso ($u = 867.5$, $p = 0.5189$). Concrete words, compared to abstract ones, were more strongly associated to hand/arm (concrete: mean = 2.134, std = 1.144, abstract: mean = 0.964, std = 0.773), whereas abstract concepts were more associated to head (concrete: mean = 2.123, std = 0.871, abstract:

mean = 2.940, std = 0.700) and mouth/throat (concrete: mean = 0.841, std = 0.791, abstract: 1.417, std = 0.783).

Median and distribution of ratings are shown in Figure 1.

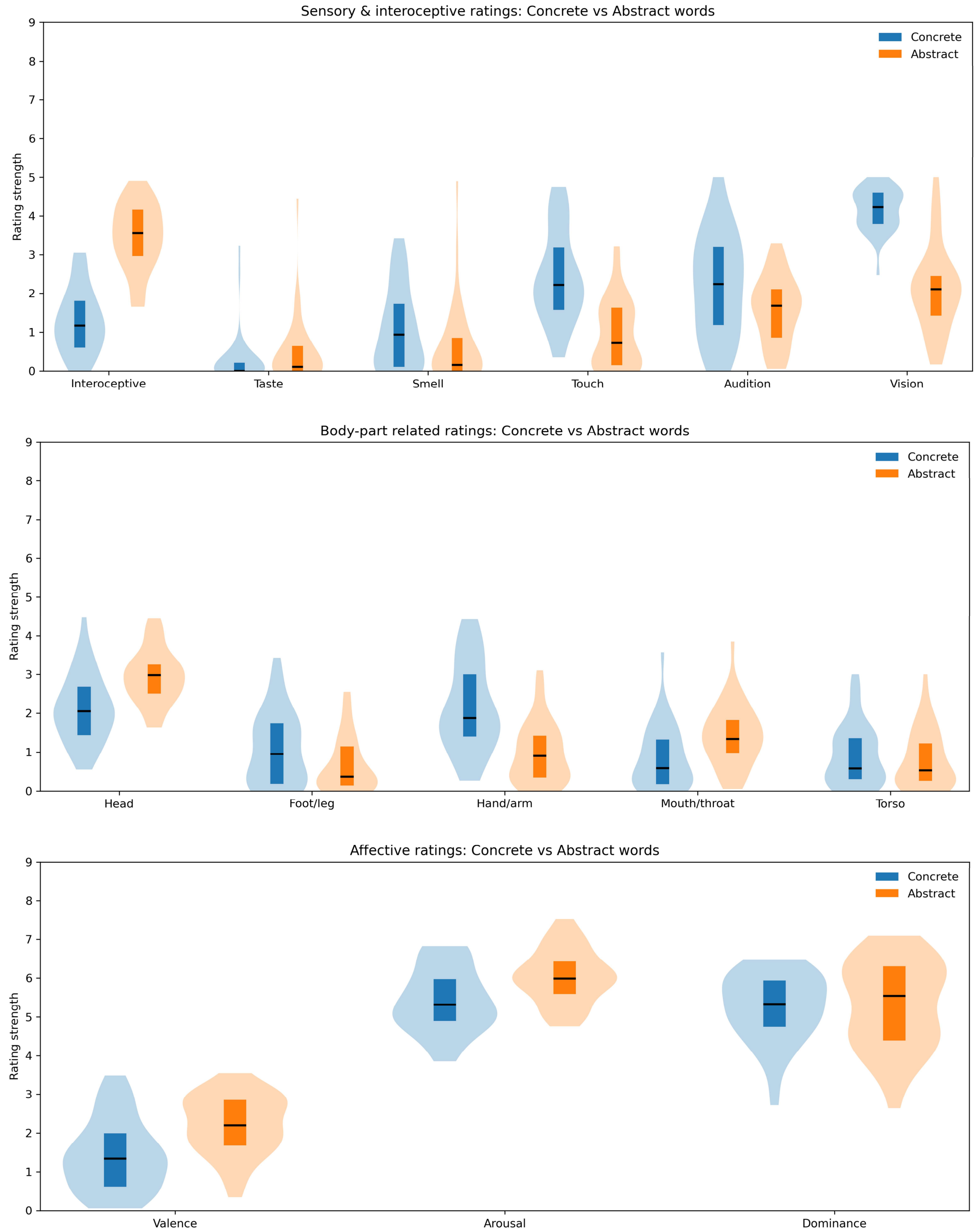


Figure 1. Distribution of ratings on experiential variables included in the experiential models, divided per concrete and abstract concepts.

Collectively, these ratings confirm previous findings on larger samples of concrete and abstract words. Abstract words were more affective (higher valence and arousal) (Kousta et al., 2011), more grounded in interoception (Connell et al., 2018; Repetto et al., 2023), and more related to the mouth effector and head, compared to concrete concepts. Conversely, concrete concepts were more grounded in vision, smell, taste, audition and touch, more related to hand/arm effector, and less affective than their abstract counterparts (Banks & Connell, 2023; Lynott et al., 2020).

4.2.4 Models

Dissimilarities across concrete and abstract, and within concrete and abstract domains, were computed in the respective Representational Dissimilarity Matrices (RDMs), where each column/row corresponds to a word, and each off-diagonal cell contains the distance between the corresponding pair of words.

4.2.4.1 Categorical model

The categorical distinction described above served as the basis of our first, categorical taxonomic model: in this model, words assigned to the same category are assigned a dissimilarity of 0, and words belonging to different categories a dissimilarity of 1.
From a theoretical point of view, the similarities in this model reflect the hierarchical organisation of concepts and the broader categorical distinctions among them.

Besides this categorical model, similarities between these words are obtained using three other types of models: two distributional models, two experiential models, and a concreteness model.

4.2.4.2 Distributional models

We used two linguistic, distributional models.
Word2Vec. The first is the Word-Embeddings Italian Semantic Space (Marelli, 2017), a Word2Vec model trained on Itwac, an Italian text corpus. This Word2Vec model uses a continuous bag-of-words (CBOW) method to obtain word vector representations by training a 3-layer neural network to predict a target word on the basis of the co-occurrence with its surrounding words within a 5-word window. Similarities in this model are based purely on linguistic information, specifically, local context linguistic information.
Glove. The second is a Glove, or Global vectors model (Pennington et al., 2014) trained on three Italian text corpora (Rollo et al., 2023, 2024). This model calculates word vectors by minimising the distance of pairs of words' vectors based on the counts of word-word co-occurrence in the same context across the whole corpus, capturing global statistical information

of words' co-occurrence. Similarities in this model are also based purely on linguistic information, integrating both local context and global statistics information.
In both distributional models, 1- the cosine between pairs of word vectors was used as a measure of dissimilarity between words.

4.2.4.3 Experiential models: Sensorimotor and affective models

The experiential models are computed based on semantic ratings obtained from Repetto and colleagues' dataset (Repetto et al., 2023) on sensorial (vision, touch, audition, smell, taste and interoception), motor/bodily (head, foot/leg, hand/arm, mouth/throat, torso) and emotional (centred valence, arousal, dominance) dimensions. We followed the same approach as Vinaya and colleagues (Vinaya et al., 2025) and calculated 1-cosine between word vectors created by concatenating the 11 sensorimotor variables for the sensorimotor model, and the three affective variables for the affective model, as a measure of dissimilarity.
In the sensorimotor model, we calculated the distances based on the sensorimotor dimensions; in the emotional model, distances are calculated using emotional dimensions. For the emotional model, valence was centred, taking the absolute value of the raw valence rating and subtracting 5 (i.e., the centre of the 1-9 Likert scale). While the raw valence represented the mean rating of the word on an unpleasant (1) to pleasant (9) scale, the centred valence represents the intensity of the valence of the word, i.e., how far from neutrality the word is, or how strongly valenced the word is, regardless of the polarity of its valence.
From a theoretical point of view, similarities in this model are grounded in experiential information, i.e., the way we experience these concepts through senses and emotions.

4.2.4.4 Concreteness model

The concreteness model is computed based on the concreteness ratings obtained from Repetto's dataset. Dissimilarities are calculated with Euclidean distances. In this model, dissimilarities represent how similar words are based on their level of concreteness.

All these models are calculated both for all words together, generating 80*80 RDMs, and separately for abstract and concrete concepts, generating respective 40*40 RDMs. The RDMs of all words are illustrated in Figure 2, and correlations between models are presented in Figure 3. These RDMs are then correlated to the spatio-temporal brain RDMs calculated based on the

MEG data, to obtain a map of where and when each model reflects brain patterns elicited by all words together, and concrete and abstract words separately.

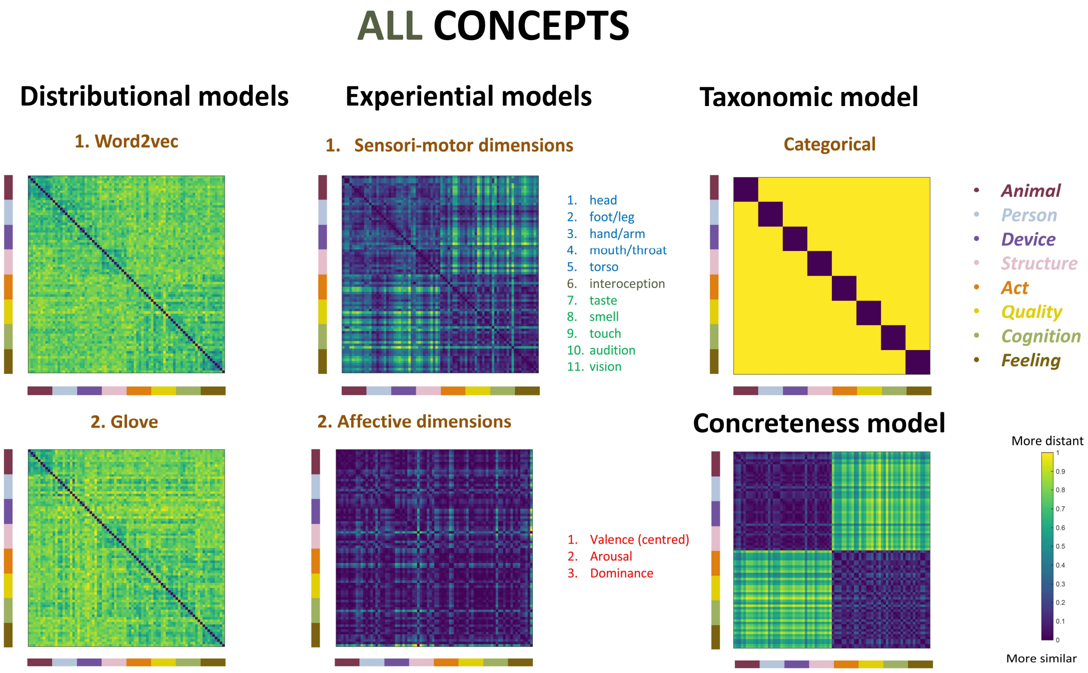


Figure 2. 80*80 Model RDMs included in the RSA analysis. In each RDM, the left top quadrant corresponds to 40*40 dissimilarities between concrete nouns, the right-bottom quadrant corresponds to the 40*40 dissimilarities between abstract nouns.

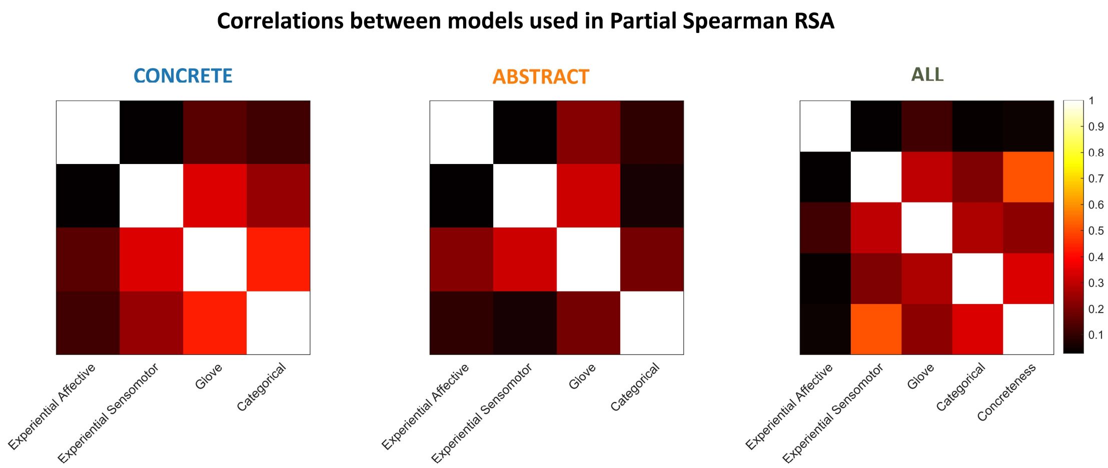


Figure 3. Correlations between model RDMs of concrete, abstract and all words. Only correlations between models used in the Partial correlation analyses are shown.

4.2.5 Semantic relatedness task

To ensure subjects' compliance, we used the 1 – back semantic relatedness trials (Borghesani et al., 2016, 2019). In 15% of trials, words were followed by catch trials, where 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. The catch words were presented for 2 seconds, followed by a 1.3-second fixation cross. In half of the catch trials, the pair of words was associated, and in the other half, they were not associated. The association of the pair of words was randomised in each run. The lateralisation of responses was counterbalanced: half of the participants pressed the right-hand button for associated words in the first 4 runs and the left-hand button for the latter 4 runs, whereas the other half of participants pressed the left-hand button for the associated words in the first 4 runs and the right-hand button for the latter 4 runs. All catch words are listed in Table 1. The presentation of stimuli and the task are illustrated in Figure 4.

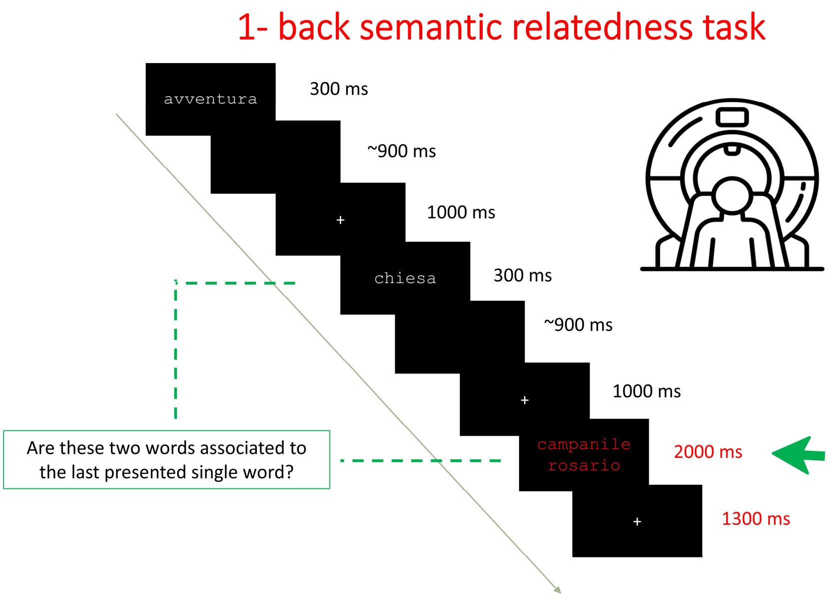


Figure 4. *1 – back semantic relatedness task.* During MEG recording, participants are presented with single words. In 15% of the trials, a pair of red catch words is presented, and participants must press a right- or left-hand button, as fast and accurately as possible, to indicate whether the pair of red nouns is semantically related to the last presented noun.

4.2.6 MEG data acquisition

Continuous MEG data was acquired for the first six participants with the Elekta Neuromag 306-channel (204 planar gradiometers, 102 magnetometers) MEG system, at CIMeC, University of Trento. From the 7th participant, we resumed collecting data with a MEGIN Triux Neo MEG system (306-channel, 204 planar gradiometers, 102 magnetometers), placed in the same two-layer Vacuum Schmelze AK-3B magnetically shielded room. Before the experiment, participants' head shape was recorded using a 3D Polhemus digitiser, including the fiducial points (nasion, left and right periauricular sites), the position of five coils (three on the forehead, two on the right and left mastoid), and extra digitisation points to map the shape of the head. The head position was acquired at the beginning of each run to control for head movements. MEG data was acquired with a sampling rate of 1000 Hz. We recorded eye movements using two pairs of electrodes for electrooculograms. Before each recording session, an empty room recording was acquired. The experiment was created using the Psychophysics Toolbox (Psychtoolbox-3) in MATLAB (Kleiner et al., 2007). It included one practice run before starting the experiment and 8 experimental runs. Each run contained two blocks separated by a short break; each block contained all experimental stimuli in randomised order. Thus, in each run, all stimuli were presented twice, for a total of 16 repetitions of all stimuli across the 8 runs. During each run, words were presented one by one in a white Courier font on a black screen for 300 ms, followed by a blank screen lasting for a jittering inter-trial interval of an average of 900 ms, and a fixation cross of 1000 ms. Participants were instructed to read the words and think about their meaning. To ensure subjects' compliance, 15% of trials were followed by catch trials, where 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. At the end of each run, participants' accuracy (in percentage) was checked to ensure participants' compliance with the experiment.

4.3 Analyses

4.3.1 Behavioural data: RTs and accuracy

We used Generalised Linear Mixed Models (GLMMs) to predict log-transformed RTs and accuracy in the catch trials. Analyses were conducted using R-Studio (version 4.3.1)

Log RTs of correct responses were analysed with linear mixed models (LMMs), computed using the "lme4" package (Bates, Mächler, et al., 2015) for modelling and the "lmerTest" package for p-values (Kuznetsova et al., 2017). Model assumptions were visually inspected with the 'plot model' function from the "sjPlot" package (M. D. Lüdecke, 2023) and did not reveal any large deviation from normality or homoscedasticity.

Accuracy was analysed with GLMMs, with family binomial and link function logit, using the "lme4" package (Bates, Mächler, et al., 2015) for modelling and "lmer-test" package (Kuznetsova et al., 2017) for p-values. Model assumptions were tested with the "DHARMa" package (Hartig & Hartig, 2017) and did not reveal any significant problems.

Estimated marginal means (EMMs) were calculated with the "emmeans" package (Lenth & Lenth, 2018) and the "ggeffects" package (D. Lüdecke, 2018).

For both RTs and accuracy, we fitted three nested models. The first, base model formula was the following:

log(RTs) ~back word concreteness + back word frequency + back word length + associated + (1|ID subject)

where back word refers to the word on which participants have to make the semantic relatedness judgement, concreteness is the mean concreteness rating of that word in the Repetto and colleagues' dataset (Repetto et al., 2023), and associated is a binary variable encoding whether or not the two catch words presented after the back word were semantically associated with the back word.

In the second model, we added main effects of Glove-based distance between the back word and the first catch word, and the back word and the second catch word:

log(RTs) ~back word concreteness + back word frequency + back word length + associated + distance back word with first catch word + distance back word with second catch word + (1|ID subject)

In the third model, we also included the interactions between the two Glove-distances and the value of associated:

log(RTs) ~back word concreteness + back word frequency + back word length + associated + distance back word with first catch word * associated + distance back word with second catch word * associated + (1|ID subject)

We compared the fit of these three models for both RTs and accuracy using the function ‘anova’, and proceeded with the analysis with the best-fitting model.

4.3.2 MEG analysis

4.3.2.1 Preprocessing

The MEG raw data was analysed to identify noisy channels and the reference run that minimised distance in the head position. After that, realignment and bad channels interpolation were conducted via the temporal signal space separation (tsss) implemented in the Maxfilter software. Additional preprocessing was conducted with Fieldtrip in Matlab (Oostenveld et al., 2011). A notch filter was applied at 50 Hz to remove electrical noise. Data were segmented into 1.2-second epochs around word triggers (-0.2, + 1 s), resulting in 160 trials for each run. Artefact removal was conducted with a semi-automated approach, following the FLUX pipeline (Ferrante et al., 2022). ICA was run with the method ‘runica’ to remove eye-blink and heartbeat-related components. On average, 7.06% (SD: 3.81) of trials and 3.96 (SD: 1.5) components were deleted for each participant.
After that, a low-pass filter of 40 Hz and a high-pass filter of 1 Hz were applied to the data, and trials were baseline-corrected. For RSA (see RSA section), they were furthermore downsampled to 200 Hz (Grootswagers et al., 2017).

4.3.2.2 Contrast between abstract and concrete words

The univariate contrast between abstract and concrete concepts was performed using non-parametric cluster-based permutation test as implemented in Fieldtrip (ft_timelockstatistics). The analysis was performed on the whole trial (from word onset to + 1 sec), using planar gradiometers data. The test was two-tailed, and statistical significance was assessed using the Monte Carlo method, with 10000 random permutations to approximate the null distribution. To correct for multiple comparisons, a cluster-based correction was applied. Clusters were initially thresholded at $\alpha = 0.05$. A minimum of two neighbouring channels were required for a sample to be included in the cluster. Cluster-level statistics was computed using the maximum cluster sum.

4.3.2.3 Sensor-level space-time searchlight RSA

Trials from the same items were averaged across runs, resulting in 80 pseudo-trials. After that, spatio-temporal RSA (Kriegeskorte et al., 2008; Su et al., 2012) was performed between the semantic models and the MEG pseudo-trials, for all words, and for concrete and abstract words separately. RSA analysis was performed using CoSMoMVPA in Matlab (Oosterhof et al., 2016). Models RDM was compared to neural MEG RDM specific for every subject, time bin and spatial neighbours. The signal from the two preceding and two succeeding time points was concatenated in the same time neighbour (resulting in a 25 ms time sliding window), and the signal from 10 neighbouring channels was concatenated for the spatial neighbours. These neighbours were crossed to calculate the dissimilarities between pair of words according to the MEG signal in every spatio-temporal searchlight. The RSA was computed using Spearman's simple and partial correlation to compare MEG-RDMs and each semantic model's RDM and assess both shared and unique variance explained by each model. The statistical significance of these maps was assessed using a cluster-based permutation test (Maris & Oostenveld, 2007). Only observed clusters with a t-value higher than 95% of random clusters' t-values were deemed significant. The main steps of RSA analysis are shown in Figure 5.

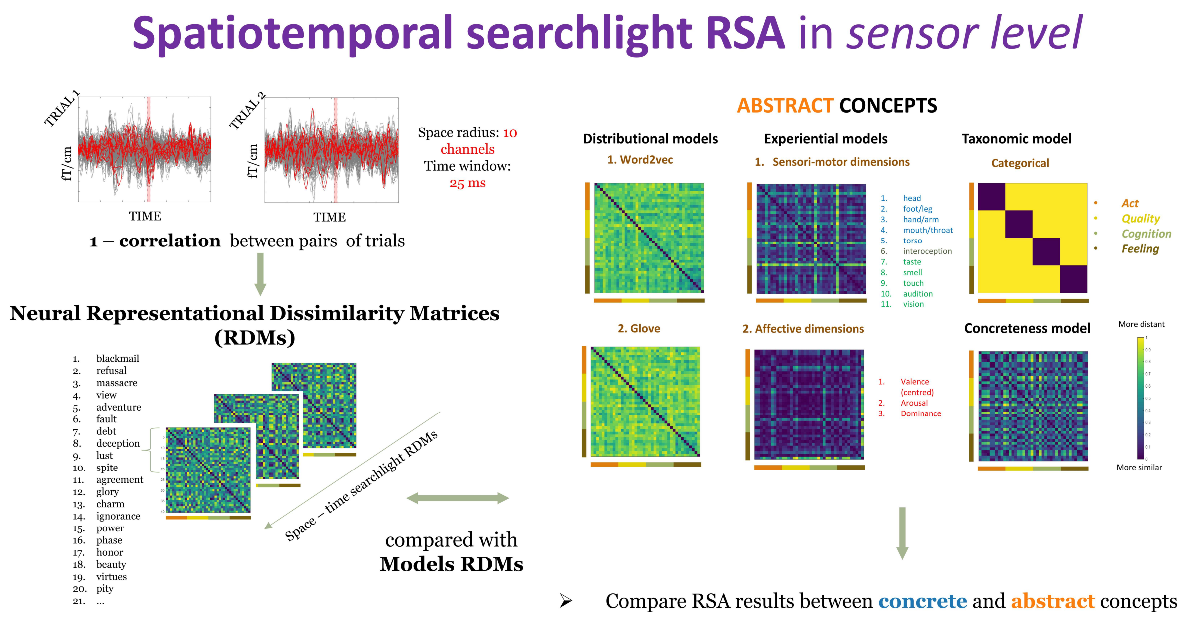


Figure 5. Spatio-temporal RSA in sensor level.

4.4 Results

All Supplementary materials are provided in Appendix 3.

4.4.1 Behavioural data: RTs and accuracy

The comparison between the three nested models revealed that, for both RTs and accuracy, adding the Glove distances between the back word and the first and the second catch words significantly improved model fit with respect to the base model (RTs: $X^2(2) = 6.82$, $p = 0.033$, Accuracy: $X^2(2) = 29.83$, $p < 0.001$). The model, which included the interactions between Glove distances between the back word and the first and the second catch words, further improved model fit with respect to the second model (RTs: $X^2(2) = 30.385$, $p < 0.001$, Accuracy: $X^2(2) = 83.494$, $p < 0.001$), and was therefore selected.

Reaction times. We observed significant effects of back word continuous concreteness ($F = 93.423$, $p < 0.001$), associated ($F = 102.965$, $p < 0.001$), the interaction between associated and the Glove-based distance between the back word and the first catch word ($F = 10.279$, $p = 0.001$), and the interaction between associated and the Glove-based distance between the back word and the second catch word ($F = 9.916$, $p = 0.002$).

Concreteness exerted a facilitatory effect: the higher the back word concreteness, the faster participants responded in the catch trials. Participants were also faster in making the semantic judgments when the catch words were associated with the back word (estimated marginal means, or EMM: 1.065 seconds, standard error or SE: 0.022 seconds) compared to when the catch words were not associated with the back word (EMM: 1.199, SE: 0.026). As for the interactions, a higher distance between the back word and first catch word and between the back word and the second catch word both slowed RTs when the catch words were associated with the back word, and sped them when the catch word where not associated. Results are illustrated in Figure 6 A-D.

Accuracy. We observed significant effects of back word continuous concreteness ($X^2 = 15.799$, $p < 0.001$), associated ($X^2 = 70.170$, $p < 0.001$), Glove-based distance between the back word and the first associate ($X^2 = 14.169$, $p < 0.001$), Glove-based distance between the back word and the second associate ($X^2 = 4.614$, $p = 0.032$), the interaction between associated and the Glove-based distance between the back word and the first catch word ($X^2 = 33.219$, $p < 0.001$), and the interaction between associated and the Glove-based distance between the back word and the second catch word ($X^2 = 16.941$, $p < 0.001$).

The effect of concreteness was again facilitatory: the higher the back word concreteness, the higher the accuracy in the responses. Participants were more accurate when the catch words were associated with the back word (associated EMM probability of responding correctly: 0.898, SE = 0.013, not associated EMM: 0.758, SE = 0.026). On average, participants were more accurate when the first and the second catch words were more Glove-distant from the back word. However, the interactions with associate revealed that this effect was strongly present when the catch words were not associated with the back word, but that when they were associated, the effect went in the opposite direction, so that higher distance between back word and first and second catch words decreased the probability of responding correctly to trials where the catch words were associated to the back word. Results are illustrated in Figure 6 E-H.

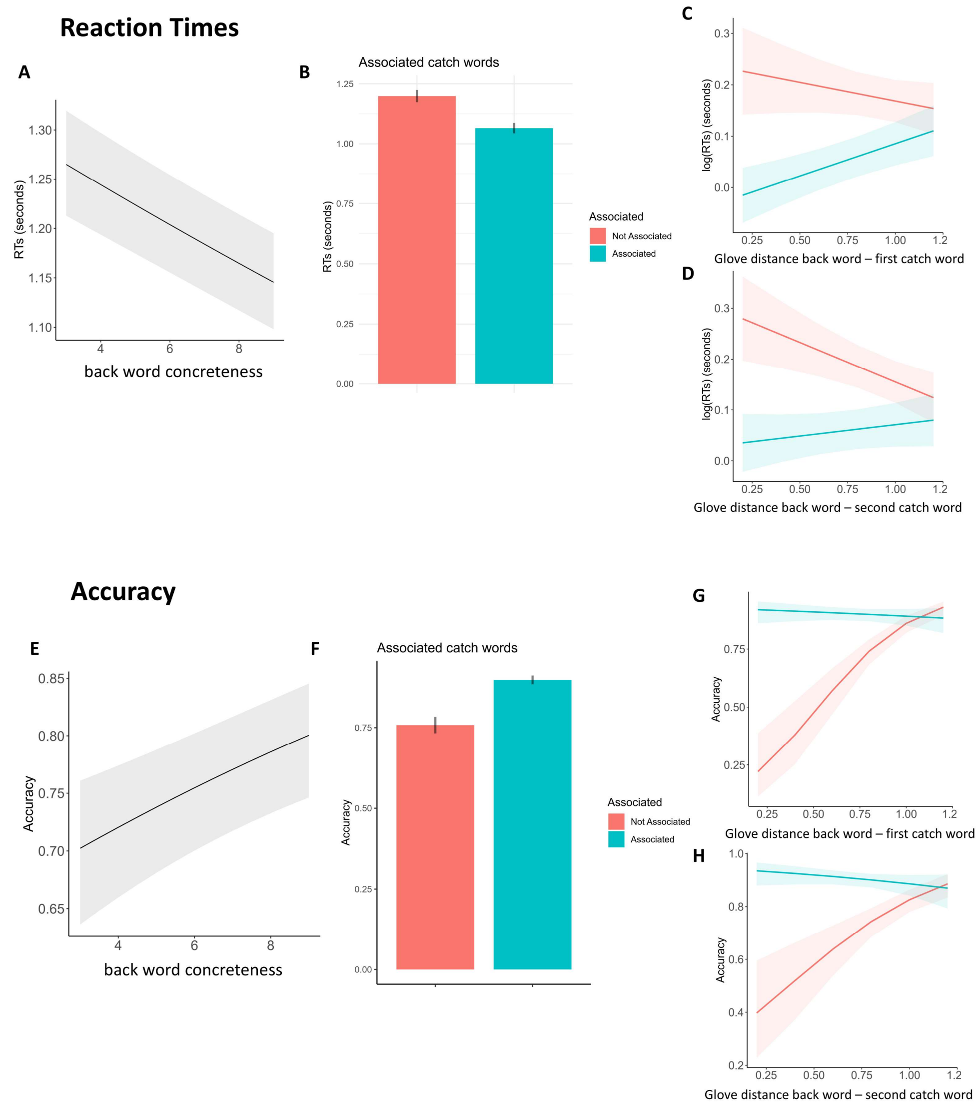


Figure 6. *Behavioural RTs and accuracy results in the 1 – back semantic relatedness task.* A & E: estimated marginal effect of word concreteness on [A] RTs and [E] accuracy. B & F: estimated marginal means of [B] RTs and [F] accuracy in trials where the catch words were associated or not associated to the back words. C & G: estimated marginal effect of the interaction between associated and Glove distance between back word and first catch word on [C] RTs and [G] accuracy. D & H: estimated marginal effect of the interaction between associated and Glove distance between back word and second catch word on [D] RTs and [H] accuracy. B & F: Error bars represent standard errors of the marginal means (SEM). A, C, D, E, G, H: Error bars represent 95% confidence intervals (CI) of the adjusted predictions.

4.4.2 MEG data:

4.4.2.1 Contrast between abstract and concrete words

The contrast abstract-concrete reveals significantly higher activity for abstract compared to concrete concepts at 264-363 ms ($p = 0.0002$) and at 373-460 ms ($p = 0.0006$). The first cluster originates from left-posterior sensors and spreads towards more central-anterior sensors, whereas the second one originates from left-anterior and right-posterior sensors and spreads posteriorly, encompassing the bilateral, posterior half of the sensors.

The opposite contrast, concrete-abstract, reveals higher activity for concrete concepts at 289-342 ms ($p = 0.0287$) and at 602-645 ms ($p = 0.0238$). The first cluster involves left anterior sensors, while the second one engages posterior bilateral sensors.

Results are illustrated in Figure 7.

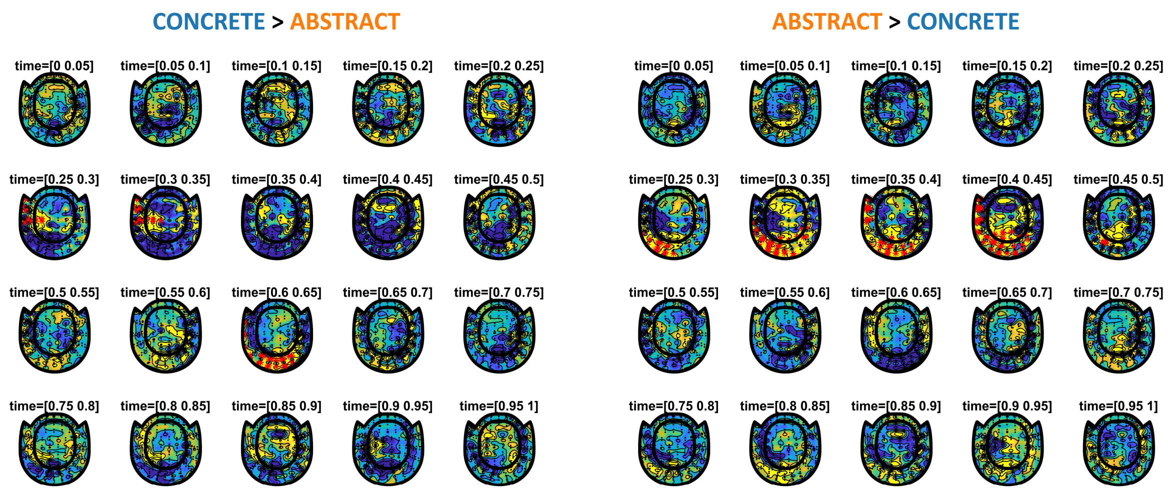


Figure 7. *Contrasts between abstract and concrete concepts activations*. Time-resolved sensor-level topographies of ERPs contrast of concrete words vs abstract words (left panel) and of abstract words vs concrete words (right panel) averaged for each 50-ms time interval. Sensors highlighted with red asterisks indicate significant clusters of activity (cluster-based permutation test, $p<0.05$) at any time point in each corresponding time interval.

MEG data: Sensor-level space-time searchlight RSA

We will first present the results of the simple correlation between the models and the neural signals. Secondly, we present the results of partial correlation, i.e., the unique variance of neural signals explained by each model.

4.4.2.2 Simple correlation

4.4.2.2.1 Concreteness model

All words' neural activity positively correlated with the concreteness model at 230-605 ms. Correlations are first found at left-anterior sensor locations (230-250 ms), and spread to more left-posterior and central locations at 250-300, and to central and right locations at 300-400 ms. At 400-500 ms, significant clusters are found at left and right sensor locations, and retreat to more localised left and posterior sensors at 500-605 ms.

There are no significant correlations between the concreteness model and the neural signal of concrete and abstract words considered separately.

Significant clusters are shown in Figure S1 in Appendix 3.

4.4.2.2.2 Distributional models: *Word2Vec and Glove*

4.4.2.2.2.1 Word2Vec

With all words, RSA results showed significant positive correlations between the Word2Vec model and neural dynamics from 230 to 605 ms. The correlation starts in a left-lateralized cluster of sensors, and then spreads over central and right sensors and reaches its maximum spread over most sensors around 400 ms, and retreats again to more lateral regions around 500 ms.

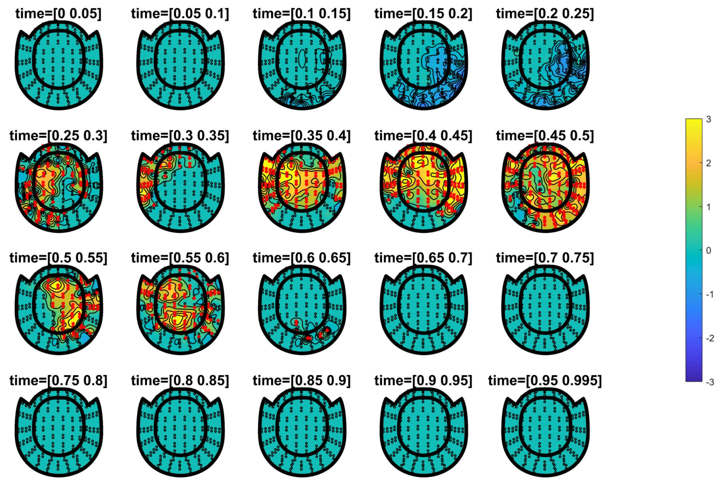
With concrete words, results show significant positive correlations with the neural activity from 250 to 610 ms. As with the correlations with all words, the correlation with concrete words starts in left-lateralized sensors and spreads bilaterally, reaching its maximum spread at 400-500 ms.

With abstract words, no significant correlations are observed with the Word2Vec model.

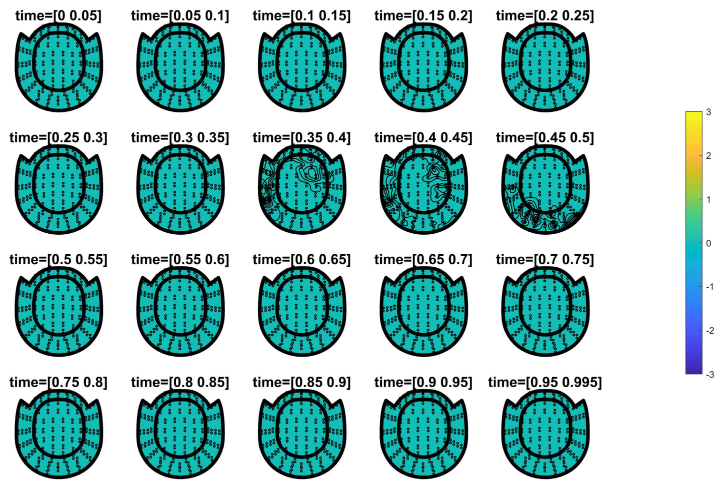
Topographies of z-values are shown in Figure 8.

Word2Vec

CONCRETE CONCEPTS



ABSTRACT CONCEPTS



ALL CONCEPTS

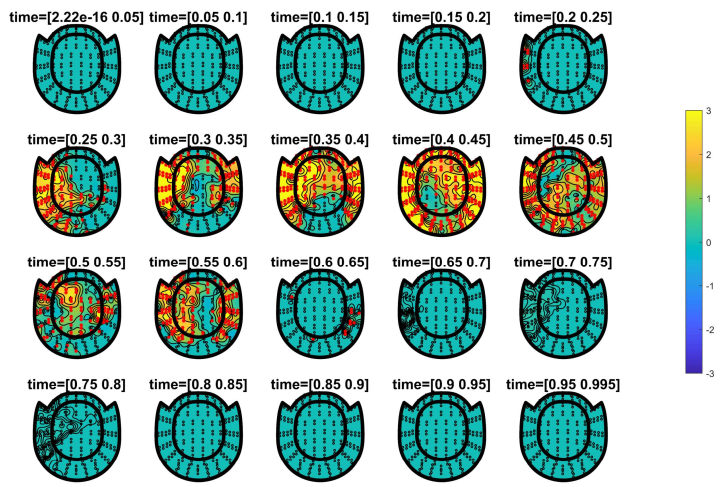


Figure 8. *Simple correlation RSA of the Word2Vec model with concrete, abstract and all words*. Time-resolved sensor-level topographies of cluster-based permutation test z-values, averaged within each time interval, of RSA results between Word2Vec model RDM and concrete (top), abstract (middle) and all (bottom) words MEG RDMs. Colours represent z-values. Sensors highlighted in red indicate channels belonging to a significant cluster ($z > 1.6449$) in any time point within the corresponding 50-ms time interval.

4.4.2.2.2 Glove

With all words, RSA results showed significant positive correlations with neural activity from 65 to 610 ms. The correlations start in central-posterior sensors at 65 ms, move to left-lateralized sensors around 150-200 ms, and spread to central and right sensor reaching the maximum peak at 350-500 ms. From 500 ms to 610 ms, correlations are mostly left-lateralized.

With concrete words, results show significant positive correlations with the neural activity from 170 to 575 ms. Similarly to correlations with all words, the correlation starts in left lateralized sensors and spreads toward more central locations from 170 to 300 ms. From 350 to 450 ms, there is the maximum spread which encompasses left, central and right sensors. From 500 ms, correlations are mostly localised in left sensors.

With abstract words, there are significant positive correlations with neural activity from 75 to 565 ms. Correlations start at 75 ms in posterior sensors and spread with a left-lateralisation toward lateral and anterior sensors from 100 to 200 ms. From 300 to 450 ms, the correlation engages more sensors, mostly left-lateralized but also in central and right locations. From 450 to 565, correlations are only left-lateralized.

Significant clusters are shown in Figure S2 in Appendix 3.

4.4.2.2.3 Experiential models: Sensorimotor and affective

4.4.2.2.3.1 Sensorimotor model

Neural activity from all words correlates positively with the sensorimotor model from 75 to 730 ms. These correlations start in posterior sensors and spread anteriorly (100-150 ms) and laterally toward the left (150-250 ms). Correlations reach maximum spread from 300 to 450 ms, involving left, central and right sensors. At 450-600 ms, they mostly involve left-lateralized sensors, at 600-730, mostly posterior sensors.

No correlations are observed between the concrete words' neural activity and the sensorimotor model.

Abstract words' neural activity positively correlated with the sensorimotor model at 45-580 ms. Positive clusters are mostly localised in posterior bilateral sensors across the whole-time window, and spread toward more middle, anterior sensors at 400-450 ms and at 500-500 ms.

Significant clusters are shown in Figure S3 in Appendix 3.

4.4.2.2.3.2 Affective model

There are no correlations with the affective model. Topographies of z-values are shown in Figure S4 in Appendix 3.

4.4.2.2.4 Categorical model

All words neural activity correlated positively with the categorical model at 230-555 ms. Significant clusters were found at left-posterior sensor locations at 230-350 ms. At 350-500 ms, significant clusters are found in left, left-central and right locations. At 500-555 ms, significant clusters retreat to left sensor locations.

Concrete words neural activity correlated positively with the categorical model at 270-535 ms. Significant sensors are found at left sensor locations (270-350 ms), and spread to central and right locations as well at 350-500 ms.

The neural activity of abstract words does not show any significant correlations with the categorical model.

Significant clusters are shown in Figure S5 in Appendix 3.

4.4.2.3 Partial correlation

To assess the unique contribution of each model in explaining neural activity variance, we repeated the same analysis using partial correlation. As a distributional mode, we selected only Glove and excluded the Word2Vec model, given the former's superior performance in simple correlation results. With all words, partial correlation analysis included the following models: concreteness, Glove, sensorimotor, affective and categorical. With concrete and abstract words, partial correlation analysis included Glove, sensorimotor, affective and categorical models.

4.4.2.3.1 Concreteness model

After partialling out other models, concreteness is negatively correlated with neural activity of all words at 0-175 ms and positively correlated at 210-470 ms. Negative clusters are localised in the posterior, right sensors and middle sensors. Positive clusters start in right-anterior sensors at 210, and move to left-middle sensors at 250-300 ms, spreading to central and right sensors at 300-350 ms and retreating to left sensors at 350-470 ms. Significant clusters are shown in Figure 9.

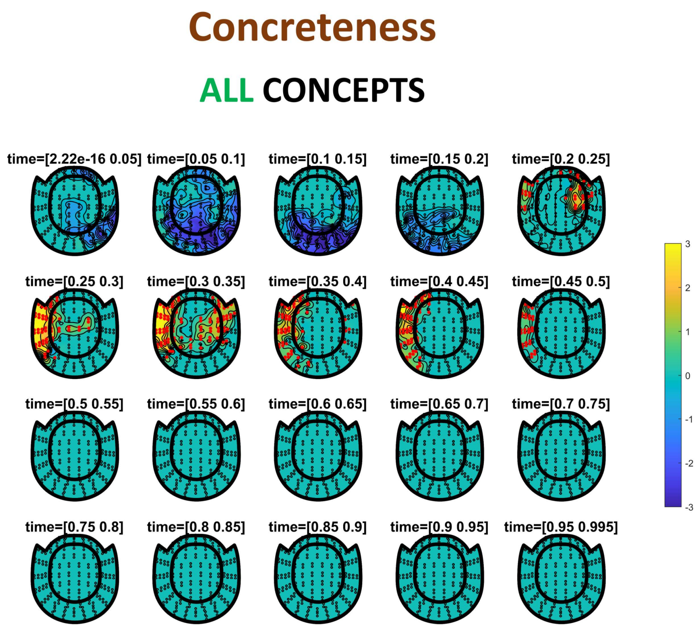


Figure 9. *Partial correlation RSA of the Concreteness model with all words*. Time-resolved sensor-level topographies of cluster-based permutation test z-values, averaged within each time interval, of RSA results between concreteness model RDM and all words MEG RDMs. Colours represent z-values. Sensors highlighted in red indicate channels belonging to a significant cluster (z > 1.6449) in any time point within the corresponding 50-ms time interval.

4.4.2.3.2 Distributional model: Glove

Partial correlation results show that Glove positively correlated with the neural activity of all words at 65-605 ms. Correlations start at posterior sensors at 65 ms, and spread to the left more anterior sensors at 150-250 ms, and to more central sensors at 250-300 ms. At 350-500, the correlations encompass most left and central sensors from the anterior to the posterior axis, and retreat to more left-lateralized locations from 500 to 600 ms.

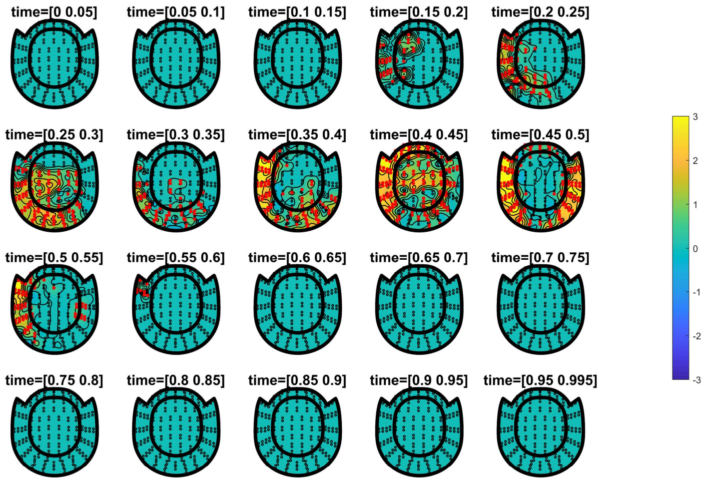
With concrete words, we observed positive partial correlations at 170-560 ms. These correlations start at the left sensors at 170 ms, and spread to more posterior sensors at 250 ms. At 350-450 ms, we observe correlations in left and central sensors mostly, while on 450-500 ms the correlations are left and right-lateralized. From 500 to 560 ms, correlations are only left lateralized.

With abstract words, positive correlations are observed at 250-575 ms. These correlations start in posterior-left sensors at 250-350 ms. At 350-450 ms, they encompass a larger portion of left-anterior sensors. At 450-575, correlations are mostly left lateralized.

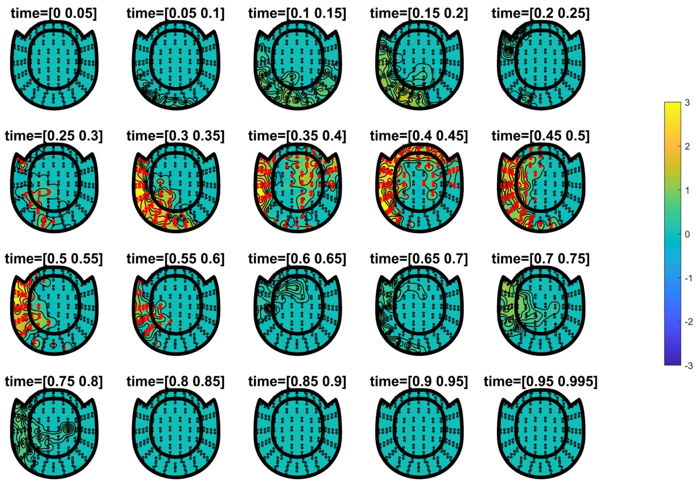
Significant clusters are shown in Figure 10.

Glove

CONCRETE CONCEPTS



ABSTRACT CONCEPTS



ALL CONCEPTS

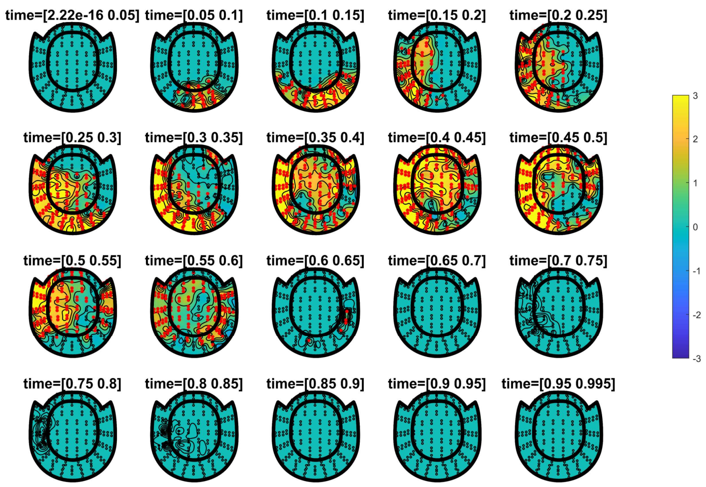


Figure 10. *Partial correlation RSA of the Glove model with concrete, abstract and all words*. Time-resolved sensor-level topographies of cluster-based permutation test z-values, averaged within each time interval, of RSA results between Glove model RDM and concrete (top), abstract (middle) and all (bottom) words MEG RDMs. Colours represent z-values. Sensors highlighted in red indicate channels belonging to a significant cluster ($z > 1.6449$) in any time point within the corresponding 50-ms time interval.

4.4.2.3.3 Experiential models: Sensorimotor and affective

4.4.2.3.3.1 Sensorimotor model

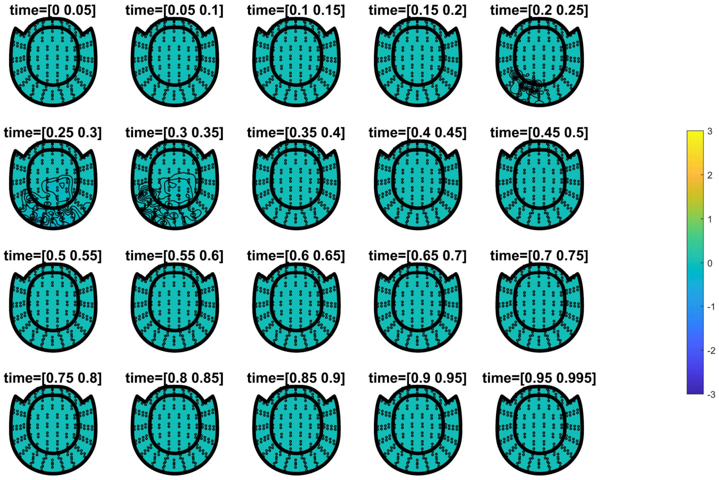
The sensorimotor model explains the unique variance of all words' neural activity at 60-460 ms, with positive correlations. These correlations start at posterior-central sensors at 60-200 ms, and reach their maximum spread at 300-450 ms, with correlations at left, central and right sensors.

No correlations are observed between concrete words and the sensorimotor model.

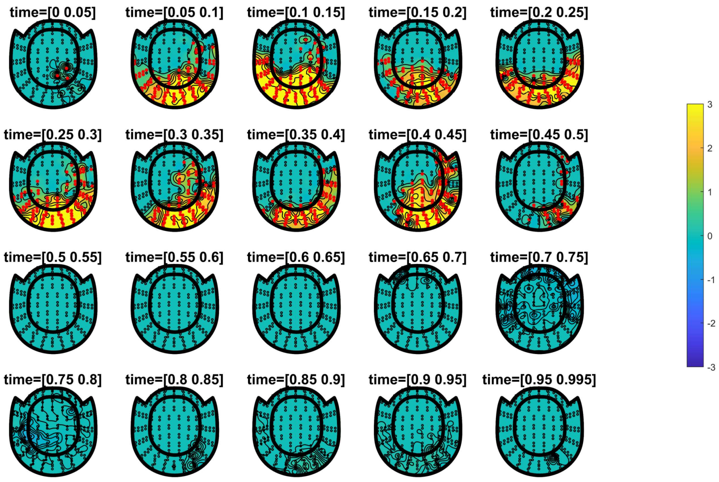
The sensorimotor model explains unique variance with abstract words at 40-480 ms. These correlations are mostly localised in posterior sensors throughout all significant time points, and reaches highest spread at 100-150 ms and at 400-450 ms. Significant clusters are shown in Figure 11.

Experiential Sensorimotor

CONCRETE CONCEPTS



ABSTRACT CONCEPTS



ALL CONCEPTS

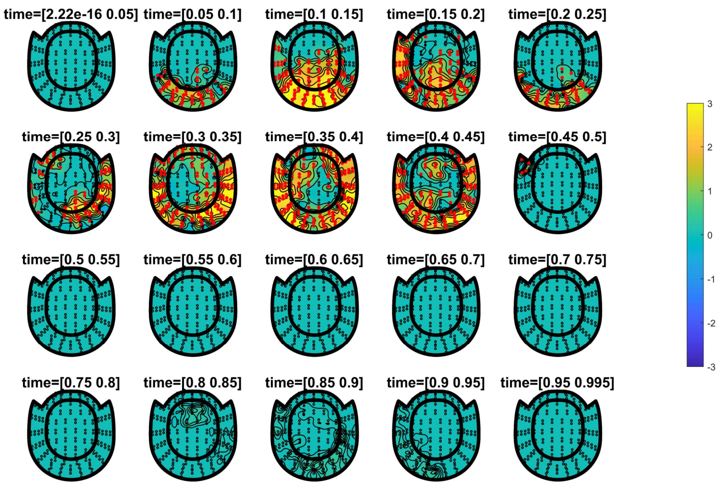


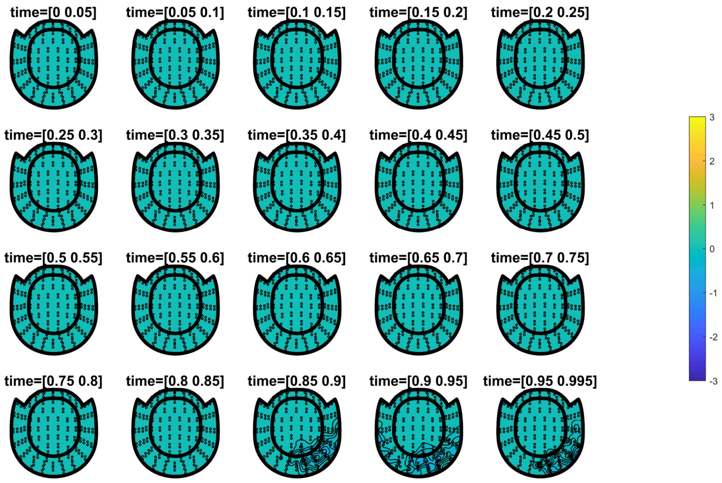
Figure 11. *Partial correlation RSA of the Experiential Sensorimotor model with concrete, abstract and all words*. Time-resolved sensor-level topographies of cluster-based permutation test z-values, averaged within each time interval, of RSA results between Experiential Sensorimotor model RDM and concrete (top), abstract (middle) and all (bottom) words MEG RDMs. Colours represent z-values. Sensors highlighted in red indicate channels belonging to a significant cluster ($z > 1.6449$) in any time point within the corresponding 50-ms time interval.

4.4.2.3.3.2 Affective model

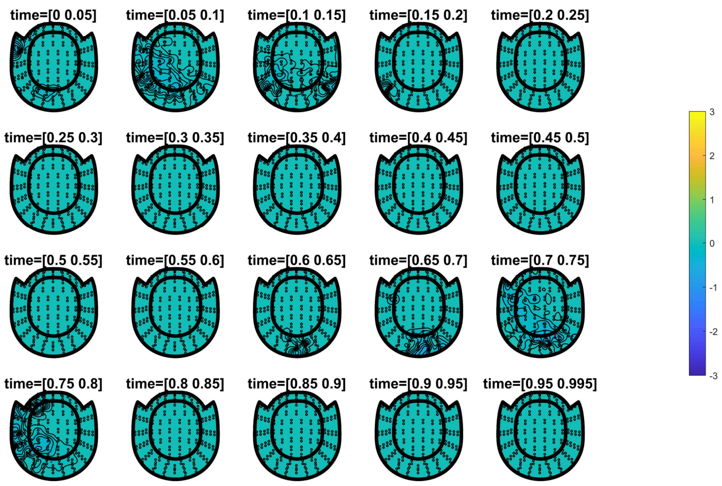
There are no significant correlations with the affective model. Topographies of z-values are shown in Figure 12.

Experiential Affective

CONCRETE CONCEPTS



ABSTRACT CONCEPTS



ALL CONCEPTS

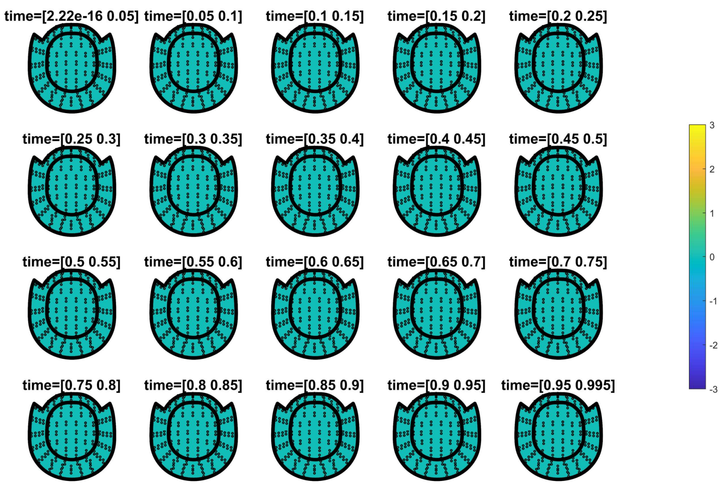


Figure 12. *Partial correlation RSA of the Experiential Affective model with concrete, abstract and all words*. Time-resolved sensor-level topographies of cluster-based permutation test z-values, averaged within each time interval, of RSA results between Experiential Affective model RDM and concrete (top), abstract (middle) and all (bottom) words MEG RDMs. Colours represent z-values.

4.4.2.3.4 Categorical model

The categorical model explained unique variance of neural activity associated with all words at 365-515 ms, with positive correlations. The significant clusters were localised at right-middle right-anterior sensors at 365-450 ms, and enlarged to include also more anterior and posterior sensors at 450-515 ms.

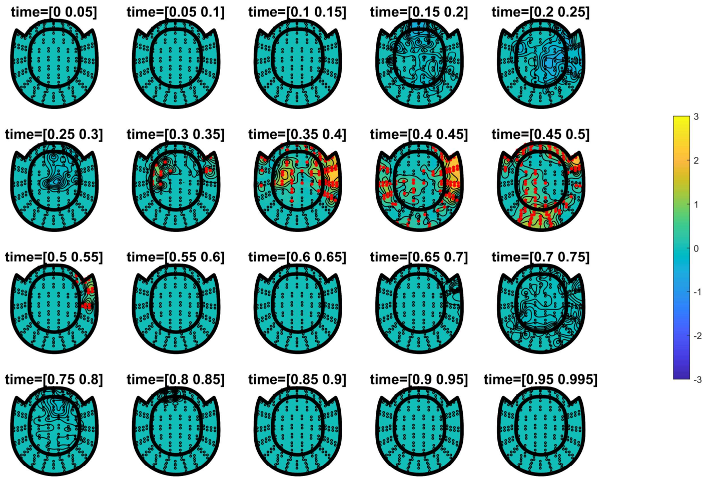
There were positive partial correlations with activity from concrete concepts, too, at 325-535 ms. The clusters were mostly right-lateralized (350-450 ms), but also more central (325-400 ms) and posterior sensors (450-500 ms) showed significant correlations.

No correlations were observed between the categorical model and the abstract words.

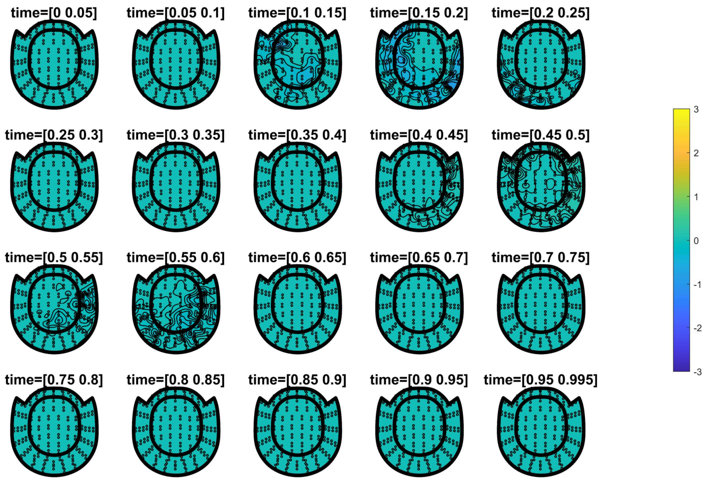
Significant clusters are shown in Figure 13.

Categorical

CONCRETE CONCEPTS



ABSTRACT CONCEPTS



ALL CONCEPTS

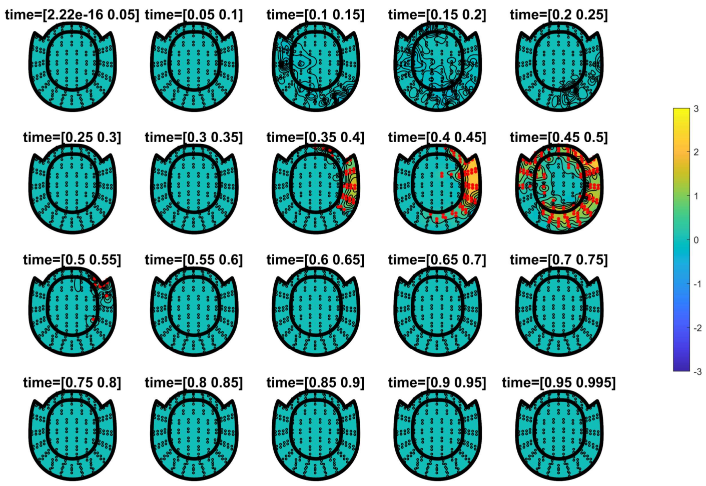


Figure 13. *Partial correlation RSA of the Categorical model with concrete, abstract and all words.* Time-resolved sensor-level topographies of cluster-based permutation test z-values, averaged within each time interval, of RSA results between Categorical model RDM and concrete (top), abstract (middle) and all (bottom) words MEG RDMs. Colours represent z-values. Sensors highlighted in red indicate channels belonging to a significant cluster ($z > 1.6449$) in any time point within the corresponding 50-ms time interval.

4.5 Discussion

In this study, we presented single concrete and abstract written words and compared their signals with theoretical models that encoded their similarities based on linguistic/distributional (Word2Vec, Glove), experiential sensorimotor, experiential affective, categorical taxonomic information and concreteness ratings.

The distributional model Word2Vec correlated with signals elicited by all and concrete words, but not when only abstract words were considered. Glove, on the other hand, correlated and explained unique variance in neural activity in all three analyses, i.e., with all words, and with concrete and abstract words considered separately.

The experiential sensorimotor model correlated and explained unique variance of neural signals elicited by all words and abstract words, but not concrete words. The affective model, instead, did not correlate with neural signals of any type of word.

The categorical model correlated and explained unique variance of neural signals elicited by all words and concrete words, but not abstract words.

First, I will illustrate the results on the behavioural task. Secondly, I discuss the correlations of each type of model, and in a third section, the relationships and relative timing between each model.

4.5.1 Behavioural data: 1 – back semantic relatedness task

Analysis of both RTs and accuracy in the catch trials reveals a significant main effect of concreteness, whereby the higher the concreteness of the word participants had to make a semantic relatedness judgement about, the faster and more accurate they were. This result aligns with the well-known concreteness effect (Connell & Lynott, 2012; Fliessbach et al., 2006; Paivio et al., 1994; Palmer et al., 2013; Romani et al., 2008). Moreover, participants were also significantly faster and more accurate in making the semantic judgement when the catch words were associated with the back words compared to when they were not, suggesting that the conflict-resolution involved in trials where catch words were not associated significantly interfered with their performance. The effect of Glove-distance also depended on the status of the trial: when catch words were associated, a lower semantic distance between the back word and the two associated words further sped up semantic judgements and increased the probability of responding correctly. The opposite effect was observed when words were not associated, so that a lower Glove-distance interfered with participants' judgements, making them slower and less accurate in correctly identifying those words as not associated. The predictive effect of Glove-based distance aligns with previous findings showing the Glove model's ability to predict performance in semantic behavioural tasks (Auguste et al., 2017; Ettinger & Linzen, 2016; Pereira et al., 2016).

4.5.2 MEG data

4.5.2.1 Contrast between abstract and concrete words

The contrast between concrete and abstract words highlighted significant differences between the two domains, mostly in the 300-450 ms time window, a result in line with previous findings on ERP components of semantic processing (Kutas & Federmeier, 2011; E. F. Lau et al., 2008).

For concrete words, the localisation (left-anterior sensors) and timing (300-350 ms) of the first cluster suggest an early, increased recruitment of left anterior regions for concrete over abstract words, a result compatible with previous findings (Orena et al., 2019; Papagno, Capasso, et al., 2009), which, together with the RSA results (see next sections), suggest an increased focus on linguistic features for concrete stimuli.

Contrasting with the Dual-Coding Theory (Paivio, 1991), and diverging from recent findings (Vignali et al., 2023), we found increased activity related to abstract words at 250-450 ms, with posterior regions being more activated by abstract compared to concrete concepts throughout all of this time window. The sensor locations and timing are similar to those of the positive correlations between the Sensorimotor model and abstract words (see ‘Experiential models: Sensorimotor and Affective model’ section), and together, these results suggest a possible higher recruitment of sensory regions for abstract compared to concrete words.

4.5.2.2. Concreteness model

Concreteness dissimilarity models, or models which encode dissimilarities between words based on their degree of concreteness, have been used in both fMRI (Graves et al., 2024; Meersmans et al., 2022) and MEG studies (Hultén et al., 2021). In our study, concreteness dissimilarities correlated and explained unique variance of neural activity associated with all words varying across concreteness levels, even after partialling out taxonomic, experiential and distributional information. This finding aligns with Hultén and colleagues' results, which also show that a concreteness model explained unique variance in source-localised MEG data even net of distributional properties (Hultén et al., 2021). The presence of a significant correlation even after accounting for experiential sensorimotor properties also suggests that concreteness values are not the direct product of words' perceptual properties, as previous behavioural findings illustrated (Connell & Lynott, 2012). When we analysed abstract and concrete words separately, conversely, there were no significant correlations with abstract or concrete words. This result suggests that fine-grained concreteness dissimilarity is not necessarily reflected in conceptual brain processing, while more coarse-grained, or bimodal information of concreteness is more inherent to words' neural representation. However, this result might also be specific to our set of stimuli, considering that we selected concepts to obtain two separate domains with distinct, and internally relatively homogeneous levels of concreteness.

4.5.2.3. Distributional models: Word2Vec and Glove

Distributional models such as Word2Vec, Glove, or fastText have successfully explained neural activity elicited by single concepts in a variety of fMRI studies, both for concrete (Carlson et al., 2014; Carota et al., 2017, 2021; Tong et al., 2022; X. Wang, Xu, et al., 2018) and abstract concepts (Kaiser et al., 2022; Meersmans et al., 2020; Pereira et al., 2018; Ulrich et al., 2025; X. Wang, Wu, et al., 2018), and more recently, by fNIRS (Montefinese et al., 2021) and by M/EEG studies too, which used both concrete and abstract words, analyzed together (Hultén et al., 2021; Sassenhagen & Fiebach, 2020) or only concrete words (Bruera & Poesio, 2022; Vinaya et al., 2025). In our study, we replicated these results: Glove model showed a significant positive correlation to the neural signal elicited by concrete and abstract words, both considered altogether and separately, also after partialling out the experiential and taxonomic models. The Word2Vec model also correlated with the activity of all words, but when we tested the correlation separately on concrete and abstract words, only the correlation with concrete words survived. Given its high correlation with the Glove model (abstract RDMs: $r = 0.63$, concrete RDMs: r = 0.55) and its unsuccessful performance with abstract concepts, the Word2Vec model was not used in the partial correlation analysis.

This discrepancy between the results of two theoretically analogous distributional models might be due to the type of information considered by their algorithms. Word2Vec is a simple neural network which learns to predict words based on their local context and thus uses localized linguistic information to build word vectors. This approach might be sufficient for concrete words, which have more homogeneous, stable local contexts. Glove, on the other hand, uses more global statistical information, as its calculation considers ratios of co-occurrence probabilities of two words with other words across the whole corpus, and the relative frequency of words to weight those probabilities, to build word vectors (Pennington et al., 2014; Rollo et al., 2024). The information considered by Word2Vec might be suboptimal for vector representations of abstract concepts, whose contexts are more heterogeneous than those of concrete concepts (Hoffman, Lambon Ralph, et al., 2013). The global approach of Glove, instead, might be more efficient to compute dissimilarities between abstract concepts, because it account for the often relational and flexible nature of their meaning, and the higher variability of their usage.

4.5.2.4 Experiential models: Sensorimotor and Affective model

Experiential models built based on sensorimotor and/or affective dimensions have been less extensively tested than distributional ones, but they have also been proven to explain unique variance, after controlling for distributional and/or taxonomic models, of neural activity associated with concrete and abstract concepts in both fMRI (Fernandino et al., 2016, 2022; Meersmans et al., 2020; Tong et al., 2022; X. Wang, Wu, et al., 2018) and EEG studies (Vinaya et al., 2025). In our study, however, the experiential affective model was never correlated with neural activity, with either concrete or abstract words, nor with all words considered together. The experiential sensorimotor model, instead, was significantly correlated with all words' neural activity, but when we considered concrete and abstract words separately, only abstract words dynamics were positively correlated with the sensorimotor model, even after partialling out the distributional and taxonomic model, while concrete words dynamics were never correlated with the sensorimotor model. This pattern of results is exactly the opposite of what we hypothesised.

4.5.2.4.1 Affective model

Abstract words are generally more emotionally valenced and associated with affective contexts than concrete ones (Kousta et al., 2011; Lenci et al., 2018). This is true in our dataset too, where the degree of valence and arousal of abstract stimuli was significantly higher for abstract than for concrete words. However, it is possible that the semantic relatedness task we used did not induce participants to focus on the emotional features of concepts. The affective model, indeed, is also the model with the lowest average correlations with the other models included in the analysis ($r = 0.06$, all other models $r > 0.21$), which suggests that it captures a very different type of conceptual information, which might not have been elicited in our paradigm. According to the Context Dependent Embodied Simulation model or CODES (Winkielman et al., 2018, 2023), which was formulated based on an analysis of the literature on emotion processing of concepts, the activation of embodied emotional properties of the stimuli at hand is not automatic, but highly dependent on the requirement of the current context: while tasks requiring participants to focus on affective features of the stimuli will prompt an embodied simulation of those affective features, a task requiring a shallow perceptual processing (e.g., judging whether the letters of the word are capitalized as in Niedenthal et al., 2009), or a task requiring the processing a different type of semantic information (e.g., concreteness), will not activate them to the same degree. This pattern has been shown recently in an fMRI study (Meersmans et al., 2022), where the authors found that correlations with a valence RDM were stronger during the valence than during the concreteness evaluation tasks. The judgment of semantic relatedness we employed in our study probably did not induce that type of deep emotional processing of the presented words.

4.5.2.4.2 Sensorimotor model

The results of the sensorimotor model are the opposites of our hypotheses. In a recent study, Vinaya and colleagues (Vinaya et al., 2025) showed that their sensorimotor model derived from the same 11 sensory and motor features we used in our paradigm (Lynott et al., 2020) could explain unique variance of single-trial EEG signal and RTs of concrete words. This study, however, included exclusively concrete words and employed a property verification task, which, again according to the CODES theory, probably induced participants to focus on the sensorimotor properties of the concepts at hand. This is further suggested by the pattern of their results, where the sensorimotor model explained unique variance mostly when the property following the word was not a typical property of the word (e.g., ‘apple’, ‘black’), as previous research suggests a higher recruitment of sensorimotor processes when combining two unlikely category-attributes (Hoenig et al., 2008). On the other hand, when the property following the word is typically associated with the word (e.g., ‘apple’, ‘red’), a less effortful processing of linguistic association would be sufficient to recognise the association word-property, with distributional properties offering a ‘shortcut’ (Connell, 2019), and thus not requiring participants to engage in an embodied simulation of sensorimotor features.

The 1-back semantic relatedness task we employed was not optimised to elicit a sensorimotor processing of the presented stimuli. The lack of sensorimotor correlations with the concrete words' neural activity might be related to the requirements of the task: for concrete words, which appear in more stable linguistic contexts, participants might not need to activate their sensorimotor properties; to assess semantic relatedness, following Connell’s linguistic shortcut proposal (Connell, 2019), they might have relied on easier-to-retrieve, distributional local context properties as a shortcut, properties which might not be equally informative for abstract words. To make an example, correctly identifying the catch words ‘tourism’ and ‘vacation’ as associates to ‘hotel’, and correctly identifying them as not associated with other concrete concepts such as ‘monkey’, ‘thief’ or ‘church’ might have not required a deeper, more accurate multimodal simulation of those concepts, but likely relied on the cheaper, shallower activations of words’ distributional properties. This interpretation aligns with previous behavioural data (Connell & Lynott, 2013; Solomon & Barsalou, 2004), and in our study, it is supported by the result showing that while concrete concepts activity is positively correlated with the Word2Vec model (i.e., reflecting stable local context linguistic information), abstract concepts activity was not. The evaluation of the semantic relatedness between abstract words and the catch words may have relied less on this stable-context linguistic shortcut, particularly given the greater semantic diversity of the contexts in which abstract concepts tend to occur (Hoffman, Lambon Ralph, et al., 2013). Indeed, a review of the topic suggests that semantic relatedness judgements are easier with words with low semantic diversity in healthy controls (Norman et al., 2025). This greater perceived difficulty might have, in turn, implicitly prompted participants to a deeper processing of their meaning, and a multimodal simulation of situations where that concept can be applied might have occurred (Connell, 2019), in line with a situated conceptualization framework (Barsalou, 2003, 2009; Barsalou et al., 2018; Barsalou & Wiemer-Hastings, 2005; Wilson-Mendenhall et al., 2013). For example, participants, while processing the word ‘adventure’ (‘avventura’), might have activated simulations of walking down a fairy forest path in a mediaeval setting to correctly identify the words ‘hero’ (‘eroe’) and ‘mystery’ (‘mistero’) as associates, or the word ‘fame’ (‘fama’), whose correct associates where ‘actor’ (‘attore’) and ‘reputation’ (‘reputazione’) might have involved the imagery of a red carpet and flashing lights, to correctly discard as not associates other pairs of catch words such as ‘strength’ (‘forza’) and ‘power’ (‘potere’), or ‘tourism’ (‘turismo’) and ‘vacation' (‘vacanza’). Indeed, most significant clusters of correlations between the sensorimotor model and abstract words' neural variability are localised in posterior sensors, which suggests that these correlations originate from posterior, sensory brain areas. An alternative, not mutually exclusive explanation can be found in the variability of the sensorimotor properties of the stimuli we used. Indeed, even though concrete concepts had generally higher sensory ratings (but not higher body-parts ratings, see Methods section), they were not better differentiated by these properties: the variance of the dissimilarities encoded in the sensorimotor model of abstract stimuli (var = 0.022) is almost twice the variance of the dissimilarities in the sensorimotor model of concrete stimuli (var = 0.012). A richer dissimilarity structure might be better aligned with dissimilarities derived from brain data, which could be the reason why we did not observe a significant correlation between the poor-discriminating concrete words sensorimotor model and their brain signals.

4.5.2.5 Categorical model

Taxonomic categorical models, often computed based on WordNet hierarchical structures, have been shown to explain neural activity associated with words’ processing in both fMRI (Borghesani et al., 2016; Carota et al., 2021; Devereux et al., 2013; Fernandino et al., 2022) and MEEG studies (Chan et al., 2011; Sassenhagen & Fiebach, 2020). In these models, concept similarity is based on their hierarchical taxonomic relationships, i.e., higher-order conceptual properties. In our study, we also found that the categorical WordNet model explained unique variance of words’ neural activity, and, in line with our predictions, this effect was only present with concrete concepts, and not with abstract concepts.

Taxonomic distinctions have been one of the first methods used to differentiate concrete concepts, based on early neuropsychological observations of dissociations between different categories, such as the living/non-things distinction (Mancano & Papagno, 2023; Papagno, 1998; Warrington & Shallice, 1984). Abstract concepts, conversely, have been treated as a monolithic domain for a long time, as categorical distinction between them are not as straightforward as for concrete concepts: while taxonomic distinctions between concrete concepts are often related to ostensible features of concepts shared between the exemplars of the same category (i.e., if it breathes and moves, it's an animal, if it has a fur, it's probably a mammal, etc etc…), categorical taxonomic distinctions among abstract concepts are not obvious, as they are not mapped onto external, unambiguous properties. In our dataset too, while all exemplars of the concrete concepts four categories (animals, persons, devices and structures) intuitively belong to those categories, the distinction between abstract categories (acts, qualities, cognitions and feelings) is more obscure: while all exemplars of 'feelings' are labels of emotional/affective states (e.g., 'panic', 'rage'), 'cognitions' seems to be made mostly philosophical/spiritual concepts (e.g., 'god', 'idea') (Villani et al., 2019), but also comprise more concrete items such as 'fragrance'. Likewise, 'qualities' resemble self and sociality concepts (e.g., 'honor', 'charm') (Villani et al., 2019), but also comprise other types of personal qualities, with elements such as 'ignorance'; finally, 'acts' are the more heterogenous category, with elements generally referring to temporally localized, potentially emotionally laden events such as 'massacre', 'deceit' or 'adventure' and others more unspecific such as 'sight'. These observations further confirm that in our dataset, too, distinctions between different taxonomic categories of abstract concepts are not as automatically activated or relevant, at the brain level, as those between taxonomic categories of concrete concepts. Furthermore, we observed these results even using a task that did not explicitly request this type of taxonomic information. Overall, these results provide further evidence that while taxonomy represents a relevant, spontaneous organising principle of concrete lexicon in our brain, it does not necessarily contribute to the representational space of abstract concepts.

4.5.2.6 Comparison between models and between concrete and abstract concepts

Overall, model correlations with brain data peaked where most present and widespread on the scalp at 300-500 ms, in line with the well-known N400 components, thought to reflect semantic processing (Kutas & Federmeier, 2011; E. F. Lau et al., 2008).

For concrete words, the model showing the earliest and longest unique correlations with neural activity was Glove (170-560 ms), a result in line with our hypothesis. The only other model that showed significant partial correlations with concrete concepts was the categorical one, with later-onset, shorter (325-535 ms) and concurrent to Glove model correlations. Whilst unique correlations with the categorical model were confined to a smaller set of mostly right-lateralized sensors, Glove's significant clusters encompassed a larger portion of the sensor space, especially in the 400-500 ms time window. Together with the positive simple correlations with the Word2Vec model, this pattern of results suggests that distributional properties of concrete words were recruited first and processed longer, and were followed by a later-onset, concurrent taxonomic representation of those words. These results are compatible with previous findings (Sassenhagen & Fiebach, 2020), which found a superior performance of distributional models over WordNet-based models. The absence of correlations with the sensorimotor model diverges from previous findings (Fernandino et al., 2022; Vinaya et al., 2025) and suggests that experiential embodied information is not necessarily recruited in concrete concepts processing during tasks that do not explicitly require it or make it salient.

For abstract words, the model showing the earliest unique correlations with neural signals was the sensorimotor model (40 ms). Correlations with the Glove model started later (250 ms), but lasted about 100 ms longer than those with the sensorimotor model (Glove: 575 ms, sensorimotor: 480 ms). These results suggest that both sensorimotor and distributional word properties played a role in the processing of abstract words, with earlier recruitment of posterior regions in correspondence with sensorimotor correlations, and a later-onset, prolonged recruitment of left-lateralized and anterior areas for processing the word's distributional properties. The absence of correlations with the taxonomic model confirms that classic taxonomy does not properly characterise the processing of abstract concepts (Crutch & Warrington, 2005; Mirman et al., 2017; Papagno et al., 2013); and the lack of correlations with the affective model aligns with the CODES theory (Winkielman et al., 2018), whereby processing of emotional features of concepts depends on the current task. However, there is no obvious interpretative framework to reconcile the absence of sensorimotor associations with concrete concepts with the early and lasting correlations with abstract concepts (see previous 'Sensorimotor section' for a discussion on this point), and further research is needed to clarify whether this pattern of results is specific to our set of stimuli, or generalizable to other stimuli and/or tasks. Future investigations, implementing methods such as temporal generalisation analysis, should also determine whether such early associations with sensorimotor features represent a fleeting neural state, or a consistent representational format, stable over time.

Another limitation of the previous study regards the type of semantic dimensions considered in the experiential models. The models we employed were computed based on the semantic and experiential dimensions (emotional, sensorimotor) included in the dataset from which we selected our stimuli (Repetto et al., 2023). However, the heterogeneity of the classes of abstract concepts included in this study might be better captured by experiential models based on other semantic dimensions, such as introspection, socialness, or metacognition (Borsa et al., 2025; Troche et al., 2014), and future rating studies might fill this gap.

4.6 Conclusion

In the current study, we aimed to assess the contribution of distributional (Glove), experiential sensorimotor, experiential affective, and categorical (WordNet) information to the dynamic processing of individual concrete and abstract written words during MEG recording. Our results showed that different models made unique contributions to concrete and abstract concepts: while distributional global linguistic properties (Glove model) successfully explained brain activity in both domains, categorical distinctions correlated only with brain activity in concrete concepts, and sensorimotor properties correlated only with brain activity in abstract concepts. Experiential affective properties were not reflected in the brain activity of either domain. These results confirm the importance of linguistic associations in brain concept representation, and provide mixed evidence in support of embodied theories of concrete and abstract concepts processing (Barsalou, 2008; Barsalou et al., 2018), suggesting that experiential simulations might not be automatic, but highly dependent on the context and task demands (Connell, 2019; Winkielman et al., 2023).

CHAPTER 5.

GENERAL DISCUSSION

Abstract concepts represent a consistent portion of human language (Lupyan & Winter, 2018), a portion which expands significantly our possibilities of communication, and that constitutes a founding block of institutions of every society: without abstract concepts, we wouldn't be able to agree on what is *justifiable* or *illegal,* we wouldn't be able to explain what *gravity* or a *magnetic field* are, or we wouldn't be able to tell each other what *friendship* and *betrayal* mean for us. However, this fundamental part of our language remains understudied, while the bulk of research focuses on concrete concepts.

In this thesis, I contributed to furthering our knowledge on this less-explored component of language. More specifically, I conducted a scoping review (Chapter 2) and two experimental studies (Chapter 3 and 4) to respond to some of the most central questions regarding the nature of abstract concepts: Are abstract concepts purely linguistic, or are they grounded in dimensions of experience (Chapter 3 and 4)? Is it possible and beneficial to distinguish between multiple categories of abstract concepts (Chapter 2, 3, and 4)?

In the next section, I will briefly summarise the relevant findings on each of our studies. Then, I will discuss the broader implications of such findings, contextualising them in light of the questions highlighted above.

5.1 Summary of main findings

In Chapter 2, I presented a scoping review to investigate concrete and abstract concepts processing in patients with Alzheimer's disease (AD) or with the semantic variant of Primary Progressive Aphasia (svPPA). The aim of the study was to analyse the evidence on the presence of a concreteness effect, and a reversal of the concreteness effect, in these patients, and their relation to Anterior Temporal Lobes (ATLs) atrophy. Furthermore, I investigated whether, within the concrete or abstract domains, those patients reported dissociations between different categories of concrete and abstract concepts. The main findings were that, while AD patients reported either a concreteness effect (i.e., a better performance with concrete with respect to abstract concepts) or no differences, the opposite pattern, namely a reversal of concreteness effect (i.e., a better performance with abstract over concrete concepts) was the most frequently reported effect in studies on svPPA patients. Moreover, five of the included studies reported a positive correlation between the degree of atrophy of the ATLs and the degree of the reversal of the concreteness effect. Importantly, dissociations occurred between not only concrete categories (namely, living/non-living distinction), but also between abstract categories, namely, social concepts and emotion concepts: while AD patients showed a selected sparing of emotion concepts, svPPA patients showed a selective impairment of social words, compared to other types of abstract words or to concrete words.

In Chapter 3, I presented a semantic rating and a TMS study that explored the semantic representations of social and emotional abstract concepts.

In the semantic ratings behavioural study, I collected ratings of the emotional and social dimensions of triplets of words divided into three categories: Emotion or emotion-labels (i.e., words referring to an internal feeling such as “happiness”), Social or social-labels (i.e., words referring to an interaction between people or a societal construct, i.e., “friendship”, “democracy*”)*, and Objects (e.g., “chair”) words. Emotion-label words were characterised by significantly higher scores on the emotion dimension compared to both social-label and object words, and social-label words by significantly higher scores on the social dimensions compared to both emotion-label and objects. However, emotion-label words also had higher scores on the social dimension compared to object words, and social-label words had higher scores on the emotion dimension compared to object words. This moderately high rating on the other scale suggests that a multidimensional approach captured information missing from the categorical approach.

Those same words were used as stimuli in the TMS study, where I applied rTMS to target the right and left Anterior Insula (AIns), and presented participants with a semantic similarity task to test their semantic performance, and with a heartbeat counting task to test their interoceptive performance. This study aimed to investigate whether a region representing interoceptive information, the AIns, could also be responsible for abstract concepts' semantics, and thus act as a potential common ground for the two processes. By analysing the differences in performance between stimulation conditions, we found that the TMS targeting right AIns significantly interfered with both interoceptive accuracy and the emotional and social dimensions of abstract concepts, including both emotion-label and social-label categories. Instead, there was no significant interaction with the categorical distinction. These results were confirmed by analyses of the TMS-induced electric field (E-field) inside right AIns, which showed that the higher the E-field induced in this area, the higher the interference with the interoceptive task and the emotional and social dimensions of abstract concepts. Together, these results show a convergence of the semantic processing of emotional and social features of abstract concepts and interoception in right AIns.

In chapter 4, I described an MEG study where written concepts, belonging to four concrete and four abstract taxonomic categories, were presented to participants during MEG recording, and sensor-level dissimilarities between concept pairs were compared to a set of theoretical models reflecting different semantic principles. The study aimed to clarify which organisational principles drive the neural dynamics of abstract and concrete concepts. I used two distributional models (Word2Vec CBOW, Glove), two experiential models (one affective model, one sensorimotor model), one taxonomic model (WordNet-based categories), and one concreteness model. Concrete categories were animals, devices, persons and structures; abstract categories were acts, qualities, cognitions and feelings. I used spatial-temporal RSA to compare neural signals elicited by all words to each model, and then ran the same analysis separately on concrete and abstract concepts. After partialling out other models, distributional properties correlated with MEG activity of both concrete and abstract concepts, although with some differences (Word2Vec correlated only with concrete, while Glove correlated with both concrete and abstract MEG activity). The taxonomic model, conversely, correlated only with activity for concrete concepts, while the sensorimotor model correlated only with activity for abstract concepts. The affective model did not correlate with the activity of either concrete or abstract, either separately or considered altogether. The concreteness model only explained neural activity of all words considered together, but not when concrete or abstract words were analysed separately. For concrete words, neural activity was first predicted by the Glove model, with the categorical model showing significant correlations in a later time window. For abstract concepts, neural activity was initially correlated with the sensorimotor model, followed by the Glove model, which correlated with the signal also at a later stage.

5.2 Embodiment of Abstract Concepts

5.2.1 Strong and weak embodiment accounts

Following the definition proposed by Borghi (Borghi, 2020; Borghi et al., 2017), there are two types of embodiment accounts of abstract concepts, namely a "strong" and a "weak" one: 'strong embodiment' accounts theorise that sensorimotor features (i.e., sight, hearing, movement, …) are necessary and sufficient properties for grounding both concrete and abstract concepts (Connell & Lynott, 2012; Gallese & Lakoff, 2005; Glenberg, Sato, & Cattaneo, 2008; Glenberg, Sato, Cattaneo, et al., 2008; Hauk et al., 2004; Pulvermüller et al., 2005). On the contrary, weak embodiment accounts differentiate the types of features grounding concrete vs abstract concepts, specifying that for abstract concepts, other dimensions (such as emotional, social, introspective and linguistic) might be fundamental for their representation and acquisition (Barsalou et al., 2018; Borghi et al., 2019; Kousta et al., 2011; Vigliocco et al., 2014).

In the studies presented in the previous chapters, I found that abstract concepts can be grounded in both classic sensorimotor features (i.e., strong embodiment account) and in socioemotional features (i.e., weak embodiment account).

The results of Chapter 3 support a weak embodiment account. The semantic ratings study (Chapter 3) found that social and emotional features are more relevant for social-labels and emotion-labels concepts as opposed to object concepts, aligning with both the Affective Embodiment Account (Kousta et al., 2011; Newcombe et al., 2012; Vigliocco et al., 2014) and Words as Social Tools proposal (Borghi, 2020; Borghi et al., 2019). Moreover, in the subsequent TMS study (Chapter 3), the same TMS stimulation that interfered with interoception, i.e., an internal sensory modality which does not appear in the classic repertoire of sensory and motor features of strong embodiment theories, also interfered with the emotional and social features of those abstract concepts, suggesting a potential overlap of the two, namely emotional and social dimensions being at least partially supported by interoceptive simulations (see section 5.2.4 for a discussion on this topic).

The results of Chapter 4 support a strong embodiment account. In the MEG experiment, indeed, there was no evidence of abstract concepts being grounded in affective dimensions: the affective model encoding dissimilarities between words based on emotional features did not explain neural variability associated with these concepts. Instead, abstract concepts' representation was supported by classic sensory and motor features: a dissimilarity model calculated on abstract concepts ratings on the classic five sensory modalities (i.e., sight, hearing, smell, taste, touch) plus interoception, and on association to five different body-parts (i.e., head, mouth, hands, torso, legs), explained unique variance of MEG neural activity associated to abstract words at 40-480 ms, even after partialling out distributional, affective and taxonomic properties. On the contrary, the MEG activity of concrete concepts was not predicted by this sensorimotor model.

In the next paragraphs, I will try to reconcile these seemingly incompatible results by focusing on differences between the two paradigms we used, and linking them to current theories on the embodiment of (abstract) concepts.

5.2.2 Methodological differences between Chapter 3 and Chapter 4

The first difference between the two studies regards the type of stimuli used. In the first semantic ratings and TMS study, only emotion-label and social-label were used as abstract words. These categories are the most widely studied in the domain of abstract concepts (Conca et al., 2021), with the highest number of published papers that investigated their behavioural and neural properties. The TMS study also included a third category, namely, the concrete control category of object concepts. In the MEG study, conversely, feelings (i.e., emotion-label words) were only one out of the four categories of abstract concepts included, while the others were taxonomically defined categories of cognition, acts and qualities. Even though we anecdotally observed that some of the ‘qualities’ concepts refer to social qualities (i.e., ‘charme’, ‘piety’), the stimulus selection did not purposely aim to select social-label stimuli. Then, the other half of the stimuli was concrete. Therefore, the first experiment included 2/3 of the stimuli that directly referred to emotions or social concepts, while the second experiment included only 1/8 of emotion concepts. The high preponderance of socio-emotional stimuli in the first experiment compared to the second one might have led participants to veer toward a socio-emotional type of processing that did not happen in the second experiment, which included a higher variety of concepts. Crucially, socio-emotional information might not be equally relevant for all types of abstract concepts (Winter, 2023) and indeed, the abstract concepts in our MEG study were better distinguished by their sensorimotor properties (sensorimotor model variance = 0.022) than by their affective properties (affective model variance = 0.013): this suggests that the characterisation of their semantic content, and seemingly their neural representation, benefited more from information on their sensorimotor associations than on their affective values. This result aligns with a previous property-generation study, which observed that when participants were asked to generate properties on a list of abstract concepts (N=296), sensorimotor features were generated in the highest number, more than emotion or social features (Harpaintner et al., 2018), contrary to previous views on abstract concepts as not particularly associated with sensorimotor qualities.

A second difference, related to the first one, is the task used. In the TMS experiment, participants performed two tasks: an interoceptive task, where they were asked to silently count their own heartbeats, and a semantic similarity task, where they had to select among two words the word more semantically similar ('target') to a probe word. The first thing that participants performed upon arrival at the lab was the interoceptive task, which was then repeated after each TMS session: this setting may have made interoceptive feedback more salient and in the foreground during the semantic similarity task too, and, given the association between interoceptive experience and emotion (Connell et al., 2018; Repetto et al., 2023; Vergallito et al., 2019; Villani et al., 2021), it may have shifted semantic processing toward a focus on the emotional properties of the stimuli. Even without this possible influence of the interoceptive task, the semantic similarity task itself may have prompted participants to focus on the valence and arousal features of the stimuli, as those features may have been the fastest strategy to perform the task or to find the target word (i.e., the word more similar to the probe) and discard the distant, as the target often presented similar valence/arousal to the probe word, while the distant usually had opposite valence and/or arousal, in emotion triplets (e.g., 'happiness' as the probe word, 'joy' as the similar positive valence target word, and 'irritation' as the opposite valence, distant word). This explanation aligns with the Context-Dependent Embodied Simulation (Winkielman et al., 2018, 2023), which claims that (affective) embodied properties of stimuli are differentially recruited based on the context and the task: the processing of concepts is not always the same, but instead, it is highly dependent on the specific requests and settings, so that affective properties become a relevant part of semantic processing only when the task requires them.

In the MEG study, instead, the 1-back semantic relatedness task was the only task used. In this task, the catch trials presented either semantically associated or non-associated catch words. The correctly associated words of abstract concepts could reflect different types of association: either words with similar meaning or synonyms of the word (e.g., 'idea' with associated words 'notion' and 'invention'), or a thematic association (e.g., 'adventure' with 'hero' and 'mystery'), or a mix of the two (e.g., 'fame' with thematic associate 'actor' and similar meaning ‘reputation’). Not associated words were randomly selected from pairs of catch words associated with different concrete or abstract words (e.g., ‘idea’ presented with ‘tourism’ and ‘vacation’, i.e., associates of the concrete word ‘hotel’, or ‘idea’ presented with ‘actor’ and ‘reputation’, associates of the abstract word ‘fame’). To correctly identify words associated and not associated with each abstract and concrete word, participants could use different strategies. Concrete words have a more stable meaning, and they appear in a narrower set of linguistic contexts compared to abstract concepts (Hoffman, Lambon Ralph, et al., 2013). To respond correctly to the task, linguistic associations might have been sufficient for trials involving concrete concepts, offering a shortcut that nullified the need for more effortful embodied simulations of those concepts (Connell, 2019; Connell & Lynott, 2013; Vinaya et al., 2025). For abstract concepts, instead, correctly judging as not-associates other concrete or abstract words might have been more difficult, as abstract words appear in more heterogeneous contexts (Hoffman, Lambon Ralph, et al., 2013). In this situation, participants might have needed to engage in situated simulations of the meaning of those abstract concepts, i.e., in multimodal embodied conceptual representations (Barsalou, 2003; Barsalou et al., 2018; Barsalou & Wiemer-Hastings, 2005), to perform the task correctly. To make an example, while ‘tourism’ and ‘vacation’ can be easily discarded as not associated to other concrete words such as ‘monkey’ or ‘thief’, based on a more superficial processing of their stable linguistic associations, the same judgement with words such as ‘fame’ or ‘adventure’ might not be able to rely on this linguistic shortcut given their more variegate context, and might have prompted participants to activate a deeper, more accurate multimodal processing of their meaning, which would be reflected in the MEG neural activity correlated with their sensorimotor model. This interpretation aligns with previous behavioural findings (Connell & Lynott, 2013; Solomon & Barsalou, 2004) and with Connell’s linguistic shortcut hypothesis (Connell, 2019), which claims that conceptual processing is variable depending on task requests, so that distributional, cheaper and faster processing is the most likely answer to shallower semantic processing tasks, or in situations of perceived high probability of performing correctly using this type of processing, whereas tasks requiring deeper semantic processing and/or tasks perceived as unlikely to be performed well with distributional linguistic processing would engage more accurate, multimodal simulations.

5.2.3 A dynamic, context-dependent view on embodiment of abstract concepts

Collectively, the results of these two studies align with a dynamic, context-dependent embodiment account of abstract concepts (Connell, 2019; Winkielman et al., 2018, 2023), which varies depending on stimulus type and task demands. The TMS study showed that social scores significantly facilitated the semantic processing of abstract concepts, in line with previous studies (Diveica et al., 2023), and there was a similar non-significant trend for emotion scores as well. In turn, the facilitation effect linked to these dimensions was hindered by the stimulation of right AIns and the magnitude of the E-field elicited inside right AIns: the higher the E-field induced, the lower the facilitation provided by higher scores on the emotion and social dimensions. These findings align with the importance attributed to emotional (Kousta et al., 2011) and social (Borghi et al., 2019) features of abstract concepts, and together with the interference observed in the interoceptive task, they support the connection between these dimensions and interoceptive experience. The MEG study, conversely, showed that affective dimensions are not necessarily recruited when they are not central to the stimuli and the task, and showed that a wider array of sensorimotor properties, comprising external sensory modalities, interoception and association to body parts, might better capture the variability of brain dynamics for abstract concepts in a situation possibly requiring situated simulations of these concepts.

5.2.4 What are, really, the experiential dimensions of weak embodiment accounts made of?

On a more speculative note, let us consider the nature of the alternative semantic features proposed to ground abstract semantics in our experience. These conceptual features, such as emotional, social, linguistic and introspective features, organise the abstract conceptual space (Crutch et al., 2013; Harpaintner et al., 2018; Troche et al., 2014, 2017; Villani et al., 2019) and are at the core of the main current proposals to explain abstract concepts grounding (Barsalou et al., 2018; Borghi et al., 2019; Kousta et al., 2011). However, these proposals are what Borghi calls ‘weak’ embodiment theories (Borghi et al., 2017), in that they put at the centre of the embodiment of abstract concepts dimensions that cannot be fully accounted for by mere bodily experiences. Reportedly, these dimensions (e.g., social, linguistic) are not directly ‘embodied’ in the same way motor or sensory associations are, or their scope is not exhausted by sensory-motor activations.

However, these features may also be conceived, at least partially, as the complex interplay of more basic, sensory-motor features. A well-established case is that of interoception (Connell et al., 2018). Emotions are associated with changes in our bodily states (Critchley & Garfinkel, 2017; W. James, 1884), and emotion abstract words are rated as more interoceptive than concrete and other types of abstract words (Connell et al., 2018; Repetto et al., 2023). Moreover, literature shows that social experience and interoception are also interconnected (Adolfi et al., 2017; Arnold et al., 2019; Gao et al., 2019; Oldroyd et al., 2019), and direct electric stimulation and fMRI methods showed that the insula is involved in both recognition of facial expressions of disgust, the comprehension of words related to disgust and the experience of unfairness (Corradi-Dell'Acqua et al., 2016; Papagno et al., 2016; Ziegler et al., 2018). In the TMS study, the interference caused by TMS to both interoception and the emotional and social dimensions of abstract concepts led us to hypothesize that in Anterior Insula, there is not only a convergence of these two processes, but that interoception might actually be an integral part of those emotional and social features: interoceptive feedback might be at the very basis of our understanding of social or emotion linguistic content, by providing an internal, sensory signature of different social and emotional meanings. Therefore, interoception might act as a fundamental sensory component of the abstract complex emotion and social dimensions. Moreover, there is evidence that motor activations specific to different body parts also contribute to the meaning of emotion abstract words (Dreyer et al., 2015; Dreyer & Pulvermüller, 2018; R. Moseley et al., 2012). Together, these findings suggest that the emotional nature of abstract concepts is at least in part the result of the interplay of classic, basic sensorimotor properties (e.g., association to movements and to interoceptive feelings).

5.2.5 Sensorimotor associations might be more important for abstract concepts than we think

In contrast to this internally-focused type of social and emotional abstract concepts, semantic ratings (Villani et al., 2019) and property listing (Harpaintner et al., 2018) showed that classic exteroceptive sensorimotor properties might be more relevant for a wide share of abstract concepts than most theories acknowledge. Villani's rating study (Villani et al., 2019) suggests that concepts referring to magnitude (space, time, physical and quantity concepts) are characterised by higher ratings on body-object interaction variables. In a later study by the same group (Villani et al., 2021), the authors asked participants to perform different tasks (chewing a gum, monitoring the heartbeat, squeezing a ball, articulatory suppression) while participants rated the concept on perceived difficulty, on the assumption that, if a task drew on the same resources grounding conceptual processing, concepts would be rated as more difficult. They found that magnitude concepts were rated as more difficult when participants were asked to squeeze a ball compared to other tasks, aligning with previous evidence connecting finger counting with number representation (di Luca & Mauro, 2011; Fischer, 2008), and they differed most from the socio-emotional concepts during the heart monitoring task, supporting the notion that this class of abstract concepts relates to external, rather than internal, sensorimotor experience.

Harpaintner and colleagues (Harpaintner et al., 2018), differently from previous approaches (Lynott et al., 2020; Troche et al., 2014, 2017), did not ask participants to rate concepts on predefined sensorimotor and abstract dimensions, but allowed them to freely generate properties for a wide set (N= 296) of abstract concepts. Later, they adapted the coding schema previously developed by Barsalou and Wiemer-Hastings (Barsalou & Wiemer-Hastings, 2005) to classify those properties into different categories. Using this method, they observed that sensorimotor properties were generated in the highest number, more than social, emotional/introspective, and verbal association properties, and dominated the cluster that comprised the highest number (N = 131) of abstract concepts. Visual, motor-related and acoustic, in turn, were the most frequent subcategories among these sensorimotor features.

Together, these results suggest that the importance of classic sensorimotor properties for abstract concepts might have been underestimated due to methodological and theoretical biases. Strength of numerical ratings on sensorimotor dimensions (Lynott et al., 2020) might not be an adequate measure of the variety of situation-specific, sensorimotor features associated with the content of abstract concepts; and the emotional, inner and social features, although critical for a subset of abstract concepts (e.g., emotion-label and social concepts), might not be in the foreground of the representation of other types of abstract concepts (Winter, 2023). To fully grasp the semantics of abstract concepts, we might need a broader conceptual framework which takes into account the full range of features associated with their content (Binder et al., 2016), as well as how the current demands (Connell, 2019; Winkielman et al., 2018) might shape the activation of those features.

5.3 Categories of Abstract concepts

5.3.1 Abstract categories in our findings

In our studies, we found mixed evidence in favour of a brain segregation of distinct abstract categories.

In the review presented in Chapter 2, emotion and social abstract concepts were differentially impaired in AD and svPPA patients, suggesting that degeneration of different brain areas differentially impacted these two types of concepts.

In the TMS study presented in Chapter 3, emotion and social categories were investigated; in particular, we tested whether TMS targeting AIns differently impacted concepts belonging to these categories. However, the interaction between TMS conditions and category was not significant, suggesting that AIns is not preferentially tuned to emotion or social categories, but stores both the emotional and social value of abstract concepts as continuous dimensions.

In the MEG experiment presented in Chapter 4, abstract categories of stimuli included were acts, qualities, cognitions and feelings. MEG activity did not correlate with the categorical model, suggesting that the taxonomic categorisation was not reflected in neural dynamics elicited by abstract words.

5.3.2 Multiple approaches for a taxonomy of abstract concepts

For a long time, research treated abstract concepts as a uniform domain, neglecting the possibility of distinct categories within it. Unlike concrete concepts, indeed, taxonomic distinctions are not straightforward for abstract concepts, and the very definition of taxonomy adopted in literature diverges between concrete and abstract words (Crutch et al., 2009; Sandberg et al., 2022; Stochel & Sandberg, 2025): taxonomic similarity for concrete concepts is based on words being a member of the same category, which is defined in terms of possessing a set of common perceptual features, whereas taxonomic similarity for abstract words is defined as words having "*the same or similar meanings, which could be interchanged in some, but not all, linguistic contexts*" (Crutch et al., 2009). Taxonomic similarity for abstract words was therefore defined as synonymy or near-synonymy. Based on patient data, Crutch and Warrington developed the Different Representational Framework (DRF) hypothesis (Crutch & Warrington, 2005), whereby concrete concepts would be preferentially organised according to their taxonomic similarity (e.g., apple-tangerine), and abstract concepts would rely on associative or thematic relationships, i.e., words belonging to the same situation/contexts (e.g., gamble, luck). This hypothesis is supported by subsequent studies on patients (Crutch & Warrington, 2010; Papagno et al., 2013) and healthy participants (Crutch et al., 2009), although recent ERPs (Sandberg et al., 2022) and fMRI (Stochel & Sandberg, 2025) studies found that there was a difference in ease of processing between taxonomic and thematic association only for concrete but not abstract words (Sandberg et al., 2022), or no difference in either (Stochel & Sandberg, 2025).

More recently, alternative approaches have been developed to characterise the taxonomy of abstract concepts, based on the collection of explicit feature ratings (Binder et al., 2016; Troche et al., 2014, 2017; Villani et al., 2019), property generation (Harpaintner et al., 2018) or implicit similarity judgements (Persichetti et al., 2024). All of these approaches then use clustering procedures to identify meaningful categories of abstract concepts. Among these studies, emotion/inner states/sociality, magnitude, and sensation are the most frequent clusters/categories (Harpaintner et al., 2018; Persichetti et al., 2024; Troche et al., 2014, 2017). These categories have been tested for their ability to predict behavioural performance. Persichetti and colleagues (Persichetti et al., 2024) found that the categories they obtained with the implicit similarity judgements derived from the odd-one-out task predicted semantic priming results better than the categories obtained with explicit feature ratings by Crutch and colleagues (Crutch et al., 2013), and also better than continuous ratings of similarity between those words, thus confirming a categorical organisation of their stimuli. Villani and colleagues (Villani et al., 2021) found that different behavioural tasks (e.g., chewing gum, monitoring the heartbeat) selectively affected processing of categories identified in their previous study (Villani et al., 2019).

A growing body of evidence suggests that different categories of abstract concepts also rely on at least partially segregated neural bases (Conca et al., 2021; Desai et al., 2018). In the MEG experiment (Chapter 4), therefore, I tested whether abstract word taxonomy was reflected in MEG activity during concept processing. However, there was no evidence of a taxonomic categorical representation of abstract words in MEG activity. This result might be attributed to various factors. First, we relied on WordNet hypernym relations (Fellbaum, 2010) to define abstract categories. Categories obtained with this method might not capture meaningful partitions of abstract concepts, and other approaches, such as those illustrated above (Persichetti et al., 2024; Villani et al., 2019), might be more aligned with brain categorisation of abstract concepts. Indeed, several concepts, such as ‘blackmail’ (‘ricatto’), ‘rejection’ (‘rifiuto’), ‘deception’ (‘inganno’), ‘lust’ (‘lussuria’), and ‘spite’ (‘dispetto’) are classified as acts, while glory (‘gloria’), ‘charm’ (‘fascino’), and ‘pity’ (‘pietà’) are classified as qualities, in the MEG experiment, but they are associated with social or emotional experiences in the TMS experiment. This instability in categorical assignments reflects the intrinsic multidimensionality of abstract concepts, in which the same concept might exhibit high scores on multiple, associated dimensions of experience (Borsa et al., 2025). Wordnet's discrete categorisations do not take into account this overlap of dimensions, and future experiments should include models reflecting categories created through clustering procedures based on semantic ratings on a wide range of semantic dimensions, and models reflecting continuous dissimilarities based on those same dimensions, similarly to the sensorimotor and affective experiential models I included in the MEG experiment.

It is also possible that categorical information was not salient in our paradigm, and that using different tasks, such as category typicality judgments with a block presentation, as used in previous literature (Fairhall & Caramazza, 2013; Giari et al., 2020; Leonardelli & Fairhall, 2022), might lead to different results.

5.3.3 Emotion and Social Concepts

Among abstract categories, emotion and social words are the ones that have been most studied across neuropsychological, neuroimaging and neurostimulation methods (Arioli et al., 2021; Conca et al., 2021). Arioli's meta-analysis (Arioli et al., 2021) compared them directly, and found that, among other areas, anterior temporal lobes were preferentially activated for social compared to emotion concepts.

The role of superior ATL in the representation of social concepts has been studied extensively in the neuroimaging literature (Amoruso et al., 2025; Binney et al., 2016; Zahn et al., 2007) and confirmed by neurostimulation studies (Catricalà et al., 2020; Pobric et al., 2016). As illustrated in Chapter 2, this literature aligns with neuropsychological evidence on svPPA patients, characterised by predominantly left ATLs atrophy, who show a selective impairment of social concepts: among the studies included in our review, three studies (Catricalà et al., 2014, 2021; Pobric et al., 2016) found that social concepts were more impaired than other types of abstract concepts, and two studies (Pobric et al., 2016; Zahn et al., 2009) found them more impaired compared to concrete concepts. Emotion words, in these patients, had a more heterogeneous profile, and did not reveal a systematic preservation or deterioration (Bertoux et al., 2020; Breedin et al., 1994; Catricalà et al., 2014; Hsieh et al., 2012; Joubert et al., 2017). However, ATL seems to be involved in the processing of emotion words too. An fMRI study showed that distinct regions of left ATL contain information on the social and emotional valence of words (X. Wang et al., 2019), and another recent fMRI study found that emotional verbs were associated with activity in the anterior to middle portion of the left middle temporal gyrus (Muraki et al., 2025). The heterogeneity of emotional words preservation in svPPA patients, therefore, might be ascribed to differences in regions of ATL affected by brain atrophy, whereby the atrophy might not always affect subregions devoted to emotion words processing, and to the ATL being relatively more central to social concepts processing, compared to emotion words processing (Arioli et al., 2021).

In our TMS study (Chapter 3), we found no evidence of differential representation of emotion and social words in right AIns, and the semantic ratings study (Chapter 3) highlighted that both emotion and social categories have moderately high ratings on the social and emotional dimensions, respectively. Indeed, an important point that has not been stressed enough in the literature regards the potential overlap of emotion and social words. Social words are often also valenced, emotion-laden words (e.g., “honour”, “justice”). However, as most studies do not specify what type of emotional words they included in their stimuli (emotion-label or emotion-laden words), effects that we attribute to emotionality might be mixed with effects due to the stimuli's socialness, and vice versa. To address this problem, a solution might be to manipulate orthogonally socialness and emotionality of the stimuli (X. Wang et al., 2019, 2021).

As dimensional ratings show, indeed, emotionality and socialness are typically associated with each other, and they are both associated with inner states: in Villani’s study (Villani et al., 2019), the PCA analysis resulted in an ‘inner grounding and social’ component, which included interoception, emotionality and sociality dimensions. Troche and colleagues (Troche et al., 2014) present a similar finding, where a factor analysis identified an ‘affective association/social cognition’ factor. In Harpaintner’s study (Harpaintner et al., 2018), the cluster 2, which was characterised by properties in the ‘internal state/emotion’ category, also included twice as many properties in the “social constellation” compared to the other two clusters. Adopting an embodied cognition lens, these results align with Adolfi’s meta-analysis (Adolfi et al., 2017), which found common activations in right AIns and a set of frontotemporal regions for interoception, emotional regulation and social cognition.

Collectively, the literature suggests that a clear definition of what ‘social’ and ‘emotion’ mean and a careful examination of their potential overlap are essential to achieve a proper understanding of the neural bases of emotion and social concepts.

5.5 Conclusions

Two of the main outstanding issues on the brain representation of abstract concepts are (1) whether abstract concepts are grounded in experiential features, and (2) whether they can be distinguished into different categories with separate neural bases. Here, I presented neuropsychological, neurostimulation and neuroimaging investigations to shed new light on this issue. The results of these investigations suggest that the representation of abstract concepts is not fixed, but differentially and dynamically grounded in affective and situational sensorimotor features according to the current demands and context. While evidence points to the differentiation of emotion and social concepts, a more robust approach is required to thoroughly disentangle their respective representations, and further investigations are necessary to move beyond classic taxonomy and achieve a meaningful partitioning of the heterogeneous abstract semantic space.

REFERENCES

Acheson, D. J., & Hagoort, P. (2013). Stimulating the Brain's Language Network: Syntactic Ambiguity Resolution after TMS to the Inferior Frontal Gyrus and Middle Temporal Gyrus. *Journal of Cognitive Neuroscience*, *25*(10), 1664–1677. https://doi.org/10.1162/jocn_a_00430

Acheson, D. J., Hamidi, M., Binder, J. R., & Postle, B. R. (2011). *A Common Neural Substrate for Language Production and Verbal Working Memory*.

Adlam, A.-L. R., Bozeat, S., Arnold, R., Watson, P., & Hodges, J. R. (2006). Semantic Knowledge in Mild Cognitive Impairment and Mild Alzheimer's Disease. *Cortex*, *42*(5), 675–684. https://doi.org/https://doi.org/10.1016/S0010-9452(08)70404-0

Adolfi, F., Couto, B., Richter, F., Decety, J., Lopez, J., Sigman, M., Manes, F., & Ibáñez, A. (2017). Convergence of interoception, emotion, and social cognition: a twofold fMRI meta-analysis and lesion approach. *Cortex*, *88*, 124–142.

Altarriba, J., & Bauer, L. M. (2004). The distinctiveness of emotion concepts: A comparison between emotion, abstract, and concrete words. *The American Journal of Psychology*, 389–410.

Altarriba, J., Bauer, L. M., & Benvenuto, C. (1999). Concreteness, context availability, and imageability ratings and word associations for abstract, concrete, and emotion words. *Behavior Research Methods, Instruments, & Computers*, *31*, 578–602.

Amalric, M., & Dehaene, S. (2016). Origins of the brain networks for advanced mathematics in expert mathematicians. *Proceedings of the National Academy of Sciences*, *113*(18), 4909–4917. https://doi.org/10.1073/pnas.1603205113

Amoruso, L., Moguilner, S., Castillo, E. M., Kleineschay, T., Geng, S., Ibáñez, A., & García, A. M. (2025). Neural dynamics of social verb processing: an MEG study. *Social Cognitive and Affective Neuroscience*, *20*(1). https://doi.org/10.1093/scan/nsae066

Anthony, P., Rosa, D., Catricalà, E., De Battisti, S., Vinson, D., Vigliocco, G., & Cappa, S. F. (2014). . In *Functional Neurology* (Vol. 29, Number 1).

Anzellotti, S. (2017). Anterior temporal lobe and the representation of knowledge about people. In *Proceedings of the National Academy of Sciences of the United States of America* (Vol. 114, Number 16, pp. 4042–4044). National Academy of Sciences. https://doi.org/10.1073/pnas.1703438114

Arioli, M., Gianelli, C., & Canessa, N. (2021). Neural representation of social concepts: a coordinate-based meta-analysis of f MRI studies. *Brain Imaging and Behavior*, *15*(4), 1912–1921.

Arnold, A. J., Winkielman, P., & Dobkins, K. (2019). Interoception and social connection. *Frontiers in Psychology*, *10*, 480176.

Arslanova, I., Galvez-Pol, A., Kilner, J., Finotti, G., & Tsakiris, M. (2022). Seeing Through Each Other's Hearts: Inferring Others' Heart Rate as a Function of Own Heart Rate Perception and Perceived Social Intelligence. *Affective Science*, *3*(4), 862–877. https://doi.org/10.1007/s42761-022-00151-4

Ash, S., Ternes, K., Bisbing, T., Min, N. E., Moran, E., York, C., McMillan, C. T., Irwin, D. J., & Grossman, M. (2016). Dissociation of quantifiers and object nouns in speech in focal neurodegenerative disease. *Neuropsychologia*, *89*, 141–152.

Ashtari, M., Lencz, T., Zuffante, P., Bilder, R., Clarke, T., Diamond, A., Kane, J., & Szeszko, P. (2004). Left middle temporal gyrus activation during a phonemic discrimination task. *NeuroReport*, *15*(3). https://journals.lww.com/neuroreport/fulltext/2004/03010/left_middle_temporal_gyrus_activation_during_a.1.aspx

Auguste, J., Rey, A., & Favre, B. (2017). Evaluation of word embeddings against cognitive processes: primed reaction times in lexical decision and naming tasks. In S. Bowman, Y. Goldberg, F. Hill, A. Lazaridou, O. Levy, R. Reichart, & A. Søgaard (Eds.), *Proceedings of the 2nd Workshop on Evaluating Vector Space Representations for NLP* (pp. 21–26). Association for Computational Linguistics. https://doi.org/10.18653/v1/W17-5304

Banks, B., & Connell, L. (2023). Multi-dimensional sensorimotor grounding of concrete and abstract categories. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *378*(1870). https://doi.org/10.1098/rstb.2021.0366

Barca, L., Diana, S. M., Duarte, D. C., Porciello, G., & Borghi, A. M. (n.d.). *Interoceptive grounding of conceptual knowledge: new insight from an interoceptive-exteroceptive categorization task of concepts*.

Barr, D. J., Levy, R., Scheepers, C., & Tily, H. J. (2013). Random effects structure for confirmatory hypothesis testing: Keep it maximal. *Journal of Memory and Language*, *68*(3), 255–278. https://doi.org/https://doi.org/10.1016/j.jml.2012.11.001

Barsalou, L. W. (2003). Situated simulation in the human conceptual system. In *Language and Cognitive Processes* (Vol. 18, Numbers 5–6, pp. 513–562). https://doi.org/10.1080/01690960344000026

Barsalou, L. W. (2008). Grounded cognition. *Annu. Rev. Psychol.*, *59*, 617–645.

Barsalou, L. W. (2009). Simulation, situated conceptualization, and prediction. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *364*(1521), 1281–1289. https://doi.org/10.1098/rstb.2008.0319

Barsalou, L. W., Dutriaux, L., & Scheepers, C. (2018). Moving beyond the distinction between concrete and abstract concepts. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *373*(1752), 20170144. https://doi.org/10.1098/rstb.2017.0144

Barsalou, L. W., & Wiemer-Hastings, K. (2005). Situating abstract concepts. *Grounding Cognition: The Role of Perception and Action in Memory, Language, and Thought*, 129–163.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01

Bates, D., Maechler, M., Bolker, B., Walker, S., Christensen, R. H. B., Singmann, H., Dai, B., Grothendieck, G., Green, P., & Bolker, M. Ben. (2015). Package 'lme4.' *Convergence*, *12*(1), 2.

Bertoux, M., Duclos, H., Caillaud, M., Segobin, S., Merck, C., de La Sayette, V., Belliard, S., Desgranges, B., Eustache, F., & Laisney, M. (2020). When affect overlaps with concept: emotion recognition in semantic variant of primary progressive aphasia. *Brain*, *143*(12), 3850–3864. https://doi.org/10.1093/brain/awaa313

Binder, J. R., Conant, L. L., Humphries, C. J., Fernandino, L., Simons, S. B., Aguilar, M., & Desai, R. H. (2016). Toward a brain-based componential semantic representation. *Cognitive Neuropsychology*, *33*(3–4), 130–174. https://doi.org/10.1080/02643294.2016.1147426

Binder, J. R., Desai, R. H., Graves, W. W., & Conant, L. L. (2009). Where Is the Semantic System? A Critical Review and Meta-Analysis of 120 Functional Neuroimaging Studies. *Cerebral Cortex*, *19*(12), 2767–2796. https://doi.org/10.1093/cercor/bhp055

Binney, R. J., Embleton, K. V, Jefferies, E., Parker, G. J. M., & Lambon Ralph, M. A. (2010). The ventral and inferolateral aspects of the anterior temporal lobe are crucial in semantic memory: evidence from a novel direct comparison of distortion-corrected fMRI, rTMS, and semantic dementia. *Cerebral Cortex*, *20*(11), 2728–2738.

Binney, R. J., Hoffman, P., & Lambon Ralph, M. A. (2016). Mapping the Multiple Graded Contributions of the Anterior Temporal Lobe Representational Hub to Abstract and Social Concepts: Evidence from Distortion-corrected fMRI. *Cerebral Cortex*, *26*(11), 4227–4241. https://doi.org/10.1093/cercor/bhw260

Binney, R. J., Parker, G. J. M., & Lambon Ralph, M. A. (2012). Convergent Connectivity and Graded Specialization in the Rostral Human Temporal Lobe as Revealed by Diffusion-Weighted Imaging Probabilistic Tractography. *Journal of Cognitive Neuroscience*, *24*(10), 1998–2014. https://doi.org/10.1162/jocn_a_00263

Boles, D. B. (1983). Dissociated imageability, concreteness, and familiarity in lateralized word recognition. In *Memory & Cognition* (Vol. 11, Number 5).

Bonner, M. F., Price, A. R., Peelle, J. E., & Grossman, M. (2016). Semantics of the visual environment encoded in parahippocampal cortex. *Journal of Cognitive Neuroscience*, *28*(3), 361–378.

Bonner, M. F., Vesely, L., Price, C., Anderson, C., Richmond, L., Farag, C., Avants, B., & Grossman, M. (2009). Reversal of the concreteness effect in semantic dementia. *Cognitive Neuropsychology*, *26*(6), 568–579.

Borghesani, V., Buiatti, M., Eger, E., & Piazza, M. (2019). Conceptual and perceptual dimensions of word meaning are recovered rapidly and in parallel during reading. *Journal of Cognitive Neuroscience*, *31*(1), 95–108.

Borghesani, V., DeLeon, J., & Gorno-Tempini, M. L. (2022). Frontotemporal dementia: A unique window on the functional role of the temporal lobes. In *Handbook of Clinical Neurology* (Vol. 187, pp. 429–448). Elsevier B.V. https://doi.org/10.1016/B978-0-12-823493-8.00011-0

Borghesani, V., Pedregosa, F., Buiatti, M., Amadon, A., Eger, E., & Piazza, M. (2016). Word meaning in the ventral visual path: a perceptual to conceptual gradient of semantic coding. *NeuroImage*, *143*, 128–140.

Borghi, A. M. (2020). A future of words: Language and the challenge of abstract concepts. *Journal of Cognition*, *3*(1).

Borghi, A. M., Barca, L., Binkofski, F., Castelfranchi, C., Pezzulo, G., & Tummolini, L. (2019). Words as social tools: Language, sociality and inner grounding in abstract concepts. In *Physics of Life Reviews* (Vol. 29, pp. 120–153). Elsevier B.V. https://doi.org/10.1016/j.plrev.2018.12.001

Borghi, A. M., Binkofski, F., Castelfranchi, C., Cimatti, F., Scorolli, C., & Tummolini, L. (2017). The challenge of abstract concepts. *Psychological Bulletin*, *143*(3), 263–292. https://doi.org/10.1037/bul0000089

Borghi, A. M., Caramelli, N., & Setti, A. (2016). How abstract is risk for workers? Expertise, context and introspection in abstract concepts. *RETI SAPERI LINGUAGGI*, *5*(1), 95–118.

Borsa, V. M., Arioli, M., Verni, R., Canessa, N., Cappa, S. F., & Catricalà, E. (2025). Quantifying the Multidimensionality of Abstract Concepts: An Italian Database. *Brain Sciences*, *15*(3). https://doi.org/10.3390/brainsci15030222

Brambati, S. M., Rankin, K. P., Narvid, J., Seeley, W. W., Dean, D., Rosen, H. J., Miller, B. L., Ashburner, J., & Gorno-Tempini, M. L. (2009). Atrophy progression in semantic dementia with asymmetric temporal involvement: a tensor-based morphometry study. *Neurobiology of Aging*, *30*(1), 103–111.

Breedin, S. D., Saffran, E. M., & Coslett, H. B. (1994). Reversal of the concreteness effect in a patient with semantic dementia. *Cognitive Neuropsychology*, *11*(6), 617–660. https://doi.org/10.1080/02643299408251987

Bright, P., Moss, H. E., Stamatakis, E. A., & Tyler, L. K. (2008). Longitudinal studies of semantic dementia: the relationship between structural and functional changes over time. *Neuropsychologia*, *46*(8), 2177–2188.

Bruera, A., & Poesio, M. (2022). Exploring the Representations of Individual Entities in the Brain Combining EEG and Distributional Semantics. *Frontiers in Artificial Intelligence*, *Volume 5-2022*. https://www.frontiersin.org/journals/artificial-intelligence/articles/10.3389/frai.2022.796793

Bruffaerts, R., De Deyne, S., Meersmans, K., Liuzzi, A. G., Storms, G., & Vandenberghe, R. (2019). Redefining the resolution of semantic knowledge in the brain: advances made by the introduction of models of semantics in neuroimaging. *Neuroscience & Biobehavioral Reviews*, *103*, 3–13.

Bucur, M., & Papagno, C. (2021). An ALE meta-analytical review of the neural correlates of abstract and concrete words. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-94506-9

Bueti, D., & Walsh, V. (2009). The parietal cortex and the representation of time, space, number and other magnitudes. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *364*(1525), 1831–1840. https://doi.org/10.1098/rstb.2009.0028

Bugden, S., Price, G. R., McLean, D. A., & Ansari, D. (2012). The role of the left intraparietal sulcus in the relationship between symbolic number processing and children's arithmetic competence. *Developmental Cognitive Neuroscience*, *2*(4), 448–457. https://doi.org/https://doi.org/10.1016/j.dcn.2012.04.001

Bushell, C. M., & Martin, A. (1997). Automatic semantic priming of nouns and verbs in patients with Alzheimer's disease. *Neuropsychologia*, *35*(8), 1059–1067.

Cappelletti, M., Muggleton, N., & Walsh, V. (2009). Quantity without numbers and numbers without quantity in the parietal cortex. *NeuroImage*, *46*(2), 522–529. https://doi.org/https://doi.org/10.1016/j.neuroimage.2009.02.016

Caramazza, A., & Mahon, B. Z. (2003). The organization of conceptual knowledge: the evidence from category-specific semantic deficits. *Trends in Cognitive Sciences*, *7*(8), 354–361. https://doi.org/10.1016/S1364-6613(03)00159-1

Caramelli, N., & Setti, A. (2005). Different domains in abstract concepts. *Proceedings of the Annual Meeting of the Cognitive Science Society*, *27*(27).

Carlson, T. A., Simmons, R. A., Kriegeskorte, N., & Robert Slevc, L. (2014). The emergence of semantic meaning in the ventral temporal pathway. *Journal of Cognitive Neuroscience*, *26*(1), 120–131. https://doi.org/10.1162/jocn_a_00458

Carota, F., Kriegeskorte, N., Nili, H., & Pulvermüller, F. (2017). Representational similarity mapping of distributional semantics in left inferior frontal, middle temporal, and motor cortex. *Cerebral Cortex*, *27*(1), 294–309. https://doi.org/10.1093/cercor/bhw379

Carota, F., Nili, H., Pulvermüller, F., & Kriegeskorte, N. (2021). Distinct fronto-temporal substrates of distributional and taxonomic similarity among words: evidence from RSA of BOLD signals. *NeuroImage*, *224*. https://doi.org/10.1016/j.neuroimage.2020.117408

Catricalà, E., Conca, F., Borsa, V. M., Cotelli, M., Manenti, R., Gobbi, E., Binetti, G., Cotta Ramusino, M., Perini, G., Costa, A., Rusconi, M. L., & Cappa, S. F. (2021). Different types of abstract concepts: Evidence from two neurodegenerative patients. *Neurocase*, *27*(3), 270–280. https://doi.org/10.1080/13554794.2021.1931345

Catricalà, E., Conca, F., Fertonani, A., Miniussi, C., & Cappa, S. F. (2020). State-dependent TMS reveals the differential contribution of ATL and IPS to the representation of abstract concepts related to social and quantity knowledge. *Cortex*, *123*, 30–41. https://doi.org/10.1016/j.cortex.2019.09.018

Catricalà, E., Rosa, P. A. Della, Plebani, V., Vigliocco, G., & Cappa, S. F. (2014). Abstract and concrete categories? Evidences from neurodegenerative diseases. *Neuropsychologia*, *64*, 271–281. https://doi.org/10.1016/j.neuropsychologia.2014.09.041

Chan, A. M., Halgren, E., Marinkovic, K., & Cash, S. S. (2011). Decoding word and category-specific spatiotemporal representations from MEG and EEG. *NeuroImage*, *54*(4), 3028–3039. https://doi.org/10.1016/j.neuroimage.2010.10.073

Cho, S., Nevler, N., Ash, S., Shellikeri, S., Irwin, D. J., Massimo, L., Rascovsky, K., Olm, C., Grossman, M., & Liberman, M. (2021). Automated analysis of lexical features in frontotemporal degeneration. *Cortex*, *137*, 215–231. https://doi.org/https://doi.org/10.1016/j.cortex.2021.01.012

Citron, F. M. M., Gray, M. A., Critchley, H. D., Weekes, B. S., & Ferstl, E. C. (2014). Emotional valence and arousal affect reading in an interactive way: neuroimaging evidence for an approach-withdrawal framework. *Neuropsychologia*, *56*, 79–89.

Clark, J. M., & Paivio, A. (1987). A Dual Coding Perspective on Encoding Processes. In M. A. McDaniel & M. Pressley (Eds.), *Imagery and Related Mnemonic Processes: Theories, Individual Differences, and Applications* (pp. 5–33). Springer New York. https://doi.org/10.1007/978-1-4612-4676-3_1

Coll, M.-P., Penton, T., & Hobson, H. (2017). Important methodological issues regarding the use of transcranial magnetic stimulation to investigate interoceptive processing: a comment on Pollatos et al.(2016). *Philosophical Transactions of the Royal Society B: Biological Sciences*, *372*(1721), 20160506.

Conca, F., Borsa, V. M., Cappa, S. F., & Catricalà, E. (2021). The multidimensionality of abstract concepts: A systematic review. *Neuroscience & Biobehavioral Reviews*, *127*, 474–491. https://doi.org/https://doi.org/10.1016/j.neubiorev.2021.05.004

Connell, L. (2019). What have labels ever done for us? The linguistic shortcut in conceptual processing. In *Language, Cognition and Neuroscience* (Vol. 34, Number 10, pp. 1308–1318). Routledge. https://doi.org/10.1080/23273798.2018.1471512

Connell, L., & Lynott, D. (2012). Strength of perceptual experience predicts word processing performance better than concreteness or imageability. *Cognition*, *125*(3), 452–465. https://doi.org/https://doi.org/10.1016/j.cognition.2012.07.010

Connell, L., & Lynott, D. (2013). Flexible and fast: Linguistic shortcut affects both shallow and deep conceptual processing. *Psychonomic Bulletin & Review*, *20*(3), 542–550. https://doi.org/10.3758/s13423-012-0368-x

Connell, L., Lynott, D., & Banks, B. (2018). Interoception: the forgotten modality in perceptual grounding of abstract and concrete concepts. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *373*(1752), 20170143.

Corradi-Dell'Acqua, C., Tusche, A., Vuilleumier, P., & Singer, T. (2016). Cross-modal representations of first-hand and vicarious pain, disgust and fairness in insular and cingulate cortex. *Nature Communications*, *7*(1), 10904.

Cousins, K. A. Q., Ash, S., Irwin, D. J., & Grossman, M. (2017). Dissociable substrates underlie the production of abstract and concrete nouns. *Brain and Language*, *165*, 45–54. https://doi.org/10.1016/j.bandl.2016.11.003

Cousins, K. A. Q., Ash, S., Olm, C. A., & Grossman, M. (2018). Longitudinal Changes in Semantic Concreteness in Semantic Variant Primary Progressive Aphasia (svPPA). *ENEURO*, *5*(6). https://doi.org/10.1523/ENEURO.0197-18.2018

Cousins, K. A. Q., York, C., Bauer, L., & Grossman, M. (2016). Cognitive and anatomic double dissociation in the representation of concrete and abstract words in semantic variant and behavioral variant frontotemporal degeneration. *Neuropsychologia*, *84*, 244–251. https://doi.org/https://doi.org/10.1016/j.neuropsychologia.2016.02.025

Craig, A. D. (2003). Interoception: The sense of the physiological condition of the body. In *Current Opinion in Neurobiology* (Vol. 13, Number 4, pp. 500–505). Elsevier Ltd. https://doi.org/10.1016/S0959-4388(03)00090-4

Craig, A. D. (2009). How do you feel—now? The anterior insula and human awareness. *Nature Reviews Neuroscience*, *10*(1), 59–70.

Critchley, H. D., & Garfinkel, S. N. (2017). Interoception and emotion. *Current Opinion in Psychology*, *17*, 7–14.

Critchley, H. D., & Harrison, N. A. (2013). Visceral influences on brain and behavior. *Neuron*, *77*(4), 624–638.

Critchley, H. D., Wiens, S., Rotshtein, P., Öhman, A., & Dolan, R. J. (2004). Neural systems supporting interoceptive awareness. *Nature Neuroscience*, *7*(2), 189–195. https://doi.org/10.1038/nn1176

Crutch, S. J., Connell, S., & Warrington, E. K. (2009). The different representational frameworks underpinning abstract and concrete knowledge: Evidence from odd-one-out judgements. *Quarterly Journal of Experimental Psychology*, *62*(7), 1377–1390. https://doi.org/10.1080/17470210802483834

Crutch, S. J., Troche, J., Reilly, J., & Ridgway, G. R. (2013). Abstract conceptual feature ratings: the role of emotion, magnitude, and other cognitive domains in the organization of abstract conceptual knowledge. *Frontiers in Human Neuroscience*, *7*, 186.

Crutch, S. J., & Warrington, E. K. (2005). Abstract and concrete concepts have structurally different representational frameworks. *Brain*, *128*(3), 615–627. https://doi.org/10.1093/brain/awh349

Crutch, S. J., & Warrington, E. K. (2006). Partial knowledge of abstract words in patients with cortical degenerative conditions. *NEUROPSYCHOLOGY*, *20*(4), 482–489. https://doi.org/10.1037/0894-4105.20.4.482

Crutch, S. J., & Warrington, E. K. (2010). The differential dependence of abstract and concrete words upon associative and similarity-based information: Complementary semantic interference and facilitation effects. *Cognitive Neuropsychology*, *27*(1), 46–71.

Dehaene, S., Bossini, S., & Giraux, P. (1993). The Mental Representation of Parity and Number Magnitude Access to Parity and Magnitude Knowledge During Number Processing. In *Journal of Experimental Psychology: General* (Vol. 122, Number 3).

Del Maschio, N., Fedeli, D., Garofalo, G., & Buccino, G. (2022). Evidence for the Concreteness of Abstract Language: A Meta-Analysis of Neuroimaging Studies. In *Brain Sciences* (Vol. 12, Number 1). MDPI. https://doi.org/10.3390/brainsci12010032

Della Rosa, P. A., Catricalà, E., Canini, M., Vigliocco, G., & Cappa, S. F. (2018). The left inferior frontal gyrus: A neural crossroads between abstract and concrete knowledge. *NeuroImage*, *175*, 449–459. https://doi.org/10.1016/j.neuroimage.2018.04.021

Della Rosa, P. A., Catricalà, E., De Battisti, S., Vinson, D., Vigliocco, G., & Cappa, S. F. (2014). How to assess abstract conceptual knowledge: construction, standardization and validation of a new battery of semantic memory tests. *Functional Neurology*, *29*(1), 47.

Della Rosa, P. A., Catricalà, E., Vigliocco, G., & Cappa, S. F. (2010). Beyond the abstract—concrete dichotomy: Mode of acquisition, concreteness, imageability, familiarity, age of acquisition, context availability, and abstractness norms for a set of 417 Italian words. *Behavior Research Methods*, *42*, 1042–1048.

Desai, R. H., Reilly, M., & Van Dam, W. (2018). The multifaceted abstract brain. In *Philosophical Transactions of the Royal Society B: Biological Sciences* (Vol. 373, Number 1752). Royal Society Publishing. https://doi.org/10.1098/rstb.2017.0122

Desmedt, O., Corneille, O., Luminet, O., Murphy, J., Bird, G., & Maurage, P. (2020). Contribution of Time Estimation and Knowledge to Heartbeat Counting Task Performance under Original and Adapted Instructions. *Biological Psychology*, *154*, 107904. https://doi.org/https://doi.org/10.1016/j.biopsycho.2020.107904

Devereux, B. J., Clarke, A., Marouchos, A., & Tyler, L. K. (2013). Representational similarity analysis reveals commonalities and differences in the semantic processing of words and objects. *Journal of Neuroscience*, *33*(48), 18906–18916. https://doi.org/10.1523/JNEUROSCI.3809-13.2013

Di Cesare, G., Marchi, M., Errante, A., Fasano, F., & Rizzolatti, G. (2018). Mirroring the social aspects of speech and actions: the role of the insula. *Cerebral Cortex*, *28*(4), 1348–1357.

di Luca, S., & Mauro, P. (2011). Finger numeral representations: More than just another symbolic code. In *Frontiers in Psychology* (Vol. 2, Number NOV). https://doi.org/10.3389/fpsyg.2011.00272

Diveica, V., Pexman, P. M., & Binney, R. J. (2023). Quantifying social semantics: An inclusive definition of socialness and ratings for 8388 English words. *Behavior Research Methods*, *55*(2), 461–473.

Dixon, M. L., Thiruchselvam, R., Todd, R., & Christoff, K. (2017). Emotion and the prefrontal cortex: An integrative review. *Psychological Bulletin*, *143*(10), 1033–1081. https://doi.org/10.1037/bul0000096

Dreyer, F. R., Frey, D., Arana, S., Saldern, S. von, Picht, T., Vajkoczy, P., & Pulvermüller, F. (2015). Is the motor system necessary for processing action and abstract emotion words? Evidence from focal brain lesions. *Frontiers in Psychology*, *6*(NOV). https://doi.org/10.3389/fpsyg.2015.01661

Dreyer, F. R., & Pulvermüller, F. (2018). Abstract semantics in the motor system? – An event-related fMRI study on passive reading of semantic word categories carrying abstract emotional and mental meaning. *Cortex*, *100*, 52–70. https://doi.org/10.1016/j.cortex.2017.10.021

Duerden, E. G., Arsalidou, M., Lee, M., & Taylor, M. J. (2013). Lateralization of affective processing in the insula. *Neuroimage*, *78*, 159–175.

Eger, E., Sterzer, P., Russ, M. O., Giraud, A.-L., & Kleinschmidt, A. (2003). A Supramodal Number Representation in Human Intraparietal Cortex. *Neuron*, *37*(4), 719–726. https://doi.org/10.1016/S0896-6273(03)00036-9

Engell, A. D., & Haxby, J. V. (2007). Facial expression and gaze-direction in human superior temporal sulcus. *Neuropsychologia*, *45*(14), 3234–3241. https://doi.org/https://doi.org/10.1016/j.neuropsychologia.2007.06.022

Etkin, A., Egner, T., & Kalisch, R. (2011). Emotional processing in anterior cingulate and medial prefrontal cortex. In *Trends in Cognitive Sciences* (Vol. 15, Number 2, pp. 85–93). https://doi.org/10.1016/j.tics.2010.11.004

Ettinger, A., & Linzen, T. (2016). Evaluating vector space models using human semantic priming results. *Proceedings of the 1st Workshop on Evaluating Vector-Space Representations for NLP*, 72–77.

Fairhall, S. L., & Caramazza, A. (2013). Brain regions that represent amodal conceptual knowledge. *Journal of Neuroscience*, *33*(25), 10552–10558. https://doi.org/10.1523/JNEUROSCI.0051-13.2013

Farah, M. J., & McClelland, J. L. (1991). A computational model of semantic memory impairment: modality specificity and emergent category specificity. *Journal of Experimental Psychology: General*, *120*(4), 339.

Farahibozorg, S. R., Henson, R. N., Woollams, A. M., & Hauk, O. (2022). Distinct roles for the anterior temporal lobe and angular gyrus in the spatiotemporal cortical semantic network. *Cerebral Cortex*, *32*(20), 4549–4564. https://doi.org/10.1093/cercor/bhab501

Faust, M., & Kenett, Y. N. (2014). Rigidity, chaos and integration: hemispheric interaction and individual differences in metaphor comprehension. *Frontiers in Human Neuroscience*, *Volume 8-2014*. https://www.frontiersin.org/journals/human-neuroscience/articles/10.3389/fnhum.2014.00511

Feldman, M. J., Jolink, T. A., Alvarez, G. M., Fendinger, N. J., Gaudier-Diaz, M. M., Lindquist, K. A., & Muscatell, K. A. (2023). The roles of inflammation, affect, and interoception in predicting social perception. *Brain, Behavior, and Immunity*, *112*, 246–253.

Fellbaum, C. (2010). WordNet. In R. Poli, M. Healy, & A. Kameas (Eds.), *Theory and Applications of Ontology: Computer Applications* (pp. 231–243). Springer Netherlands. https://doi.org/10.1007/978-90-481-8847-5_10

Feng, C., Gu, R., Li, T., Wang, L., Zhang, Z., Luo, W., & Eickhoff, S. B. (2021). Separate neural networks of implicit emotional processing between pictures and words: a coordinate-based meta-analysis of brain imaging studies. *Neuroscience & Biobehavioral Reviews*, *131*, 331–344.

Fernandino, L., Binder, J. R., Desai, R. H., Pendl, S. L., Humphries, C. J., Gross, W. L., Conant, L. L., & Seidenberg, M. S. (2016). Concept Representation Reflects Multimodal Abstraction: A Framework for Embodied Semantics. *Cerebral Cortex*, *26*(5), 2018–2034. https://doi.org/10.1093/cercor/bhv020

Fernandino, L., Tong, J.-Q., Conant, L. L., Humphries, C. J., & Binder, J. R. (2022). Decoding the information structure underlying the neural representation of concepts. *Proceedings of the National Academy of Sciences*, *119*(6), e2108091119.

Ferrante, O., Liu, L., Minarik, T., Gorska, U., Ghafari, T., Luo, H., & Jensen, O. (2022). FLUX: A pipeline for MEG analysis. *NeuroImage*, *253*, 119047.

Ferré, P., Guasch, M., Stadthagen-González, H., Hinojosa, J. A., Fraga, I., Marín, J., & Pérez-Sánchez, M. Á. (2024). What makes a word a good representative of the category of "emotion"? The role of feelings and interoception. *Emotion*, *24*(3), 745.

Fischer, M. H. (2008). Finger counting habits modulate spatial-numerical associations. *Cortex*, *44*(4), 386–392. https://doi.org/10.1016/j.cortex.2007.08.004

Fischer, M. H., & Shaki, S. (2018). Number concepts: Abstract and embodied. In *Philosophical Transactions of the Royal Society B: Biological Sciences* (Vol. 373, Number 1752). Royal Society Publishing. https://doi.org/10.1098/rstb.2017.0125

Fleming, K., Kim, S. H., Doo, M., Maguire, G., & Potkin, S. G. (2003). Memory for emotional stimuli in patients with Alzheimer's disease. *American Journal of Alzheimer's Disease and Other Dementias*, *18*(6), 340–342. https://doi.org/10.1177/153331750301800604

Fliessbach, K., Weis, S., Klaver, P., Elger, C. E., & Weber, B. (2006). The effect of word concreteness on recognition memory. *NeuroImage*, *32*(3), 1413–1421. https://doi.org/https://doi.org/10.1016/j.neuroimage.2006.06.007

Gallese, V., & Lakoff, G. (2005). The brain's concepts: The role of the sensory-motor system in conceptual knowledge. *Cognitive Neuropsychology*, *22*(3–4), 455–479.

Gao, Q., Ping, X., & Chen, W. (2019). Body influences on social cognition through interoception. *Frontiers in Psychology*, *10*, 2066.

Garfinkel, S. N., & Critchley, H. D. (2013). Interoception, emotion and brain: new insights link internal physiology to social behaviour. Commentary on: "Anterior insular cortex mediates bodily sensibility and social anxiety" by Terasawa et al.(2012). *Social Cognitive and Affective Neuroscience*, *8*(3), 231–234.

Gasquoine, P. G. (2014). Contributions of the insula to cognition and emotion. In *Neuropsychology Review* (Vol. 24, Number 2, pp. 77–87). Springer New York LLC. https://doi.org/10.1007/s11065-014-9246-9

Geraudie, A., Battista, P., García, A. M., Allen, I. E., Miller, Z. A., Gorno-Tempini, M. L., & Montembeault, M. (2021). Speech and language impairments in behavioral variant frontotemporal dementia: A systematic review. *Neuroscience & Biobehavioral Reviews*, *131*, 1076–1095. https://doi.org/https://doi.org/10.1016/j.neubiorev.2021.10.015

Giari, G., Leonardelli, E., Tao, Y., Machado, M., & Fairhall, S. L. (2020). Spatiotemporal properties of the neural representation of conceptual content for words and pictures – an MEG study. *NeuroImage*, *219*. https://doi.org/10.1016/j.neuroimage.2020.116913

Giffard, B., Laisney, M., Desgranges, B., & Eustache, F. (2015). An exploration of the semantic network in Alzheimer's disease: Influence of emotion and concreteness of concepts. *Cortex*, *69*, 201–211. https://doi.org/https://doi.org/10.1016/j.cortex.2015.05.020

Glenberg, A. M., Sato, M., & Cattaneo, L. (2008). Use-induced motor plasticity affects the processing of abstract and concrete language. *Current Biology*, *18*(7), R290–R291. https://doi.org/https://doi.org/10.1016/j.cub.2008.02.036

Glenberg, A. M., Sato, M., Cattaneo, L., Riggio, L., Palumbo, D., & Buccino, G. (2008). Processing abstract language modulates motor system activity. *Quarterly Journal of Experimental Psychology*, *61*(6), 905–919. https://doi.org/10.1080/17470210701625550

Göbel, S. M., Rushworth, M. F., & Walsh, V. (2006). Inferior Parietal RTMS Affects Performance in an Addition Task. *Cortex*, *42*(5), 774–781. https://doi.org/https://doi.org/10.1016/S0010-9452(08)70416-7

González-Arias, M., & Aracena, D. (2022). Are the concepts of emotion special? A comparison between basic-emotion, secondary-emotion, abstract, and concrete words. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.915165

Goodglass, H., & Kaplan, E. (1983). Boston diagnostic aphasia examination (BDAE) lea and febiger. *Philadelphia, Pennsylvania*.

Goodglass, H., Kaplan, E., & Barressi, B. (1983). Cookie theft picture. *Boston Diagnostic Aphasia Examination. Philadelphia, PA: Lea & Febiger*.

Gorno-Tempini, M. L., Dronkers, N. F., Rankin, K. P., Ogar, J. M., Phengrasamy, L., Rosen, H. J., Johnson, J. K., Weiner, M. W., & Miller, B. L. (2004). Cognition and anatomy in three variants of primary progressive aphasia. *Annals of Neurology: Official Journal of the American Neurological Association and the Child Neurology Society*, *55*(3), 335–346.

Gorno-Tempini, M. L., Hillis, A. E., Weintraub, S., Kertesz, A., Mendez, M., Cappa, S. F., Ogar, J. M., Rohrer, J. D., Black, S., Boeve, B. F., Manes, F., Dronkers, N. F., Vandenberghe, R., Rascovsky, K., Patterson, K., Miller, B. L., Knopman, D. S., Hodges, J. R., Mesulam, M. M., & Grossman, M. (2011). Classification of primary progressive aphasia and its variants. *Neurology*, *76*(11), 1006–1014. https://doi.org/10.1212/WNL.0b013e31821103e6

Graves, W. W., Levinson, H. J., Staples, R., Boukrina, O., Rothlein, D., & Purcell, J. (2024). An inclusive multivariate approach to neural localization of language components. *Brain Structure and Function*, *229*(5), 1243–1263. https://doi.org/10.1007/s00429-024-02800-9

Grecucci, A., Giorgetta, C., Bonini, N., & Sanfey, A. G. (2013). Reappraising social emotions: the role of inferior frontal gyrus, temporo-parietal junction and insula in interpersonal emotion regulation. *Frontiers in Human Neuroscience*, *7*, 523.

Grindrod, C. M., Bilenko, N. Y., Myers, E. B., & Blumstein, S. E. (2008). The role of the left inferior frontal gyrus in implicit semantic competition and selection: An event-related fMRI study. *Brain Research*, *1229*, 167–178. https://doi.org/https://doi.org/10.1016/j.brainres.2008.07.017

Grootswagers, T., Wardle, S. G., & Carlson, T. A. (2017). Decoding dynamic brain patterns from evoked responses: A tutorial on multivariate pattern analysis applied to time series neuroimaging data. *Journal of Cognitive Neuroscience*, *29*(4), 677–697.

Grossman, M., Koenig, P., DeVita, C., Glosser, G., Alsop, D., Detre, J., & Gee, J. (2002). Neural representation of verb meaning: An fMRI study. *Human Brain Mapping*, *15*(2), 124–134. https://doi.org/https://doi.org/10.1002/hbm.10117

Gu, X., Hof, P. R., Friston, K. J., & Fan, J. (2013). Anterior insular cortex and emotional awareness. *Journal of Comparative Neurology*, *521*(15), 3371–3388.

Günther, F., Dudschig, C., & Kaup, B. (2015). LSAfun - An R package for computations based on Latent Semantic Analysis. *Behavior Research Methods*, *47*(4), 930–944. https://doi.org/10.3758/s13428-014-0529-0

Hamilton, M., & Rajaram, S. (2001). The Concreteness Effect in Implicit and Explicit Memory Tests. *Journal of Memory and Language*, *44*(1), 96–117. https://doi.org/https://doi.org/10.1006/jmla.2000.2749

Harpaintner, M., Trumpp, N. M., & Kiefer, M. (2018). The semantic content of abstract concepts: A property listing study of 296 abstract words. *Frontiers in Psychology*, *9*(SEP). https://doi.org/10.3389/fpsyg.2018.01748

Hartig, F., & Hartig, M. F. (2017). Package 'DHARMa.' *R Package*.

Hauk, O., Johnsrude, I., & Pulvermüller, F. (2004). Somatotopic Representation of Action Words in Human Motor and Premotor Cortex. *Neuron*, *41*(2), 301–307. https://doi.org/10.1016/S0896-6273(03)00838-9

Hayashi, M. J., Kanai, R., Tanabe, H. C., Yoshida, Y., Carlson, S., Walsh, V., & Sadato, N. (2013). Interaction of numerosity and time in prefrontal and parietal cortex. *Journal of Neuroscience*, *33*(3), 883–893. https://doi.org/10.1523/JNEUROSCI.6257-11.2013

Henco, L., Brandi, M.-L., Lahnakoski, J. M., Diaconescu, A. O., Mathys, C., & Schilbach, L. (2020). Bayesian modelling captures inter-individual differences in social belief computations in the putamen and insula. *Cortex*, *131*, 221–236.

Hoenig, K., Sim, E.-J., Bochev, V., Herrnberger, B., & Kiefer, M. (2008). Conceptual Flexibility in the Human Brain: Dynamic Recruitment of Semantic Maps from Visual, Motor, and Motion-related Areas. *Journal of Cognitive Neuroscience*, *20*(10), 1799–1814. https://doi.org/10.1162/jocn.2008.20123

Hoffman, P., & Bair, M. (2025). How do brain regions specialised for concrete and abstract concepts align with functional brain networks? A neuroimaging meta-analysis. In *Neuroscience and Biobehavioral Reviews* (Vol. 174). Elsevier Ltd. https://doi.org/10.1016/j.neubiorev.2025.106214

Hoffman, P., Binney, R. J., & Lambon Ralph, M. A. (2015). Differing contributions of inferior prefrontal and anterior temporal cortex to concrete and abstract conceptual knowledge. *Cortex*, *63*, 250–266. https://doi.org/https://doi.org/10.1016/j.cortex.2014.09.001

Hoffman, P., Jones, R. W., & Lambon Ralph, M. A. (2013). Be concrete to be comprehended: Consistent imageability effects in semantic dementia for nouns, verbs, synonyms and associates. *Cortex*, *49*(5), 1206–1218. https://doi.org/10.1016/j.cortex.2012.05.007

Hoffman, P., Jones, R. W., & Ralph, M. A. L. (2012). The degraded concept representation system in semantic dementia: damage to pan-modal hub, then visual spoke. *Brain*, *135*(12), 3770–3780.

Hoffman, P., Lambon Ralph, M. A., & Rogers, T. T. (2013). Semantic diversity: A measure of semantic ambiguity based on variability in the contextual usage of words. *Behavior Research Methods*, *45*(3), 718–730. https://doi.org/10.3758/s13428-012-0278-x

Hoffman, P., Meteyard, L., & Patterson, K. (2014). Broadly speaking: Vocabulary in semantic dementia shifts towards general, semantically diverse words. *Cortex*, *55*, 30–42. https://doi.org/https://doi.org/10.1016/j.cortex.2012.11.004

Hoffman, P., & Ralph, M. A. L. (2011). Reverse concreteness effects are not a typical feature of semantic dementia: Evidence for the hub-and-spoke model of conceptual representation. *Cerebral Cortex*, *21*(9), 2103–2112. https://doi.org/10.1093/cercor/bhq288

Howard, D., & Patterson, K. E. (1992). *The pyramids and palm trees test*.

Hsieh, S., Foxe, D., Leslie, F., Savage, S., Piguet, O., & Hodges, J. R. (2012). Grief and joy: emotion word comprehension in the dementias. *Neuropsychology*, *26*(5), 624.

Hubbard, E. M., Piazza, M., Pinel, P., & Dehaene, S. (2005). Interactions between number and space in parietal cortex. *Nature Reviews Neuroscience*, *6*(6), 435–448. https://doi.org/10.1038/nrn1684

Hultén, A., van Vliet, M., Kivisaari, S., Lammi, L., Lindh-Knuutila, T., Faisal, A., & Salmelin, R. (2021). The neural representation of abstract words may arise through grounding word meaning in language itself. *Human Brain Mapping*, *42*(15), 4973–4984.

Huth, A. G., De Heer, W. A., Griffiths, T. L., Theunissen, F. E., & Gallant, J. L. (2016). Natural speech reveals the semantic maps that tile human cerebral cortex. *Nature*, *532*(7600), 453–458. https://doi.org/10.1038/nature17637

Immordino-Yang, M. H., Yang, X.-F., & Damasio, H. (2014). Correlations between social-emotional feelings and anterior insula activity are independent from visceral states but influenced by culture. *Frontiers in Human Neuroscience*, *8*, 728.

Jackson, R. L. (2021). The neural correlates of semantic control revisited. *NeuroImage*, *224*, 117444. https://doi.org/https://doi.org/10.1016/j.neuroimage.2020.117444

James, C. T. (1975). The Role of Semantic Information in Lexical Decisions. In *Journal of Experimental Psychology: Human Perception and Performance* (Vol. 104, Number 2).

James, W. (1884). What is an Emotion? *Mind*, *9*(34), 188–205. http://www.jstor.org/stable/2246769

Jefferies, E., Patterson, K., Jones, R. W., & Lambon Ralph, M. A. (2009). Comprehension of concrete and abstract words in semantic dementia. *Neuropsychology*, *23*, 492–499. https://doi.org/10.1037/a0015452

Jones, C. S. (1985). An empirical study of the evidence for contingency theories of management accounting systems in conditions of rapid change. *Accounting, Organizations and Society*, *10*(3), 303–328. https://doi.org/https://doi.org/10.1016/0361-3682(85)90022-4

Joubert, S., Vallet, G. T., Montembeault, M., Boukadi, M., Wilson, M. A., Laforce, R., Rouleau, I., & Brambati, S. M. (2017). Comprehension of concrete and abstract words in semantic variant primary progressive aphasia and Alzheimer's disease: A behavioral and neuroimaging study. *BRAIN AND LANGUAGE*, *170*, 93–102. https://doi.org/10.1016/j.bandl.2017.04.004

Kafkas, A., Mayes, A. R., & Montaldi, D. (2023). The hippocampus assumes a special role in supporting abstract concept representation. *BioRxiv*, 2023.07.04.547678. https://doi.org/10.1101/2023.07.04.547678

Kaiser, D., Jacobs, A. M., & Cichy, R. M. (2022). Modelling brain representations of abstract concepts. *PLoS Computational Biology*, *18*(2), e1009837.

Kiefer, M., & Pulvermüller, F. (2012). Conceptual representations in mind and brain: Theoretical developments, current evidence and future directions. In *Cortex* (Vol. 48, Number 7, pp. 805–825). https://doi.org/10.1016/j.cortex.2011.04.006

Kleiner, M., Brainard, D., & Pelli, D. (2007). *What's new in Psychtoolbox-3?*

Kousta, S.-T., Vigliocco, G., Vinson, D. P., Andrews, M., & Del Campo, E. (2011). The representation of abstract words: why emotion matters. *Journal of Experimental Psychology: General*, *140*(1), 14.

Kriegeskorte, N., Mur, M., & Bandettini, P. A. (2008). Representational similarity analysis-connecting the branches of systems neuroscience. *Frontiers in Systems Neuroscience*, *2*, 249.

Kumfor, F., Landin-Romero, R., Devenney, E., Hutchings, R., Grasso, R., Hodges, J. R., & Piguet, O. (2016). On the right side? A longitudinal study of left-versus right-lateralized semantic dementia. *Brain*, *139*(3), 986–998.

Kutas, M., & Federmeier, K. D. (2011). Thirty years and counting: Finding meaning in the N400 component of the event-related brain potential (ERP). *Annual Review of Psychology*, *62*, 621–647. https://doi.org/10.1146/annurev.psych.093008.131123

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest Package: Tests in Linear Mixed Effects Models. *Journal of Statistical Software*, *82*(13), 1–26. https://doi.org/10.18637/jss.v082.i13

Lambon Ralph, M. A., Patterson, K., Garrard, P., & Hodges, J. R. (2003). Semantic dementia with category specificity: acomparative case-series study. *Cognitive Neuropsychology*, *20*(3–6), 307–326.

Lambon Ralph, M. A., Sage, K., Jones, R. W., & Mayberry, E. J. (2010). Coherent concepts are computed in the anterior temporal lobes. *Proceedings of the National Academy of Sciences of the United States of America*, *107*(6), 2717–2722. https://doi.org/10.1073/pnas.0907307107

Landauer, T. K., & Dumais, S. T. (1997). A solution to Plato's problem: The latent semantic analysis theory of acquisition, induction, and representation of knowledge. *Psychological Review*, *104*(2), 211.

Lau, E. F., Phillips, C., & Poeppel, D. (2008). A cortical network for semantics: (De)constructing the N400. In *Nature Reviews Neuroscience* (Vol. 9, Number 12, pp. 920–933). https://doi.org/10.1038/nrn2532

Lau, T., Gershman, S. J., & Cikara, M. (2020). Social structure learning in human anterior insula. *Elife*, *9*, e53162.

Lebois, L. A. M., Wilson-Mendenhall, C. D., Simmons, W. K., Barrett, L. F., & Barsalou, L. W. (2020). Learning situated emotions. *Neuropsychologia*, *145*, 106637.

Lenci, A., Lebani, G. E., & Passaro, L. C. (2018). The Emotions of Abstract Words: A Distributional Semantic Analysis. *Topics in Cognitive Science*, *10*(3), 550–572. https://doi.org/10.1111/tops.12335

Lenth, R., & Lenth, M. R. (2018). Package 'lsmeans.' *The American Statistician*, *34*(4), 216–221.

Leonardelli, E., & Fairhall, S. L. (2022). Similarity-based fMRI-MEG fusion reveals hierarchical organisation within the brain's semantic system. *NeuroImage*, *259*. https://doi.org/10.1016/j.neuroimage.2022.119405

Levelt, W. J. M. (1993). *Speaking: From intention to articulation*. MIT press.

Li, J., Du, D., Gao, W., Sun, X., Xie, H., Zhang, G., Li, J., Li, H., & Li, K. (2017). The regional neuronal activity in left posterior middle temporal gyrus is correlated with the severity of chronic aphasia. *Neuropsychiatric Disease and Treatment*, *13*(null), 1937–1945. https://doi.org/10.2147/NDT.S140091

Li, W., Xu, Q., Liu, S., Yu, L., Yang, Y., Zhang, L., & He, X. (2022). Emotion concept in perception of facial expressions: Effects of emotion-label words and emotion-laden words. *Neuropsychologia*, *174*. https://doi.org/10.1016/j.neuropsychologia.2022.108345

Li, Y., Hu, Y., Wang, Y., Weng, J., & Chen, F. (2013). Individual structural differences in left inferior parietal area are associated with schoolchildrens' arithmetic scores. *Frontiers in*

Human Neuroscience, *Volume 7-2013*. https://www.frontiersin.org/journals/human-neuroscience/articles/10.3389/fnhum.2013.00844

Lindquist, K. A., Wager, T. D., Kober, H., Bliss-Moreau, E., & Barrett, L. F. (2012). The brain basis of emotion: A meta-analytic review. In *Behavioral and Brain Sciences* (Vol. 35, Number 3, pp. 121–143). https://doi.org/10.1017/S0140525X11000446

Liuzzi, A. G., Bruffaerts, R., Dupont, P., Adamczuk, K., Peeters, R., De Deyne, S., Storms, G., & Vandenberghe, R. (2015). Left perirhinal cortex codes for similarity in meaning between written words: comparison with auditory word input. *Neuropsychologia*, *76*, 4–16.

Liuzzi, A. G., Bruffaerts, R., Peeters, R., Adamczuk, K., Keuleers, E., De Deyne, S., Storms, G., Dupont, P., & Vandenberghe, R. (2017). Cross-modal representation of spoken and written word meaning in left pars triangularis. *Neuroimage*, *150*, 292–307.

Loiselle, M., Rouleau, I., Nguyen, D. K., Dubeau, F., Macoir, J., Whatmough, C., Lepore, F., & Joubert, S. (2012). Comprehension of concrete and abstract words in patients with selective anterior temporal lobe resection and in patients with selective amygdalo-hippocampectomy. *Neuropsychologia*, *50*(5), 630–639. https://doi.org/https://doi.org/10.1016/j.neuropsychologia.2011.12.023

Lüdecke, D. (2018). ggeffects: Tidy Data Frames of Marginal Effects from Regression Models. *Journal of Open Source Software*, *3*(26), 772. https://doi.org/10.21105/joss.00772

Lüdecke, M. D. (2023). *Package 'sjPlot.'*

Lugli, L., Baroni, G., Anelli, F., Borghi, A. M., & Nicoletti, R. (2013). Counting Is Easier while Experiencing a Congruent Motion. *PLoS ONE*, *8*(5). https://doi.org/10.1371/journal.pone.0064500

Lugli, L., D'Ascenzo, S., Borghi, A. M., & Nicoletti, R. (2018). Clock walking and gender: How circular movements influence arithmetic calculations. *Frontiers in Psychology*, *9*(SEP). https://doi.org/10.3389/fpsyg.2018.01599

Lupyan, G., & Winter, B. (2018). Language is more abstract than you think, or, why aren't languages more iconic? In *Philosophical Transactions of the Royal Society B: Biological Sciences* (Vol. 373, Number 1752). Royal Society Publishing. https://doi.org/10.1098/rstb.2017.0137

Lynott, D., Connell, L., Brysbaert, M., Brand, J., & Carney, J. (2020). The Lancaster Sensorimotor Norms: multidimensional measures of perceptual and action strength for 40,000 English words. *Behavior Research Methods*, *52*(3), 1271–1291. https://doi.org/10.3758/s13428-019-01316-z

Macoir, J. (2009). Is a plum a memory problem? Longitudinal study of the reversal of concreteness effect in a patient with semantic dementia. *NEUROPSYCHOLOGIA*, *47*(2), 518–535. https://doi.org/10.1016/j.neuropsychologia.2008.10.006

Macoir, J., Laforce, R., Brisson, M., & Wilson, M. A. (2015). Preservation of lexical-semantic knowledge of adjectives in the semantic variant of primary progressive aphasia:

Implications for theoretical models of semantic memory. *JOURNAL OF NEUROLINGUISTICS*, *34*, 1–14. https://doi.org/10.1016/j.jneuroling.2014.11.003

Magnusson, A., Skaug, H., Nielsen, A., Berg, C., Kristensen, K., Maechler, M., van Bentham, K., Bolker, B., Brooks, M., & Brooks, M. M. (2017). Package 'glmmtmb.' *R Package Version 0.2. 0*, *25*.

Mahon, B. Z., & Caramazza, A. (2009). Concepts and categories: A cognitive neuropsychological perspective. *Annual Review of Psychology*, *60*(1), 27–51.

Mai, S., Braun, J., Probst, V., Kammer, T., & Pollatos, O. (2019). Changes in emotional processing following interoceptive network stimulation with rTMS. *Neuroscience*, *406*, 405–419.

Mancano, M., & Papagno, C. (2023). Concrete and Abstract Concepts in Primary Progressive Aphasia and Alzheimer's Disease: A Scoping Review. *Brain Sciences*, *13*(5). https://doi.org/10.3390/brainsci13050765

Mancano, M., & Papagno, C. (2026). Emotional and Social Dimension of Abstract Concepts Meet with Interoception in Right Anterior Insula. *The Journal of Neuroscience*, *46*(2), e0238252025. https://doi.org/10.1523/JNEUROSCI.0238-25.2025

Marelli, M. (2017). Word-Embeddings Italian Semantic Spaces: a semantic model for psycholinguistic research. *Psihologija*, *50*. https://doi.org/10.2298/PSI161208011M

Maris, E., & Oostenveld, R. (2007). Nonparametric statistical testing of EEG-and MEG-data. *Journal of Neuroscience Methods*, *164*(1), 177–190.

Martin, A., & Fedio, P. (1983). Word production and comprehension in Alzheimer's disease: The breakdown of semantic knowledge. *Brain and Language*, *19*(1), 124–141.

Martin, S., Ferrante, M., Bruera, A., & Hartwigsen, G. (2025). Causal contributions of left inferior and medial frontal cortex to semantic and executive control. *Communications Biology*, *8*(1), 1343. https://doi.org/10.1038/s42003-025-08848-5

Martínez-Nicolás, I., Carro, J., Llorente, T. E., & Meilán, J. J. G. (2019). The deterioration of semantic networks in Alzheimer's disease. *Exon Publications*, 179–191.

Mattarozzi, K., Colonnello, V., Thayer, J. F., & Ottaviani, C. (2019). Trusting your heart: Long-term memory for bad and good people is influenced by resting vagal tone. *Consciousness and Cognition*, *75*, 102810.

Meersmans, K., Bruffaerts, R., Jamoulle, T., Liuzzi, A. G., De Deyne, S., Storms, G., Dupont, P., & Vandenberghe, R. (2020). Representation of associative and affective semantic similarity of abstract words in the lateral temporal perisylvian language regions. *Neuroimage*, *217*, 116892.

Meersmans, K., Storms, G., De Deyne, S., Bruffaerts, R., Dupont, P., & Vandenberghe, R. (2022). Orienting to different dimensions of word meaning alters the representation of word meaning in early processing regions. *Cerebral Cortex*, *32*(15), 3302–3317. https://doi.org/10.1093/cercor/bhab416

Merck, C., Jonin, P.-Y., Laisney, M., Vichard, H., & Belliard, S. (2014). When the zebra loses its stripes but is still in the savannah: Results from a semantic priming paradigm in semantic dementia. *Neuropsychologia*, *53*, 221–232.

Meteyard, L., Cuadrado, S. R., Bahrami, B., & Vigliocco, G. (2012). Coming of age: A review of embodiment and the neuroscience of semantics. *Cortex*, *48*(7), 788–804. https://doi.org/10.1016/j.cortex.2010.11.002

Mirman, D., Landrigan, J. F., & Britt, A. E. (2017). Taxonomic and thematic semantic systems. *Psychological Bulletin*, *143*(5), 499–520. https://doi.org/10.1037/bul0000092

Moffat, M., Siakaluk, P. D., Sidhu, D. M., & Pexman, P. M. (2015). Situated conceptualization and semantic processing: effects of emotional experience and context availability in semantic categorization and naming tasks. *Psychonomic Bulletin & Review*, *22*(2), 408–419. https://doi.org/10.3758/s13423-014-0696-0

Montefinese, M., Ambrosini, E., Fairfield, B., & Mammarella, N. (2014). The adaptation of the affective norms for English words (ANEW) for Italian. *Behavior Research Methods*, *46*, 887–903.

Montefinese, M., Pinti, P., Ambrosini, E., Tachtsidis, I., & Vinson, D. (2021). Inferior parietal lobule is sensitive to different semantic similarity relations for concrete and abstract words. *Psychophysiology*, *58*(3), e13750.

Moseley, R., Carota, F., Hauk, O., Mohr, B., & Pulvermüller, F. (2012). A role for the motor system in binding abstract emotional meaning. *Cerebral Cortex*, *22*(7), 1634–1647.

Moseley, R. L., Shtyrov, Y., Mohr, B., Lombardo, M. V., Baron-Cohen, S., & Pulvermüller, F. (2015). Lost for emotion words: What motor and limbic brain activity reveals about autism and semantic theory. *NeuroImage*, *104*, 413–422. https://doi.org/10.1016/j.neuroimage.2014.09.046

Moss, H. E., Abdallah, S., Fletcher, P., Bright, P., Pilgrim, L., Acres, K., & Tyler, L. K. (2005). Selecting Among Competing Alternatives: Selection and Retrieval in the Left Inferior Frontal Gyrus. *Cerebral Cortex*, *15*(11), 1723–1735. https://doi.org/10.1093/cercor/bhi049

Moss, H. E., Tyler, L. K., Hodges, J. R., & Patterson, K. (1995). Exploring the loss of semantic memory in semantic dementia: Evidence from a primed monitoring study. *Neuropsychology*, *9*(1), 16.

Motomura, K., Terasawa, Y., Natsume, A., Iijima, K., Chalise, L., Sugiura, J., Yamamoto, H., Koyama, K., Wakabayashi, T., & Umeda, S. (2019). Anterior insular cortex stimulation and its effects on emotion recognition. *Brain Structure and Function*, *224*, 2167–2181.

Muraki, E. J., Pexman, P. M., & Binney, R. J. (2025). Mapping Contributions of the Anterior Temporal Semantic Hub to the Processing of Abstract and Concrete Verbs. *Human Brain Mapping*, *46*(6). https://doi.org/10.1002/hbm.70210

Muraki, E. J., Speed, L. J., & Pexman, P. M. (2023). Insights into embodied cognition and mental imagery from aphantasia. In *Nature Reviews Psychology* (Vol. 2, Number 10, pp. 591–605). Nature Publishing Group. https://doi.org/10.1038/s44159-023-00221-9

Nakai, T., & Sakai, K. L. (2014). Neural Mechanisms Underlying the Computation of Hierarchical Tree Structures in Mathematics. *PLOS ONE*, *9*(11), e111439-. https://doi.org/10.1371/journal.pone.0111439

Neary, D., Snowden, J. S., Gustafson, L., Passant, U., Stuss, D., Black, S., Freedman, M., Kertesz, A., Robert, P. H., & Albert, M. (1998). Frontotemporal lobar degeneration: a consensus on clinical diagnostic criteria. *Neurology*, *51*(6), 1546–1554.

Newcombe, P. I., Campbell, C., Siakaluk, P. D., & Pexman, P. M. (2012). Effects of emotional and sensorimotor knowledge in semantic processing of concrete and abstract nouns. *Frontiers in Human Neuroscience*, *6*, 275.

Nguyen, V. T., Breakspear, M., Hu, X., & Guo, C. C. (2016). The integration of the internal and external milieu in the insula during dynamic emotional experiences. *NeuroImage*, *124*, 455–463.

Niedenthal, P. M., Winkielman, P., Mondillon, L., & Vermeulen, N. (2009). Embodiment of Emotion Concepts. *Journal of Personality and Social Psychology*, *96*(6), 1120–1136. https://doi.org/10.1037/a0015574

Nieder, A., & Dehaene, S. (2009). Representation of number in the brain. In *Annual Review of Neuroscience* (Vol. 32, pp. 185–208). https://doi.org/10.1146/annurev.neuro.051508.135550

Norman, R., Taylor, J. S. H., & Rodd, J. M. (2025). The effects of contextual diversity on lexical processing: A scoping review. In *Psychonomic Bulletin and Review* (Vol. 32, Number 6, pp. 2763–2806). Springer. https://doi.org/10.3758/s13423-025-02761-y

Oldroyd, K., Pasupathi, M., & Wainryb, C. (2019). Social antecedents to the development of interoception: Attachment related processes are associated with interoception. *Frontiers in Psychology*, *10*, 413478.

Olson, I. R., McCoy, D., Klobusicky, E., & Ross, L. A. (2013). Social cognition and the anterior temporal lobes: A review and theoretical framework. *Social Cognitive and Affective Neuroscience*, *8*(2), 123–133. https://doi.org/10.1093/scan/nss119

Oostenveld, R., Fries, P., Maris, E., & Schoffelen, J.-M. (2011). FieldTrip: Open Source Software for Advanced Analysis of MEG, EEG, and Invasive Electrophysiological Data. *Computational Intelligence and Neuroscience*, *2011*(1), 156869. https://doi.org/https://doi.org/10.1155/2011/156869

Oosterhof, N. N., Connolly, A. C., & Haxby, J. V. (2016). CoSMoMVPA: Multi-modal multivariate pattern analysis of neuroimaging data in matlab/GNU octave. *Frontiers in Neuroinformatics*, *10*(JUL). https://doi.org/10.3389/fninf.2016.00027

Orena, E. F., Caldiroli, D., Acerbi, F., Barazzetta, I., & Papagno, C. (2019). Investigating the functional neuroanatomy of concrete and abstract word processing through direct electric stimulation (DES) during awake surgery. *Cognitive Neuropsychology*, *36*(3–4), 167–177. https://doi.org/10.1080/02643294.2018.1477748

Ouzzani, M., Hammady, H., Fedorowicz, Z., & Elmagarmid, A. (2016). Rayyan—a web and mobile app for systematic reviews. *Systematic Reviews*, *5*. https://doi.org/10.1186/s13643-016-0384-4

Paivio, A. (1991). Dual coding theory: Retrospect and current status. *Canadian Journal of Psychology/Revue Canadienne de Psychologie*, *45*(3), 255.

Paivio, A., Walsh, M., & Bons, T. (1994). Concreteness effects on memory: When and why? *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *20*(5), 1196.

Paivio, A., Yuille, J. C., & Madigan, S. A. (1968). Concreteness, imagery, and meaningfulness values for 925 nouns. *Journal of Experimental Psychology*, *76*(1p2), 1.

Palmer, S. D., MacGregor, L. J., & Havelka, J. (2013). Concreteness effects in single-meaning, multi-meaning and newly acquired words. *Brain Research*, *1538*, 135–150. https://doi.org/https://doi.org/10.1016/j.brainres.2013.09.015

Papagno, C. (1998). Transient Retrograde Amnesia Associated with Impaired Naming of Living Categories. *Cortex*, *34*(1), 111–121. https://doi.org/https://doi.org/10.1016/S0010-9452(08)70740-8

Papagno, C. (2022). The neural correlates of abstract and concrete words. *Handbook of Clinical Neurology*, *187*, 263–275. https://doi.org/10.1016/B978-0-12-823493-8.00018-3

Papagno, C., Capasso, R., & Miceli, G. (2009). Reversed concreteness effect for nouns in a subject with semantic dementia. *Neuropsychologia*, *47*(4), 1138–1148.

Papagno, C., Fogliata, A., Catricalà, E., & Miniussi, C. (2009). The lexical processing of abstract and concrete nouns. *Brain Research*, *1263*, 78–86. https://doi.org/10.1016/j.brainres.2009.01.037

Papagno, C., Martello, G., & Mattavelli, G. (2013). The neural correlates of abstract and concrete words: Evidence from brain-damaged patients. *Brain Sciences*, *3*(3), 1229–1243.

Papagno, C., Pisoni, A., Mattavelli, G., Casarotti, A., Comi, A., Fumagalli, F., Vernice, M., Fava, E., Riva, M., & Bello, L. (2016). Specific disgust processing in the left insula: new evidence from direct electrical stimulation. *Neuropsychologia*, *84*, 29–35.

Papeo, L., Agostini, B., & Lingnau, A. (2019). The Large-Scale Organization of Gestures and Words in the Middle Temporal Gyrus. *Journal of Neuroscience*, *39*(30), 5966–5974. https://doi.org/10.1523/JNEUROSCI.2668-18.2019

Parrinello, N., Napieralski, J., Gerlach, A. L., & Pohl, A. (2022). Embodied feelings–A meta-analysis on the relation of emotion intensity perception and interoceptive accuracy. *Physiology & Behavior*, *254*, 113904.

Patterson, K., & Lambon Ralph, M. A. (2015). The Hub-and-Spoke Hypothesis of Semantic Memory. In *Neurobiology of Language* (pp. 765–775). Elsevier Inc. https://doi.org/10.1016/B978-0-12-407794-2.00061-4

Patterson, K., Nestor, P. J., & Rogers, T. T. (2007). Where do you know what you know? The representation of semantic knowledge in the human brain. *Nature Reviews Neuroscience*, *8*(12), 976–987.

Pennington, J., Socher, R., & Manning, C. (2014). GloVe: Global Vectors for Word Representation. In A. Moschitti, B. Pang, & W. Daelemans (Eds.), *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)* (pp. 1532–1543). Association for Computational Linguistics. https://doi.org/10.3115/v1/D14-1162

Pereira, F., Gershman, S., Ritter, S., & Botvinick, M. (2016). A comparative evaluation of off-the-shelf distributed semantic representations for modelling behavioural data. *Cognitive Neuropsychology*, *33*(3–4), 175–190. https://doi.org/10.1080/02643294.2016.1176907

Pereira, F., Lou, B., Pritchett, B., Ritter, S., Gershman, S. J., Kanwisher, N., Botvinick, M., & Fedorenko, E. (2018). Toward a universal decoder of linguistic meaning from brain activation. *Nature Communications*, *9*(1). https://doi.org/10.1038/s41467-018-03068-4

Persichetti, A. S., Shao, J., Denning, J. M., Gotts, S. J., & Martin, A. (2024). Taxonomic structure in a set of abstract concepts. *Frontiers in Psychology*, *14*, 1278744.

Peters, F., Majerus, S., De Baerdemaeker, J., Salmon, E., & Collette, F. (2009). Impaired semantic knowledge underlies the reduced verbal short-term storage capacity in Alzheimer's disease. *Neuropsychologia*, *47*(14), 3067–3073. https://doi.org/10.1016/j.neuropsychologia.2009.07.002

Piazza, M., Pinel, P., Le Bihan, D., & Dehaene, S. (2007). A Magnitude Code Common to Numerosities and Number Symbols in Human Intraparietal Cortex. *Neuron*, *53*(2), 293–305. https://doi.org/10.1016/j.neuron.2006.11.022

Plaut, D. C., & Shallice, T. (1991). *Effects of Word Abstractness in a Connectionist Model of Deep Dyslexia*.

Plaut, D. C., & Shallice, T. (1993). Deep dyslexia: A case study of connectionist neuropsychology. *Cognitive Neuropsychology*, *10*(5), 377–500.

Pobric, G., Lambon Ralph, M. A., & Jefferies, E. (2009). The role of the anterior temporal lobes in the comprehension of concrete and abstract words: rTMS evidence. *Cortex*, *45*(9), 1104–1110. https://doi.org/https://doi.org/10.1016/j.cortex.2009.02.006

Pobric, G., Ralph, M. A. L., & Zahn, R. (2016). Hemispheric specialization within the superior anterior temporal cortex for social and nonsocial concepts. *Journal of Cognitive Neuroscience*, *28*(3), 351–360. https://doi.org/10.1162/jocn_a_00902

Pollatos, O., Gramann, K., & Schandry, R. (2007). Neural systems connecting interoceptive awareness and feelings. *Human Brain Mapping*, *28*(1), 9–18.

Pollatos, O., Herbert, B. M., Mai, S., & Kammer, T. (2016). Changes in interoceptive processes following brain stimulation. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *371*(1708). https://doi.org/10.1098/rstb.2016.0016

Pollatos, O., Matthias, E., & Keller, J. (2015). When interoception helps to overcome negative feelings caused by social exclusion. *Frontiers in Psychology*, *6*, 140662.

Pollatos, O., Schandry, R., Auer, D. P., & Kaufmann, C. (2007). Brain structures mediating cardiovascular arousal and interoceptive awareness. *Brain Research*, *1141*, 178–187.

Ponari, M., Norbury, C. F., & Vigliocco, G. (2018). Acquisition of abstract concepts is influenced by emotional valence. *Developmental Science*, *21*(2). https://doi.org/10.1111/desc.12549

Poos, J. M., Van Den Berg, E., Visch-Brink, E., Eikelboom, W. S., Franzen, S., Van Hemmen, J., Pijnenburg, Y. A. L., Satoer, D., Dopper, E. G. P., & van Swieten, J. C. (2022). Exploring abstract semantic associations in the frontotemporal dementia spectrum in a Dutch Population. *Archives of Clinical Neuropsychology*, *37*(1), 104–116.

Posner, J., Russell, J. A., & Peterson, B. S. (2005). The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. *Development and Psychopathology*, *17*(3), 715–734.

Pulvermüller, F. (2001). Brain reflections of words and their meaning. *Trends in Cognitive Sciences*, *5*(12), 517–524. https://doi.org/10.1016/S1364-6613(00)01803-9

Pulvermüller, F., Cooper-Pye, E., Dine, C., Hauk, O., Nestor, P. J., & Patterson, K. (2010). The Word Processing Deficit in Semantic Dementia: All Categories Are Equal, but Some Categories Are More Equal than Others. *Journal of Cognitive Neuroscience*, *22*(9), 2027–2041. https://doi.org/10.1162/jocn.2009.21339

Pulvermüller, F., Hauk, O., Nikulin, V. V., & Ilmoniemi, R. J. (2005). Functional links between motor and language systems. *European Journal of Neuroscience*, *21*(3), 793–797. https://doi.org/10.1111/j.1460-9568.2005.03900.x

Rascovsky, K., Hodges, J. R., Knopman, D., Mendez, M. F., Kramer, J. H., Neuhaus, J., Van Swieten, J. C., Seelaar, H., Dopper, E. G. P., & Onyike, C. U. (2011). Sensitivity of revised diagnostic criteria for the behavioural variant of frontotemporal dementia. *Brain*, *134*(9), 2456–2477.

Redcay, E., Velnoskey, K. R., & Rowe, M. L. (2016). Perceived communicative intent in gesture and language modulates the superior temporal sulcus. *Human Brain Mapping*, *37*(10), 3444–3461. https://doi.org/https://doi.org/10.1002/hbm.23251

Reilly, J., Cross, K., Troiani, V., & Grossman, M. (2007). Single-word semantic judgements in semantic dementia: Do phonology and grammatical class count? *Aphasiology*, *21*(6), 558–569. https://doi.org/10.1080/02687030701191986

Repetto, C., Rodella, C., Conca, F., Santi, G. C., & Catricalà, E. (2023). The Italian Sensorimotor Norms: Perception and action strength measures for 959 words. *Behavior Research Methods*, *55*(8), 4035–4047.

Rice, G. E., Hoffman, P., & Lambon Ralph, M. A. (2015). Graded specialization within and between the anterior temporal lobes. *Annals of the New York Academy of Sciences*, *1359*(1), 84–97. https://doi.org/https://doi.org/10.1111/nyas.12951

Richardson, J. T. E. (1975). The effect of word imageability in acquired dyslexia. *Neuropsychologia*, *13*(3), 281–288. https://doi.org/https://doi.org/10.1016/0028-3932(75)90004-4

Richardson, J. T. E. (1976). Imageability and concreteness. *Bulletin of the Psychonomic Society*, *7*(5), 429–431. https://doi.org/10.3758/BF03337237

Rissenberg, M., & Glanzer, M. (1987). Free recall and word finding ability in normal aging and senile dementia of the Alzheimer's type: The effect of item concreteness. *Journal of Gerontology*, *42*(3), 318–322.

Rodríguez-Ferreiro, J., Gennari, S. P., Davies, R., & Cuetos, F. (2011). Neural Correlates of Abstract Verb Processing. *Journal of Cognitive Neuroscience*, *23*(1), 106–118. https://doi.org/10.1162/jocn.2010.21414

Roell, M., Cachia, A., Matejko, A. A., Houdé, O., Ansari, D., & Borst, G. (2021). Sulcation of the intraparietal sulcus is related to symbolic but not non-symbolic number skills. *Developmental Cognitive Neuroscience*, *51*, 100998. https://doi.org/https://doi.org/10.1016/j.dcn.2021.100998

Rollo, F., Bonisoli, G., & Po, L. (2023). *Italian GloVe models*. Zenodo. https://doi.org/10.5281/zenodo.8427306

Rollo, F., Bonisoli, G., & Po, L. (2024). A Comparative Analysis of Word Embeddings Techniques for Italian News Categorization. *IEEE Access*, *12*, 25536–25552. https://doi.org/10.1109/ACCESS.2024.3367246

Rolls, E. T. (2023). Emotion, motivation, decision-making, the orbitofrontal cortex, anterior cingulate cortex, and the amygdala. In *Brain Structure and Function* (Vol. 228, Number 5, pp. 1201–1257). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1007/s00429-023-02644-9

Romani, C., Mcalpine, S., & Martin, R. C. (2008). Concreteness effects in different tasks: Implications for models of short-term memory. *Quarterly Journal of Experimental Psychology*, *61*(2), 292–323.

Rosch, E. H. (1973). Natural categories. *Cognitive Psychology*, *4*(3), 328–350. https://doi.org/https://doi.org/10.1016/0010-0285(73)90017-0

Ross, L. A., & Olson, I. R. (2010). Social cognition and the anterior temporal lobes. *NeuroImage*, *49*(4), 3452–3462. https://doi.org/10.1016/j.neuroimage.2009.11.012

Rouse, M. A., Halai, A. D., Ramanan, S., Rogers, T. T., Garrard, P., Patterson, K., Rowe, J. B., & Lambon Ralph, M. A. (2024). Social-semantic knowledge in frontotemporal dementia and after anterior temporal lobe resection. *Brain Communications*, *6*(6). https://doi.org/10.1093/braincomms/fcae378

Sagliano, L., Magliacano, A., Parazzini, M., Fiocchi, S., Trojano, L., & Grossi, D. (2019). Modulating interoception by insula stimulation: A double-blinded tDCS study. *Neuroscience Letters*, *696*, 108–113.

Said, C. P., Moore, C. D., Engell, A. D., Todorov, A., & Haxby, J. V. (2010). Distributed representations of dynamic facial expressions in the superior temporal sulcus. *Journal of Vision*, *10*(5), 11. https://doi.org/10.1167/10.5.11

Salillas, E., Korostenskaja, M., Kleineschay, T., Mehta, S., Vega, A., & Castillo, E. M. (2019). A MEG Study on the Processing of Time and Quantity: Parietal Overlap but Functional Divergence. *Frontiers in Psychology*, *Volume 10-2019*. https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2019.00139

Sandberg, C. W., Exton, E., Coburn, K. L., Chun, S., & Miller, C. (2022). Event related potential exploration of the organizational structure of abstract versus concrete words in neurologically intact younger adults. *Brain and Language*, *230*. https://doi.org/10.1016/j.bandl.2022.105138

Sandrini, M., Rossini, P. M., & Miniussi, C. (2004). The differential involvement of inferior parietal lobule in number comparison: a rTMS study. *Neuropsychologia*, *42*(14), 1902–1909. https://doi.org/https://doi.org/10.1016/j.neuropsychologia.2004.05.005

Sassenhagen, J., & Fiebach, C. J. (2020). Traces of Meaning Itself: Encoding Distributional Word Vectors in Brain Activity. *Neurobiology of Language*, *1*(1), 54–76. https://doi.org/10.1162/nol_a_00003

Schel, M. A., & Klingberg, T. (2017). Specialization of the Right Intraparietal Sulcus for Processing Mathematics During Development. *Cerebral Cortex*, *27*(9), 4436–4446. https://doi.org/10.1093/cercor/bhw246

Schwanenflugel, P. J., & Shoben, E. J. (1983). Differential context effects in the comprehension of abstract and concrete verbal materials. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *9*(1), 82.

Schwanenflugel, P. J., & Stowe, R. W. (1989). Context Availability and the Processing of Abstract and Concrete Words in Sentences. *Reading Research Quarterly*, *24*(1), 114–126. https://doi.org/10.2307/748013

Sheppard, S. M., Stockbridge, M. D., Keator, L. M., Murray, L. L., Blake, M. L., group, R. H. D. working, & Committee, E.-B. C. R. (2022). The company prosodic deficits keep following right hemisphere stroke: a systematic review. *Journal of the International Neuropsychological Society*, *28*(10), 1075–1090.

Siakaluk, P. D., Newcombe, P. I., Duffels, B., Li, E., Sidhu, D. M., Yap, M. J., & Pexman, P. M. (2016). Effects of emotional experience in lexical decision. *Frontiers in Psychology*, *7*, 1157.

Sidtis, D. V. L., & Sidtis, J. J. (2018). The affective nature of formulaic language: A right-hemisphere subcortical process. *Frontiers in Neurology*, *9*, 573.

Simmons, W. K., Pecher, D., Hamann, S. B., Zeelenberg, R., & Barsalou, L. W. (2003). *fMRI evidence for modality-specific processing of conceptual knowledge on six modalities*.

Skipper, L. M., & Olson, I. R. (2014). Semantic memory: Distinct neural representations for abstractness and valence. *Brain and Language*, *130*, 1–10. https://doi.org/https://doi.org/10.1016/j.bandl.2014.01.001

Snyder, H. R., Banich, M. T., & Munakata, Y. (2011). Choosing Our Words: Retrieval and Selection Processes Recruit Shared Neural Substrates in Left Ventrolateral Prefrontal Cortex. *Journal of Cognitive Neuroscience*, *23*(11), 3470–3482. https://doi.org/10.1162/jocn_a_00023

Solomon, K. O., & Barsalou, L. W. (2004). Perceptual simulation in property verification. *Memory & Cognition*, *32*(2), 244–259. https://doi.org/10.3758/BF03196856

Stochel, J. F., & Sandberg, C. W. (2025). Functional magnetic resonance imaging of taxonomic and thematic processing of abstract and concrete word pairs. *Journal of Neuropsychology*.

Stockbridge, M. D., Venezia, J. H., Vitti, E., Tippett, D. C., & Hillis, A. E. (2022). Verb Frequency and Density Drive Naming Performance in Primary Progressive Aphasia. *Aphasiology*, *0*(0), 1–17. https://doi.org/10.1080/02687038.2022.2142036

Strain, E., Patterson, K., & Seidenberg, M. S. (1995). Semantic effects in single-word naming. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *21*(5), 1140.

Su, L., Fonteneau, E., Marslen-Wilson, W., & Kriegeskorte, N. (2012). Spatiotemporal searchlight representational similarity analysis in EMEG source space. *Proceedings - 2012 2nd International Workshop on Pattern Recognition in NeuroImaging, PRNI 2012*, 97–100. https://doi.org/10.1109/PRNI.2012.26

Sugimoto, H., Abe, M. S., & Otake-Matsuura, M. (2023). Word-producing brain: Contribution of the left anterior middle temporal gyrus to word production patterns in spoken language. *Brain and Language*, *238*, 105233.

Tablante, J., Krossa, L., Azimi, T., & Chen, L. (2023). Dysfunctions associated with the intraparietal sulcus and a distributed network in individuals with math learning difficulties: An ALE meta-analysis. *Human Brain Mapping*, *44*(7), 2726–2740. https://doi.org/https://doi.org/10.1002/hbm.26240

Tang, D., Fu, Y., Wang, H., Liu, B., Zang, A., & Kärkkäinen, T. (2023). The embodiment of emotion-label words and emotion-laden words: Evidence from late Chinese–English bilinguals. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1143064

Thielscher, A., Antunes, A., & Saturnino, G. B. (2015). Field modeling for transcranial magnetic stimulation: A useful tool to understand the physiological effects of TMS? *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 222–225.

Tong, J., Binder, J. R., Humphries, C., Mazurchuk, S., Conant, L. L., & Fernandino, L. (2022). A Distributed Network for Multimodal Experiential Representation of Concepts. *Journal of Neuroscience*, *42*(37), 7121–7130. https://doi.org/10.1523/JNEUROSCI.1243-21.2022

Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., Moher, D., Peters, M. D. J., Horsley, T., Weeks, L., Hempel, S., Akl, E. A., Chang, C., McGowan, J., Stewart, L., Hartling, L., Aldcroft, A., Wilson, M. G., Garritty, C., … Straus, S. E. (2018). PRISMA extension for scoping reviews (PRISMA-ScR): Checklist and explanation. In *Annals of Internal Medicine* (Vol. 169, Number 7, pp. 467–473). American College of Physicians. https://doi.org/10.7326/M18-0850

Troche, J., Crutch, S. J., & Reilly, J. (2017). Defining a Conceptual Topography of Word Concreteness: Clustering Properties of Emotion, Sensation, and Magnitude among 750 English Words. *Frontiers in Psychology*, *8*. https://www.frontiersin.org/articles/10.3389/fpsyg.2017.01787

Troche, J., Crutch, S., & Reilly, J. (2014). Clustering, hierarchical organization, and the topography of abstract and concrete nouns. *Frontiers in Psychology*, *5*(APR). https://doi.org/10.3389/fpsyg.2014.00360

Ulrich, M., Harpaintner, M., Trumpp, N. M., Berger, A., Günther, F., & Kiefer, M. (2025). Indirect experiential grounding: semantic similarity of abstract scientific concepts is reflected in activity patterns in visual and motor cortex. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-32189-2

Van Hoornweder, S., Nuyts, M., Frieske, J., Verstraelen, S., Meesen, R. L. J., & Caulfield, K. A. (2023). Outcome measures for electric field modeling in tES and TMS: A systematic review and large-scale modeling study. *NeuroImage*, *281*, 120379. https://doi.org/https://doi.org/10.1016/j.neuroimage.2023.120379

Vergallito, A., Petilli, M. A., Cattaneo, L., & Marelli, M. (2019). Somatic and visceral effects of word valence, arousal and concreteness in a continuum lexical space. *Scientific Reports*, *9*(1), 20254.

Vergallito, A., Petilli, M. A., & Marelli, M. (2020). Perceptual modality norms for 1,121 Italian words: A comparison with concreteness and imageability scores and an analysis of their impact in word processing tasks. *Behavior Research Methods*, *52*(4), 1599–1616.

Vigliocco, G., Kousta, S.-T., Della Rosa, P. A., Vinson, D. P., Tettamanti, M., Devlin, J. T., & Cappa, S. F. (2014). The neural representation of abstract words: the role of emotion. *Cerebral Cortex*, *24*(7), 1767–1777.

Vignali, L., Xu, Y., Turini, J., Collignon, O., Crepaldi, D., & Bottini, R. (2023). Spatiotemporal dynamics of abstract and concrete semantic representations. *Brain and Language*, *243*, 105298.

Villani, C., Lugli, L., Liuzza, M. T., & Borghi, A. M. (2019). Varieties of abstract concepts and their multiple dimensions. *Language and Cognition*, *11*(3), 403–430.

Villani, C., Lugli, L., Liuzza, M. T., Nicoletti, R., & Borghi, A. M. (2021). Sensorimotor and interoceptive dimensions in concrete and abstract concepts. *Journal of Memory and Language*, *116*, 104173. https://doi.org/10.1016/J.JML.2020.104173

Vinaya, H., Trott, S., Pecher, D., Zeelenberg, R., & Coulson, S. (2025). Words and Worlds Both: Dynamic Effects of Distributional and Sensorimotor Information in Semantic Processing. *Open Mind*, *9*, 2149–2174. https://doi.org/10.1162/OPMI.a.316

Vinson, D., Ponari, M., & Vigliocco, G. (2014). How does emotional content affect lexical processing? *Cognition and Emotion*, *28*(4), 737–746. https://doi.org/10.1080/02699931.2013.851068

Visser, M., Jefferies, E., Embleton, K. V, & Lambon Ralph, M. A. (2012). Both the middle temporal gyrus and the ventral anterior temporal area are crucial for multimodal semantic processing: distortion-corrected fMRI evidence for a double gradient of information convergence in the temporal lobes. *Journal of Cognitive Neuroscience*, *24*(8), 1766–1778.

Wang, J., Conder, J. A., Blitzer, D. N., & Shinkareva, S. V. (2010). Neural representation of abstract and concrete concepts: A meta-analysis of neuroimaging studies. *Human Brain Mapping*, *31*(10), 1459–1468. https://doi.org/10.1002/hbm.20950

Wang, X., Li, G., Zhao, G., Li, Y., Wang, B., Lin, C. P., Liu, X., & Bi, Y. (2021). Social and emotion dimensional organizations in the abstract semantic space: the neuropsychological evidence. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-02824-9

Wang, X., Wang, B., & Bi, Y. (2019). Close yet independent: Dissociation of social from valence and abstract semantic dimensions in the left anterior temporal lobe. *Human Brain Mapping*, *40*(16), 4759–4776. https://doi.org/10.1002/hbm.24735

Wang, X., Wu, W., Ling, Z., Xu, Y., Fang, Y., Wang, X., Binder, J. R., Men, W., Gao, J.-H., & Bi, Y. (2018). Organizational principles of abstract words in the human brain. *Cerebral Cortex*, *28*(12), 4305–4318.

Wang, X., Xu, Y., Wang, Y., Zeng, Y., Zhang, J., Ling, Z., & Bi, Y. (2018). Representational similarity analysis reveals task-dependent semantic influence of the visual word form area. *Scientific Reports*, *8*(1). https://doi.org/10.1038/s41598-018-21062-0

Warrington, E. K. (1975). The selective impairment of semantic memory. *The Quarterly Journal of Experimental Psychology*, *27*(4), 635–657.

Warrington, E. K., & Shallice, T. (1984). Category specific semantic impairments. *Brain*, *107*(3), 829–853. https://doi.org/10.1093/brain/107.3.829

Westbury, C., Bub, D., & Chertkow, H. (2002). Distinct neurolinguistic symptom clusters in Alzheimer's type dementia and primary progressive aphasia. *Brain and Cognition*, *48*(2), 611–617. https://research.ebsco.com/c/kq2nos/search/details/o7scx4qr3z?db=psyh

Wilson-Mendenhall, C. D., Barrett, L. F., Simmons, W. K., & Barsalou, L. W. (2011). Grounding emotion in situated conceptualization. *Neuropsychologia*, *49*(5), 1105–1127.

Wilson-Mendenhall, C. D., Simmons, W. K., Martin, A., & Barsalou, L. W. (2013). Contextual processing of abstract concepts reveals neural representations of nonlinguistic semantic content. *Journal of Cognitive Neuroscience*, *25*(6), 920–935.

Winkielman, P., Coulson, S., & Niedenthal, P. (2018). Dynamic grounding of emotion concepts. In *Philosophical Transactions of the Royal Society B: Biological Sciences* (Vol. 373, Number 1752). Royal Society Publishing. https://doi.org/10.1098/rstb.2017.0127

Winkielman, P., Davis, J. D., & Coulson, S. (2023). Moving thoughts: emotion concepts from the perspective of context dependent embodied simulation. *Language, Cognition and Neuroscience*, *38*(10), 1531–1553. https://doi.org/10.1080/23273798.2023.2236731

Winter, B. (2023). Abstract concepts and emotion: Cross-linguistic evidence and arguments against affective embodiment. *Philosophical Transactions of the Royal Society B*, *378*(1870), 20210368.

Woollams, A. M. (2015). For richer or poorer? Imageability effects in semantic dementia patients' reading aloud. *NEUROPSYCHOLOGIA*, *76*, 254–263. https://doi.org/10.1016/j.neuropsychologia.2015.03.023

Wu, C., & Zhang, J. (2025). Emotion word is an ambiguous concept: dividing, defining, and connecting emotion-label words and emotion-laden words. *Cognition and Emotion*. https://doi.org/10.1080/02699931.2025.2551080

Wurm, M. F., & Schubotz, R. I. (2018). The role of the temporoparietal junction (TPJ) in action observation: Agent detection rather than visuospatial transformation. *NeuroImage*, *165*, 48–55. https://doi.org/https://doi.org/10.1016/j.neuroimage.2017.09.064

Yi, H. A., Moore, P., & Grossman, M. (2007). Reversal of the concreteness effect for verbs in patients with semantic dementia. *NEUROPSYCHOLOGY*, *21*(1), 9–19. https://doi.org/10.1037/0894-4105.21.1.9

York, C., Olm, C., Boller, A., McCluskey, L., Elman, L., Haley, J., Seltzer, E., Chahine, L., Woo, J., Rascovsky, K., McMillan, C., & Grossman, M. (2014). Action verb comprehension in amyotrophic lateral sclerosis and Parkinson's disease. *Journal of Neurology*, *261*(6), 1073–1079. https://doi.org/10.1007/s00415-014-7314-y

Younes, K., Borghesani, V., Montembeault, M., Spina, S., Mandelli, M. L., Welch, A. E., Weis, E., Callahan, P., Elahi, F. M., Hua, A. Y., Perry, D. C., Karydas, A., Geschwind, D., Huang, E., Grinberg, L. T., Kramer, J. H., Boxer, A. L., Rabinovici, G. D., Rosen, H. J., … Gorno-Tempini, M. L. (2022). Right temporal degeneration and socioemotional semantics: Semantic behavioural variant frontotemporal dementia. *Brain*, *145*(11), 4080–4096. https://doi.org/10.1093/brain/awac217

Zahn, R., Green, S., Beaumont, H., Burns, A., Moll, J., Caine, D., Gerhard, A., Hoffman, P., Shaw, B., Grafman, J., & Lambon Ralph, M. A. (2017). Frontotemporal lobar degeneration and social behaviour: Dissociation between the knowledge of its consequences and its conceptual meaning. *Cortex*, *93*, 107–118. https://doi.org/10.1016/j.cortex.2017.05.009

Zahn, R., Moll, J., Iyengar, V., Huey, E. D., Tierney, M., Krueger, F., & Grafman, J. (2009). Social conceptual impairments in frontotemporal lobar degeneration with right anterior temporal hypometabolism. *Brain*, *132*(3), 604–616. https://doi.org/10.1093/brain/awn343

Zahn, R., Moll, J., Krueger, F., Huey, E. D., Garrido, G., & Grafman, J. (2007). Social concepts are represented in the superior anterior temporal cortex. *Proceedings of the National Academy of Sciences*, *104*(15), 6430–6435. https://doi.org/10.1073/pnas.0607061104

Zaki, J., Davis, J. I., & Ochsner, K. N. (2012). Overlapping activity in anterior insula during interoception and emotional experience. *Neuroimage*, *62*(1), 493–499.

Zhang, B. B. B., Stöhrmann, P., Godbersen, G. M., Unterholzner, J., Kasper, S., Kranz, G. S., & Lanzenberger, R. (2022). Normal component of TMS-induced electric field is correlated with depressive symptom relief in treatment-resistant depression. *Brain Stimulation*, *15*(5), 1318–1320. https://doi.org/https://doi.org/10.1016/j.brs.2022.09.006

Zhang, J., Wu, C., Yuan, Z., & Meng, Y. (2019). Differentiating emotion-label words and emotion-laden words in emotion conflict: an ERP study. *Experimental Brain Research*, *237*(9), 2423–2430. https://doi.org/10.1007/s00221-019-05600-4

Zhang, J. X., Bo, K., Wager, T. D., & Gross, J. J. (2025). The brain bases of emotion generation and emotion regulation. In *Trends in Cognitive Sciences* (Vol. 29, Number 10, pp. 879–891). Elsevier Ltd. https://doi.org/10.1016/j.tics.2025.04.013

Zhang, Q., Wang, H., Luo, C., Zhang, J., Jin, Z., & Li, L. (2019). The neural basis of semantic cognition in Mandarin Chinese: A combined fMRI and TMS study. *Human Brain Mapping*, *40*(18), 5412–5423. https://doi.org/https://doi.org/10.1002/hbm.24781

Zhou, F., & Becker, B. (2025). The default mode network and emotion — dual roles of the medial prefrontal cortex in emotional experience and regulation. In *Current Opinion in Behavioral Sciences* (Vol. 66). Elsevier Ltd. https://doi.org/10.1016/j.cobeha.2025.101613

Ziegler, J. C., Montant, M., Briesemeister, B. B., Brink, T. T., Wicker, B., Ponz, A., Bonnard, M., Jacobs, A. M., & Braun, M. (2018). Do words stink? Neural reuse as a principle for understanding emotions in reading. *Journal of Cognitive Neuroscience*, *30*(7), 1023–1032.

APPENDIX 1. CHAPTER 2 SUPPLEMENTARY MATERIALS

Table S1. Records with Primary Progressive Aphasia patients

REFERENCE	PARTICIPANTS	LESION	TASK	STIMULI/ MATERIAL	RESULTS
Breedin et al., 1994	1 svPPA patient, DM. SINGLE CASE. 10 controls, matched in age to DM, in the Auditory lexical decision test	Atrophy of ATL, particularly on the left side	Abstract/Concrete contrast: **1.** Defining Abstract and Concrete Words **2.** Concrete/Abstract Word/Picture Matching **3.** Abstract-Concrete Synonymy Task **4.** Auditory Lexical Decision Test **5.** Verb-Noun Synonymy Task Perceptual components of concepts: **6.** Living non-living attribute test **7.** Perceptual features of verbs	**1.** 386 words, controlled for concreteness and frequency. **2.** 30 abstract words, 30 concrete words, 15 emotion words **3.** 52 synonymy triplets, half concrete and half abstract nouns **4.** 360 stimuli, half words (abstract and concrete) and half non-words **5.** 16 verbs triplets and 16 noun triplets **6.** 39 living and 39 non-living items **7.** 27 triplets of verbs per conditions: non-relational, manner, and relational triplets	**A>C** Abstract/Concrete contrast: DM was better in defining abstract compared to concrete words, and better in picture matching of abstract compared to concrete words, although the difference was not statistically significant. Also, there was no difference in performance on synonymy judgement tasks between abstract/concrete triplets and between noun/verbs triplets. In the auditory lexical decision test, similar performance on concrete and abstract words. Perceptual components of concepts: Worse with perceptual than non-perceptual features. Worse with manner triplets compared to the other two conditions
Reilly et al., 2007	4 svPPA No control group	n.a.	- Concreteness judgement	- 40 nouns and 40 verbs, divided into concrete and abstract	**A>C** Patients showed overall higher accuracy for three-syllable abstract, compared to concrete items
Macoir et al., 2008	SC, 1 svPPA patient 5 controls matched for age and education	Infero-lateral ATL atrophy, particularly on left side	Longitudinal study: T1, T2, T3 Abstract and concrete concepts knowledge. 5 tasks: 1. Semantic similarity judgement on homophones,	1.32 noun homophones with both an abstract and a concrete meaning, from which 64 triplets, half with semantic similarity	**A>C** Contrast abstract/concrete items reveals a strong reversal of CE: SC performed better on abstract

			2. Semantic similarity judgement on living, non-living, and abstract concepts, 3. Concrete/abstract word-to-picture matching, 4. Concrete/abstract word definition, 5. Concrete/abstract word spelling to dictation Living and non-living concrete items. 6. Picture naming 7. Naming to definition	judgement of the concrete and the other half of the abstract meaning 2.20 concrete living, 20 concrete non-living, and 40 abstract triplets. 3.40 stimuli of concrete concepts (20 living, 20 non-living), 40 stimuli of abstract concepts 4.43 concrete (living and non-living) and 47 abstract words 5. 45 concrete (19 living and 26 non-living) and 45 abstract word stimuli 6. 127 stimuli. The living set: 61 pictures of animals (38) and fruits and vegetables (23); the non-living set: 66 pictures of vehicles (7), tools (8), articles of clothing (11), musical instruments (8) and household items (32). 7.same as in 6 -	compared to concrete items. This difference progressively diminishes as the disease evolves. No difference in performance between living and non-living entities
Bonner et al., 2009	11 svPPA, 16 controls, age- and education-matched	MRI on a subset of 5 patients: bilateral, infero-lateral ATL atrophy	Verb similarity test	20 concrete verbs, 20 abstract verbs	**A>C** Controls: CE svPPA: reversal of CE (worse performance with concrete than with abstract verbs). The size of the reversal of CE increases with right anterolateral temporal cortex atrophy
Jefferies et al., 2009	11 svPPA, 11 controls, matched for age	n.a.	Synonymy judgement task	Concrete and abstract, with one probe, one target and two distractors	**C>A** SvPPA performed better on more imageable trials. No relationship between the degree of semantic impairment and the size of the CE
Papagno et al., 2009	1 svPPA 5 controls, sex, age and education matched	Hypodensity in the left temporal pole and medial temporal cortex	Concrete nouns: 1. proper names 2. living and inanimate objects (i) a reality judgement task; (ii) a picture naming task; (iii) a semantic memory questionnaire 3. knowledge of visual features: (i) Size comparison test	1.50 pictures of celebrities, interspersed with 50 pictures of unknown people. 2.30 stimuli of living entities, 30 stimuli of inanimate objects 3.(i) 16 pairs of items (ii) 8 pairs of animals	**A>C** Concrete nouns: Impaired performance in naming proper names of conspecifics and landmarks. Significant greater difficulty with naming animals compared to inanimate objects and significant loss of

			(ii) animal tails task (iii) colour attribution task Abstract and concrete words: 4. Naming concrete and abstract nouns from definition 5. Word fluency 6. Synonymy task 7. Word-definition verification task	(iii) 60 stimuli, 40 biological and 20 inanimate 4.38 definitions (28 of concrete and 10 of abstract words) 5. categories: concrete animate (wild animals, pets, insects, citrus fruits, green vegetables) and inanimate (pieces of furniture, vehicles, tools), and abstract (positive and negative feelings) 6. sublist A: triplets of abstract and concrete nouns (26 each) sublist B: triplets of nouns (16), verbs (16), and adjectives (40) sublist C:3 groups of verbs triplets: manner triplets, opposite triplets, relational triplets (27 each) 7.236 definitions of words: 28 concrete and 52 abstract nouns, to 41 concrete and 47 abstract verbs, and to 30 concrete and 37 abstract adjectives	semantic knowledge for biological, whereas at ceiling with inanimate objects. Knowledge of visual features is preserved for artefacts, but not for biological entities. Abstract and concrete words: Perfect naming for abstract concepts, impaired in naming concrete concepts (reversal of CE). Fluency comparable to controls for abstract concepts, and impaired for concrete concepts (reversal of CE) In sublist A, patients were significantly worse than controls in concrete, but not in abstract triplets (reversal of CE). In sublist B, performance gradually better from (lower to higher) nouns, adjectives, and verbs. In sublist C, performance is indistinguishable from controls. In the word-definition verification task, better performance with abstract compared to concrete concepts, but only with nouns (reversal of CE, specific to nouns)
Hoffman and Ralph, 2011	7 svPPA, No control group	Bilateral ATL atrophy in all cases. 4 patients present stronger atrophy on the left, 3 on the right side	7 tasks: 1. Synonym Judgment Task, (Jefferies et al., 2009) 2. Description-to-Noun Matching Task (Yi et al., 2007) 3. Description-to-Verb Matching Task, (Yi et al., 2007) 4. Verb Similarity Test, (Bonner et al., 2009) 5. Shallice and McGill (Unpublished Data) Word--Picture Matching Task, 6. Mischievous Monkey Test with Pictures 7. Mischievous Monkey Test with Words	1. 64 trials (56 nouns, 5 adjectives, 3 verbs). 3 levels of imageability 2. 20 concrete and 20 abstract nouns 3. 20 verbs of motion and 20 verbs of cognition 4. 40 trials, 20 concrete and 20 abstract 5. 30 abstract and 30 concrete trials 6. 48 concrete and 48 abstract words 7. Same as 6.	**C>A** Overall, better performance with concrete than with abstract items. Size of CE varies between tasks: stronger on synonymy judgement task, no effect on tasks probing verbs.

Hoffman et al., 2013	6 svPPA 10 controls, matched for age and educational level	n.a.	Experiment 1. Synonymy matching task Experiment 2. Associative relationship task, with a probe word and three choices	Experiment 1. 60 nouns and 60 verbs, half concrete and half abstract Experiment 2. 3 conditions: 1. 40 trials with abstract words with shared associative relationship 2. 40 trials with concrete words shared associative relationship, not perceptually similar 8. 40 trials with the same concrete probes, associative relationship, and also perceptually similar	**C>A** Experiment 1. SvPPA showed larger CE than controls, for both word classes Experiment 2. SvPPA performed more poorly in abstract condition, compared to both concrete conditions, and better on perceptual concrete compared to the associative concrete condition
Hoffman et al., 2014	7 svPPA, 8 controls, age- and education-matched	n.a.	Autobiographical memory interview. Frequency, imageability and semantic diversity of words produced obtained		**A>C** SvPPA produced more high-frequency and high semantic diversity words than controls and less high-imageable words
Macoir et al., 2015	4 svPPA patients, 12 controls	Bilateral ATL atrophy	Experiment 1. 1. Semantic judgment tasks about concrete and abstract adjectives 2. Semantic knowledge task about colour adjectives Experiment 2 1. Adjective-to-concrete noun matching task:	Experiment 1. Adjectives of concrete (colour, dimension, physical property) and abstract (human propensity, value) semantic types. Experiment 1. 1. 50 triplets for the synonymy judgement task, and 50 triplets the for antonymy judgement task. 25 concrete, 25 abstract Experiment 2. 1. Same adjectives used in experiment 1. 80 stimuli comprising the adjective and three object nouns	**C=A** SvPPA performed significantly below controls in all tasks and semantic categories. No significant difference across categories in patients' performance (no effect of concreteness)
Woollams, 2015	10 svPPA,	n.a.	Reading aloud	80 monosyllabic words, varied by imageability and consistency	**A>C**

	30 healthy (not matched)				In controls, faster RTs for inconsistent high vs low imageability items, in svPPA, reversal: faster RTs for inconsistent low vs high imageability items
Cousins et al., 2016	12 svPPA, 18 bvFTD, 18 controls	SvPPA: cortical atrophy of temporal lobes, particularly on the left hemisphere. BvFTD: frontal lobe regions atrophy	Associativity judgement task	60 triads of nouns, half concrete and half abstract.	**A>C** Controls: no abstract-concrete difference SvPPA: reversal of CE, i.e. higher accuracy for abstract compared to concrete triads BvFTD: CE, i.e. higher accuracy for concrete than abstract triads. In svPPA, reversal of CE is related to atrophy of the left anterior temporal cortex
Pobric et al., 2016	2 svPPA patients 30 controls	One patient with predominant right superior ATL atrophy, and the other with predominant left superior ATL atrophy	Synonym judgement task	Triplets of words, with two conditions: social concepts and non-social concepts (describing non-social behaviour or properties of animals)	**C>A** Both cases were impaired compared to the control group in both conditions. Social concepts were significantly more impaired compared to non-social concepts in the right ATL than in the left ATL patient.
Cousins et al., 2017	20 svPPA, 42 bvFTD, 32 controls	SvPPA: cortical atrophy of left IFG, left FG, and right ITG. BvFTD: atrophy of frontal lobe regions, also extended to temporal lobes	Cookie theft picture description task. The abstractness of transcribed descriptions (nouns) was rated		**A>C** SvPPA produced significantly more abstract nouns than bvFTD. SvPPA more impaired in other measures of semantic knowledge also produced more abstract nouns than those less impaired. Increased abstractness in svPPA related to atrophy in PHG and portions of left ATL
Cousins et al., 2018	11 svPPA, 15 bvFTD No control group	SvPPA: grey matter atrophy in medial and lateral temporal regions, and inferior frontal lobe	Longitudinal study: T1 and T2 Cookie Theft Picture description task. The abstractness of transcribed descriptions (nouns) was rated		**A>C** Longitudinal decrease of concreteness of produced nouns in svPPA, but not in bvFTD. The decrease of concreteness in svPPA was related to progressive atrophythe of right ventral and left superior temporal regions
Cho et al., 2021	138 FTD: 42 svPPA, 22 nfPPA, 74 bvFTD 37 controls	SvPPA: cortical thinning in ATL and orbitofrontal cortex, particularly on the left hemisphere.	Cookie Theft Picture description task. Abstractness and other lexical variables of transcribed descriptions (nouns) were rated		**A>C** SvPPA produced more abstract nouns compared to bvFTD, nfPPA and controls. In svPPA, an increase the in the abstractness of produced nouns correlated with cortical thinning in left anterior temporal regions

		NfPPA left middle frontal, inferior temporal and middle temporal regions. BvFTD cortical thinning in frontal and temporal lobes bilaterally			
Catricalà et al., 2021	2 patients: P01, svPPA patients P02, CBS patient 8 controls	n.a.	Lexical decision task, with a semantic priming paradigm	120 nouns, 120 pairs. Conditions: word-pseudowords pairs, word-word pairs of the SAME category, word-word pairs of DIFFERENT categories Concrete categories: animals, tools Abstract categories: emotion, social, quantity	**C>A** Controls showed a priming effect for all categories. P01 showed abolished priming for social pairs. P02 showed abolished priming for quantity-related concepts
Poos et al., 2022	FTD diagnosed: 9 svPPA, 10 lPPA, 9 nfPPA, 6 bvFTD FTD genetically risk: 10 bvFTD, 1 nfPPA 59 controls, matched for sex, age and education	n.a.	- Test Relaties Abstracte Concepten (TRACE). One probe word, one target and three distractors - Semantic Association Test (SAT): concrete counterpart of TRACE. One probe, one target, three distractors	- 30 items, abstract concepts - 30 items, concrete concepts	**C=A** Difference between TRACE and SAT (abstract and concrete concepts knowledge): bvFTD, nfPPA, lPPA were significantly worse on TRACE than on SAT, while svPPA were equally impaired (i.e., no CE in svPPA)
Stockbridge et al., 2022	72 SvPPA, 103 lPPA, 63 nfPPA, 29 uPPA	svPPA: left anterior and inferior temporal atrophy lPPA: left temporo-parietal atrophy nfPPA: asymmetric frontal atrophy	Hopkins Action Naming Assessment (HANA), a verb picture naming tasks	30-item verb pictures	**C>A** Similar CE for lPPA, svPPA and unclassified PPA: increased verb concreteness related to better performance

Abbreviations. IFG: Inferior frontal gyrus, FG: fusiform gyrus, ITG: inferior temporal gyrus, ATL: anterior temporal lobes, PHG: para-hippocampal gyrus, n.a.: not available, CE: Concreteness effect, SvPPA: semantic variant of primary progressive aphasia, nfPPA: nonfluent variant of Primary Progressive Aphasia, lPPA: logopenic variant primary progressive aphasia, bvFTD: behavioural-variant Frontotemporal dementia, CBS: Cortico-Basal Syndrome, C>A: Concreteness effect, A>C: Reversal of concreteness effect, C=A: no difference between concrete and abstract. The effects of concreteness reported in the abbreviations refer to svPPA patients.

Table S2. Records with Alzheimer's disease patients

REFERENCE	PARTICIPANTS	TASK	STIMULI/ MATERIAL	RESULTS
Martin and Fedio, 1983	14 AD, 11 controls, matched for age, sex and education	Word-finding tests: 1-Boston naming test, 2-Fluency test Word meaning tests: 3-Pleasantness ratings. 4-Symbol referent test	1-85 line-drawings of objects 2- n.a. 3-10 pleasant words, 10 unpleasant words, 10 neutral words 4-42 cards: 9 objects, 15 actions, 9 emotion words, 9 modifiers	**A>C** AD performed significantly worse than controls in the Boston naming test and generated fewer words than controls in the fluency test. There was no difference in performance in the pleasantness ratings. In the symbol referent test, AD performed worse than controls in objects, actions, and modifiers but not in emotions.
Rissenberg and Glanzer, 1987	Experiment 1. 14 AD, 31 young healthy, 31 old healthy Experiment 2. 12 AD, 20 young, 15 old healthy	Experiment 1. Free recall of word lists Experiment 2. Word-finding	Experiment 1. 5 16-item word lists of abstract and concrete words Experiment 2. Definitions of 44 concrete and abstract words	**C>A** Experiment 1. Typical strong CE in the young, and in the AD group, but no CE in the old healthy group. Experiment 2. Word-finding ability was impaired in AD but not in the old healthy group. AD showed strong CE: they were significantly more impaired with word finding for abstract compared to concrete items
Bushell and Martin, 1997	20 AD, 16 controls	Semantic priming paradigm	80 related stimulus pairs, 20 for each condition: motion verb pairs, non-motion verb pairs, concrete nouns, and abstract nouns. + Unrelated stimulus pairs	**C>A** Neither controls nor AD showed semantic priming for abstract nouns and non-motion verbs. While controls showed priming for both motion verbs and concrete nouns, AD showed priming only for concrete nouns.

Fleming et al., 2003	25 AD, 19 old healthy, 27 young healthy	Immediate recall	3 lists, 15-words lists for young, and 12 words lists for old and AD. Each word had positive, neutral, or negative connotations. Words were matched for concreteness	**A>C** AD performed better on immediate recall of emotionally laden words than neutral words, and negative words were recalled more than positive or neutral
Peters et al., 2009	16 AD, 16 controls matched for age and sex, 16 young	- Immediate serial recall, - Synonym judgement task	- Lists of high-imageable and low-imageable words - Pairs of low- and high-imageable words	**C>A** CE in both tasks: AD performed worse than controls and young only in the low-imageability lists, and were less accurate with low-imageable pairs, compared to controls and young
Giffard and al., 2015	15 AD, 31 controls	Semantic priming paradigm, with 4 semantic priming effects tested for: Concrete-neutral SP, Abstract neutral SP, Concrete emotional SP, Abstract emotional SP	576 pairs of stimuli, rated on concreteness and emotional valence 9 prime-target conditions: 1. Concrete semantic and emotional relationship 2. Abstract semantic and emotional relationship 3. Concrete semantic relationship 4. Abstract semantic relationship 5. Concrete no semantic relationship but emotional target 6. Abstract no semantic relationship but emotional target 7. Neutral concrete words 8. Neutral abstract word 9. Word-nonword pairs	**C>A** In AD, in neutral conditions, CE: priming for concrete, no priming for abstract neutral concepts. In emotional conditions, no CE: similar priming effects for concrete negative and abstract negative SP conditions.

Abbreviations: AD: Alzheimer's disease, CE: concreteness effect, SP: semantic priming, C>A: Concreteness effect, A>C: Reversal of concreteness effect, C=A: no difference between concrete and abstract

Table S3. Records with both Alzheimer's disease and Primary Progressive Aphasia patients

REFERENCE	PARTICIPANTS	ATROPHY SITE	TASK	STIMULI/ MATERIAL	RESULTS
Westbury et al., 2002	11 AD, 11 PPA, No controls group	n.a.	Psycholinguistic Assessment of Language (PAL) battery	n.a.	**UNCLASSIFIABLE** No significant difference in naming tests. Large differences in abstract words comprehension: PPA were significantly more impaired than AD, in both auditory and written modalities
Crutch and Warrington, 2006	20 AD, 9 svPPA, 40 controls	n.a.	1. Synonym comprehension test 2. as in 1., with three conditions: a. antonym distractor b. distant distractor c. close distractor	1. abstract and concrete words 2. 48 abstract words	**AD: C=A** **svPPA: C=A** 1. svPPA achieved significantly lower scores than AD and controls. No difference between concrete and abstract concepts' performance 2. AD and svPPA showed a steeper rate of decline than controls from the more general to more specific synonym judgement condition
Yi et al., 2007	29 AD, 12 svPPA, 17 controls	n.a.	Multiple-choice naming-to-description task	40 verbs (motion and cognition) 40 nouns (20 concrete and 20 abstract)	**AD: C>A** **svPPA: A>C** AD: more impaired with abstract compared to concrete nouns, and with verbs than nouns. No significant difference between motion and cognition verbs SvPPA: more impaired with verbs compared to nouns. No difference between concrete and abstract nouns. Reversal of CE with verbs: svPPA were more impaired with motion compared to cognition verbs
Hsieh et al., 2012	12 AD 16 FTD: 8 svPPA, 8 bvFTD 15 controls	svPPA: ATL atrophy, predominantly on the left bvFTD: frontal atrophy	1-Graded Synonyms test 2-Emotion word tests 2.a. Emotion word synonyms test 2. b. Emotion word association test	1-concrete and abstract non-emotional words 2-80 emotion words, 40 positive and 40 negative	**AD: C=A** **svPPA: C=A** 1 and 2.a.: svPPA were significantly more impaired than all other groups.

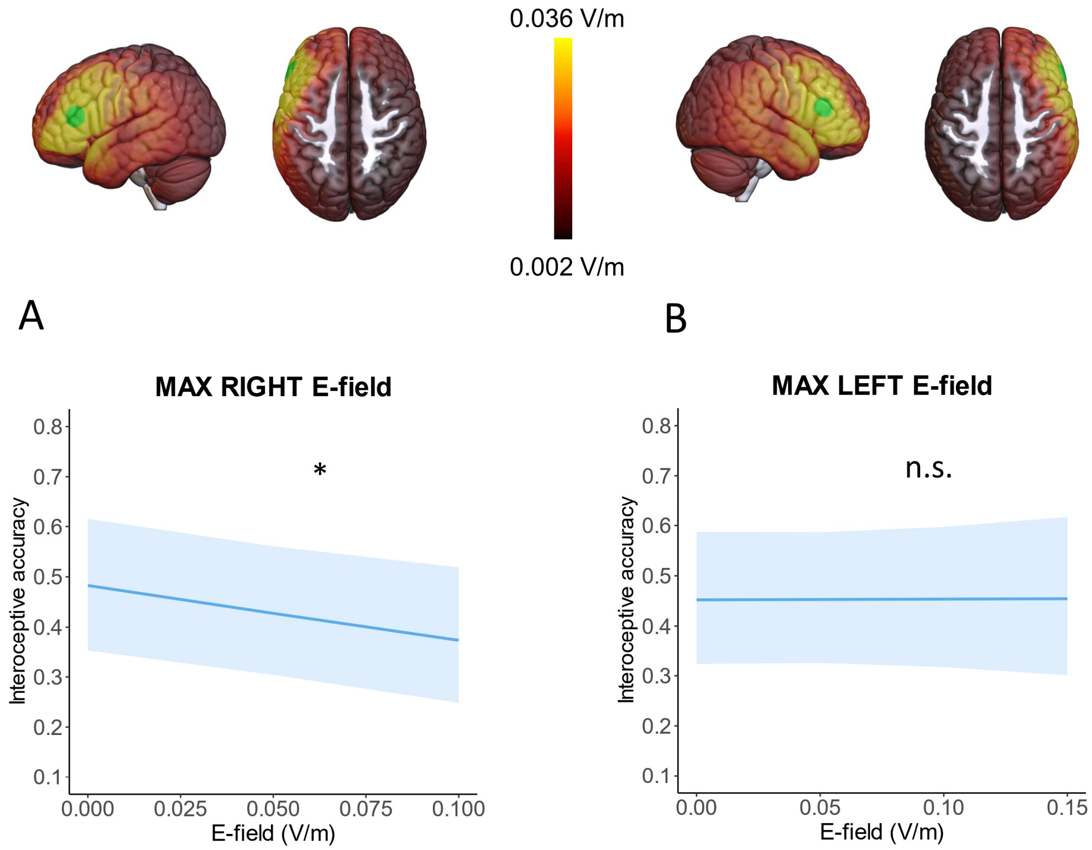
					2.b.: both svPPA and bvFTD showed worse performance than the other groups. No difference between positive and negative emotion words in all dementia and the control group.
Catricalà et al., 2014	14 AD, 6 svPPA, 20 controls	n.a.	1)For concrete concepts, three tests of the CaGi battery: 1-Picture naming task 2-naming on oral description 3-sentence verification of 480 features 2)For abstract concepts, Three tests from the DeCAbs battery 1-sentence completion task, 2-Multiple verbal choice matching, 3-Association task	1)48 stimuli, divided into 2 categories: living and non-living categories 2)same 40 stimuli divided into 5 categories: Emotions, Cognitions, Traits, Social relations, Human actions	**AD: C=A** **svPPA: A>C** Reversal of CE in svPPA: patients showed better performance with abstract concepts, particularly in comprehension tasks AD showed better performance with non-living than living entities in the naming on oral description task AD show a normal performance on Emotion concepts in 2 tasks out of 3, while svPPA show impaired performance on Social Relations in the association task
Joubert et al., 2017	12 AD, 9 svPPA, 11 controls, matched for age and education		Similarity judgement task	30 trials with 10 triplets for each condition: 1. concrete 2. emotional abstract 3. non-emotional abstract	**AD: C=A** **svPPA: A>C** SvPPA performed worse than AD and controls, and AD performed worse than controls. In controls, better performance for emotion triplets; in AD, no word type effect, in svPPA, better performance with non-emotional abstract words compared to concrete, while the difference with emotional words is not significant. Positive correlation between the semantic judgement of concrete triplets and GM volume in left ATL, medial and lateral

Abbreviations. AD: Alzheimer's disease, svPPA: semantic variant Primary Progressive Aphasia, bvFTD: behavioural-variant Frontotemporal dementia, n.a.: not available, GM = grey matter, ATL: Anterior Temporal Lobe, C>A: Concreteness effect, A>C: Reversal of concreteness effect, C=A: no difference between concrete and abstract

APPENDIX 2. CHAPTER 3 EXTENDED DATA

Figures

Figure 5-1. MAX E-field as predictor of Interoceptive accuracy



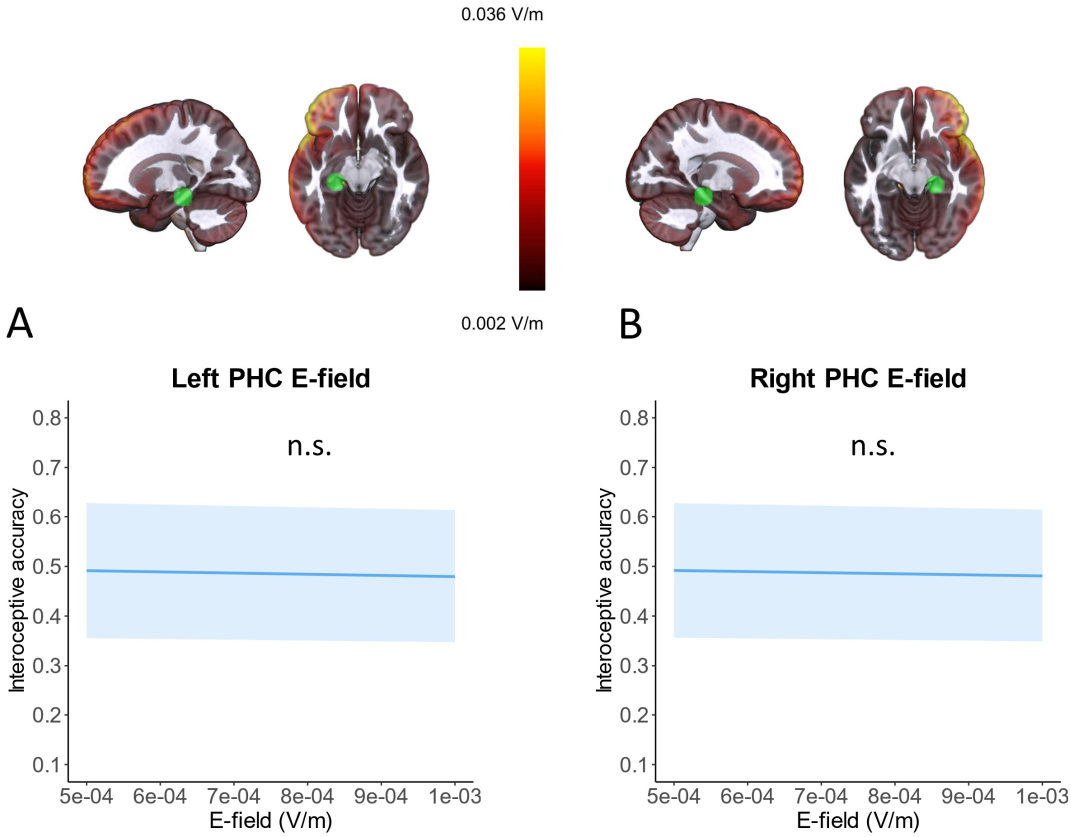
MAX: maximum, E-field: electric field.

(A) Adjusted predictions of the effect of the E-field induced in left MAX on interoceptive accuracy. The effect of left MAX E-field is not significant ($X^2 = 0.001$, $p = 0.970$).

(B) Adjusted predictions of the effect of the E-field induced in right MAX on interoceptive accuracy. The degree of right MAX E-field significantly lowers interoceptive accuracy: higher E-field values in right MAX led to lower interoceptive accuracy ($X^2 = 5.861$, $p = 0.015$)

(A-B) Error bars represent 95% confidence intervals (CI) of the adjusted predictions.

Figure 5-2. PHC E-field as predictor of Interoceptive accuracy

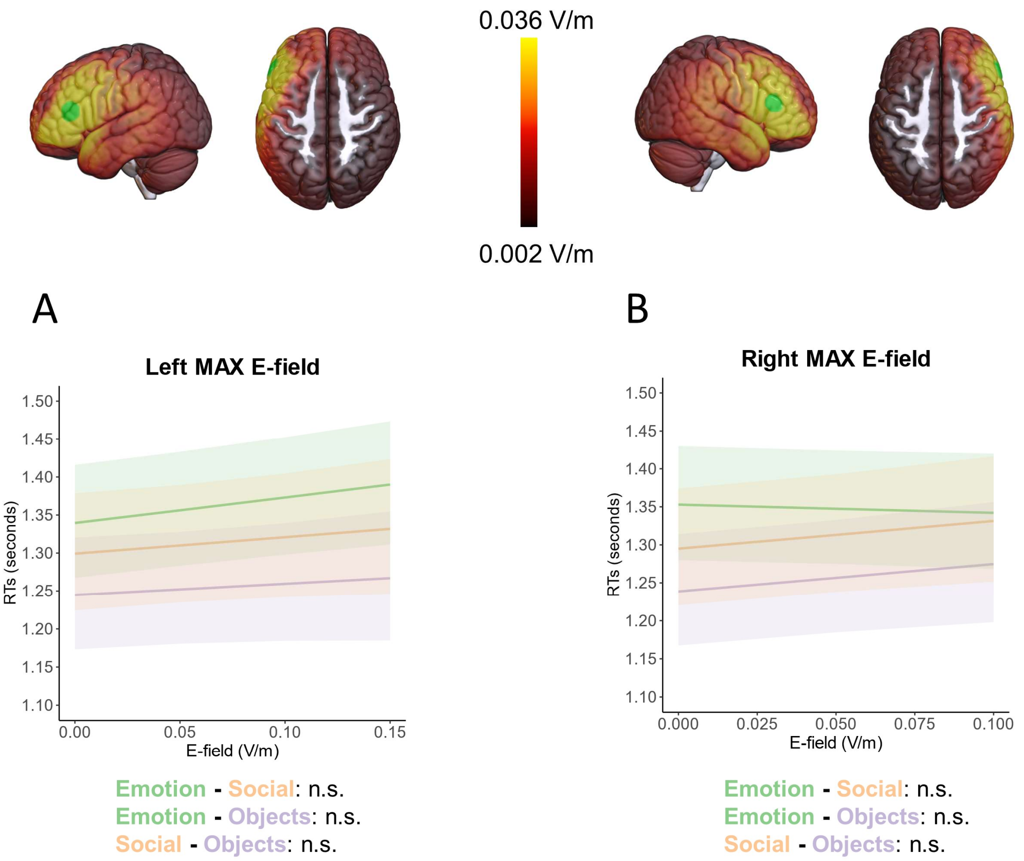


PHC: parahippocampal cortex, E-field: electric field.

- **(A)** Adjusted predictions of the effect of the E-field induced in left PHC on interoceptive accuracy. The effect of left PHC E-field is not significant (X^{2} = 3.502, p = 0.061).
- **(B)** Adjusted predictions of the effect of the E-field induced in right PHC on interoceptive accuracy. The effect of right PHC E-field is not significant (X^{2} = 3.539, p = 0.060).

(A-B) Error bars represent 95% confidence intervals (CI) of the adjusted predictions.

Figure 6-4. Interaction between MAX E-field and category as predictors of Reaction Times



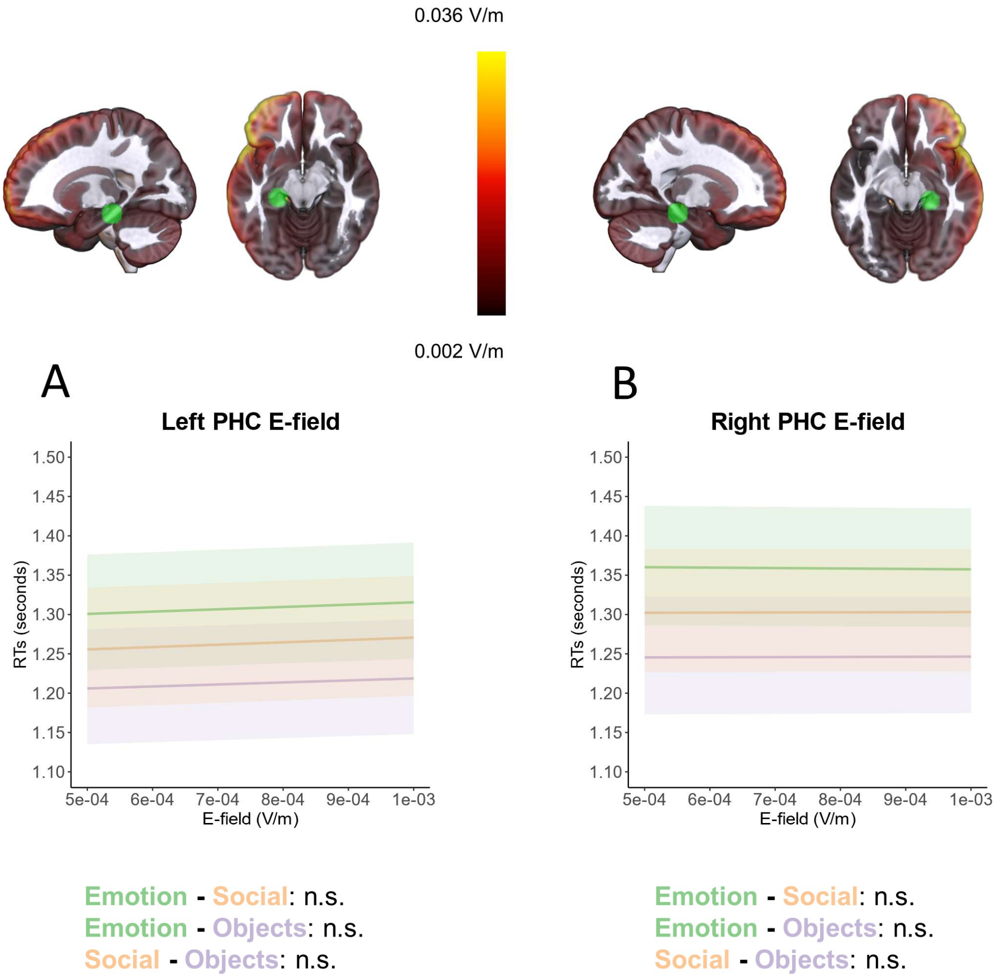
MAX: maximum, E-field: electric field.

(A) Adjusted predictions of the interaction between the electric field (E-field) induced in left MAX and category on RTs. Planned comparisons were non-significant (Emotion-Social: t = 0.420, p = 1, Emotion-Objects: t = 0.668, p = 1, Social-Objects: t = 0.246, p = 1).

(B) Adjusted predictions of the interaction between the electric field (E-field) induced in right MAX and category on RTs. Planned comparisons were non-significant (Emotion-Social: t = -1.756, p = 0.209, Emotion-Objects: t = -1.815, p = 0.209, Social-Objects: t = -0.051, p = 0.959).

(A-B) Error bars represent 95% confidence interval (CI) of the adjusted predictions. All p values were corrected for multiple comparisons using Holm correction. n.s. p > 0.05

Figure 6-5. Interaction between PHC E-field and category as predictors of Reaction Times



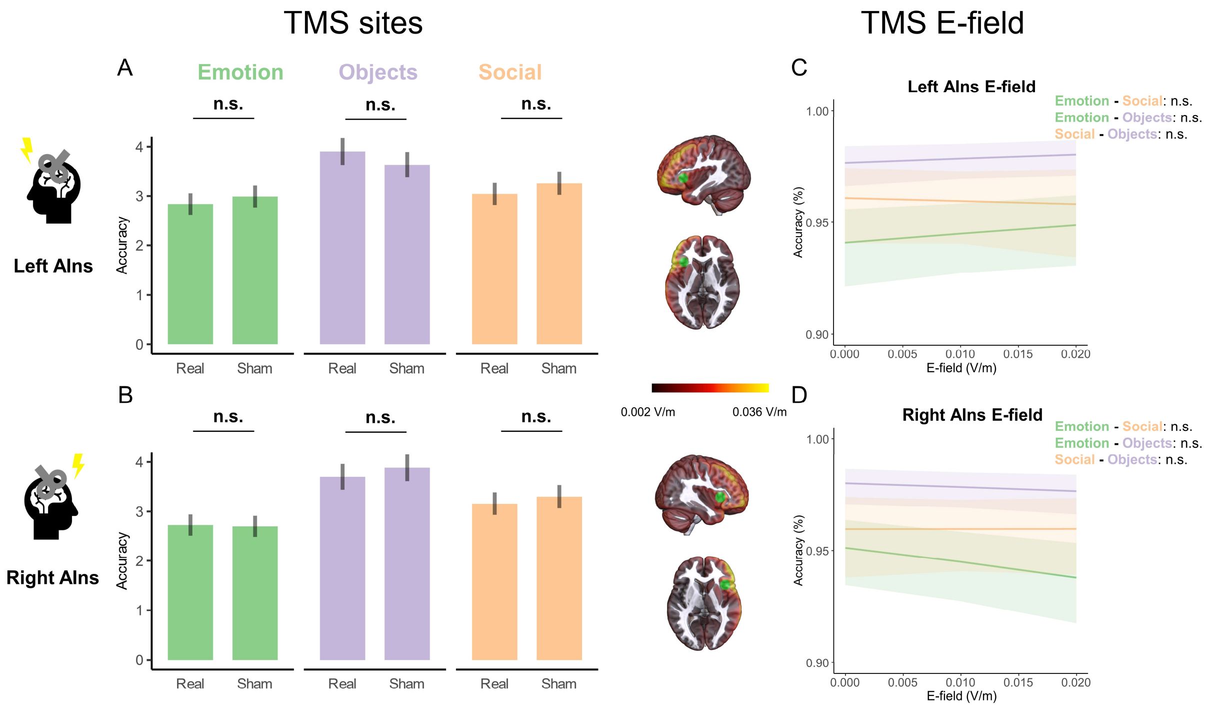
PHC: parahippocampal cortex, E-field: electric field.

(A) Adjusted predictions of the interaction between the electric field (E-field) induced in left PHC and category on RTs. Planned comparisons were non-significant (Emotion-Social: t value = -0.241, p = 1, Emotion-Objects: t value = 0.258, p = 1, Social-Objects: t value: 0.508, p = 1).

(B) Adjusted predictions of the interaction between the electric field (E-field) induced in right PHC and category on RTs. Planned comparisons were non-significant (Emotion-Social: t value = -1.193, p = 0.644, Emotion-Objects: t value = -1.241, p = 0.644, Social-Objects: t value: -0.048, p = 0.962).

(A-B) Error bars represent 95% confidence interval (CI) of the adjusted predictions. All p values were corrected for multiple comparisons using Holm correction. n.s. p > 0.05

Figure 6-9. Semantic similarity task. Category results. Accuracy



AIns: Anterior Insula, E-field: electric field

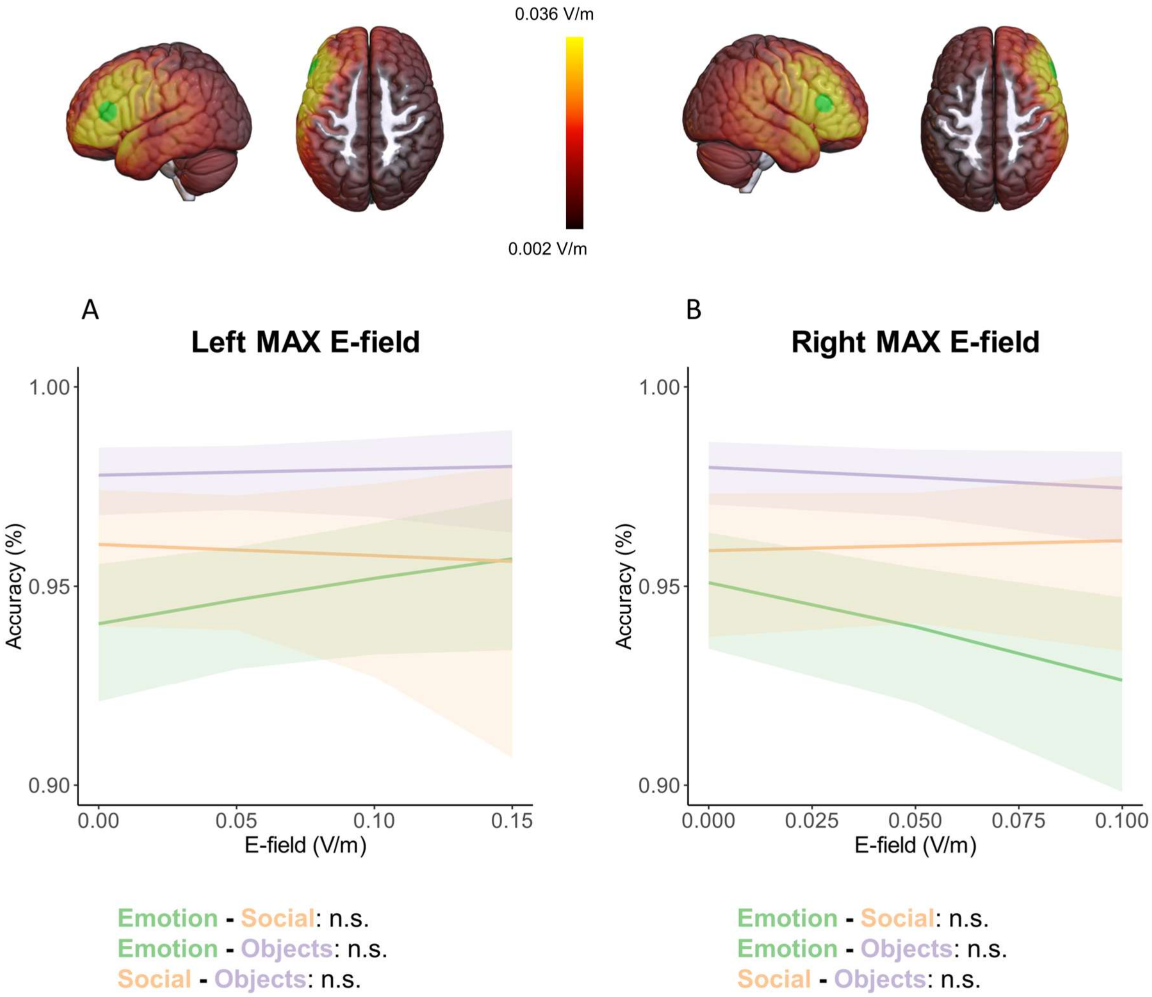
(A-B) Estimated marginal means of Accuracy (on the logit scale) following left (A) and right (B) TMS conditions. Planned comparisons were non-significant.

(C) Adjusted predictions of the interaction between the electric field (E-field) induced in left Anterior Insula (AIns) and category on Accuracy. Planned comparisons were non-significant.

(D) Adjusted predictions of the interaction between the electric field (E-field) induced in right Anterior Insula (AIns) and category on Accuracy. Planned comparisons were non-significant.

(A-B) Error bars represent standard errors of the marginal means. (C-D) Error bars represent 95% confidence interval (CI) of the adjusted predictions. All p values were corrected for multiple comparisons using Holm correction. n.s. $p > 0.05$

Figure 6-10 Interaction between MAX E-field and category as predictors of Accuracy



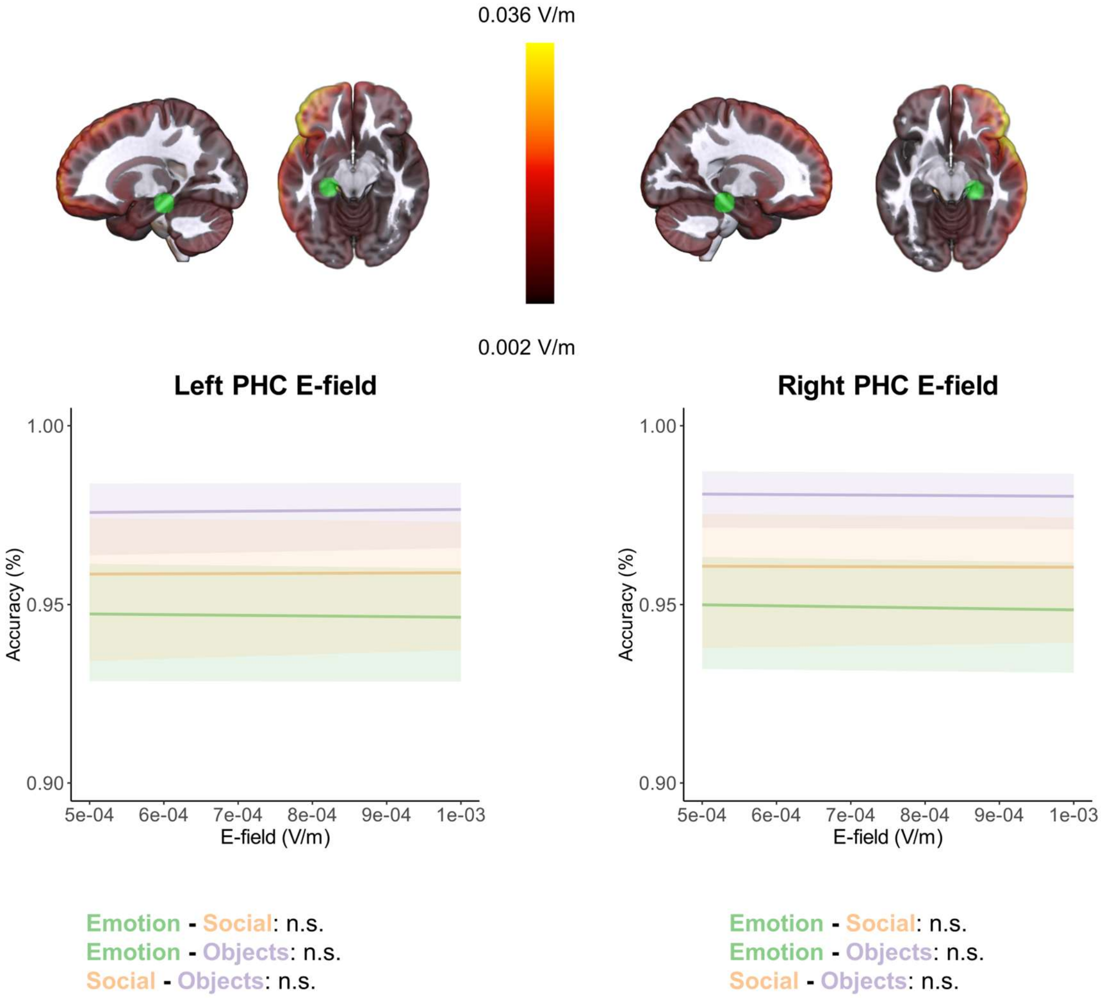
MAX: maximum, E-field: electric field.

(A) Adjusted predictions of the interaction between the electric field (E-field) induced in left MAX and category on Accuracy. Planned comparisons were non-significant (Emotion-Social: z value = 0.965, p = 1, Emotion-Objects: z value = 0.426, p = 1, Social-Objects: z value: -0.382, p = 1).

(B) Adjusted predictions of the interaction between the electric field (E-field) induced in right MAX and category on Accuracy. Planned comparisons were non-significant (Emotion-Social: z value = -1.588, p = 0.337, Emotion-Objects: z value = -0.545, p = 0.864, Social-Objects: z value: 0.786, p = 0.864).

(A-B) Error bars represent standard errors of the marginal means. (C-D) Error bars represent 95% confidence interval (CI) of the adjusted predictions. All p values were corrected for multiple comparisons using Holm correction. n.s. p > 0.05

Figure 6-11 Interaction between PHC E-field and category as predictors of Accuracy

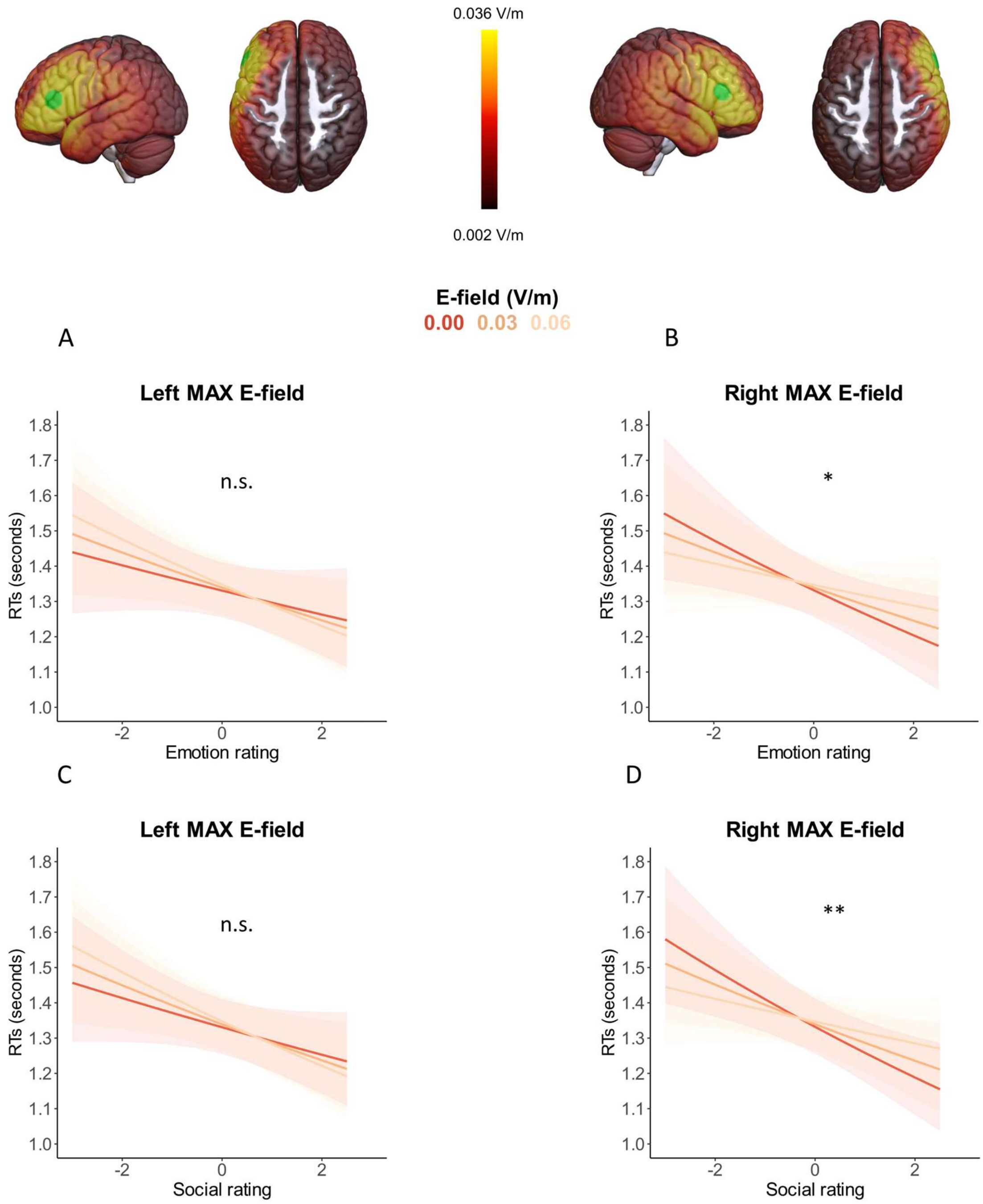


PHC: parahippocampal cortex, E-field: electric field.

(A) Adjusted predictions of the interaction between the electric field (E-field) induced in left PHC and category on Accuracy. Planned comparisons were non-significant (Emotion-Social: z value = -0.629, p = 1, Emotion-Objects: z value = -1.034, p = 0.903, Social-Objects: z value: -0.492, p = 1).

(B) Adjusted predictions of the interaction between the electric field (E-field) induced in right PHC and category on Accuracy. Planned comparisons were non-significant (Emotion-Social: z value = -0.638, p = 1, Emotion-Objects: z value = 0.086, p = 1, Social-Objects: z value: 0.616, p = 1).

Figure 7-1 Interaction between MAX E-field and semantic ratings as predictors of Reaction Times of Abstract triplets



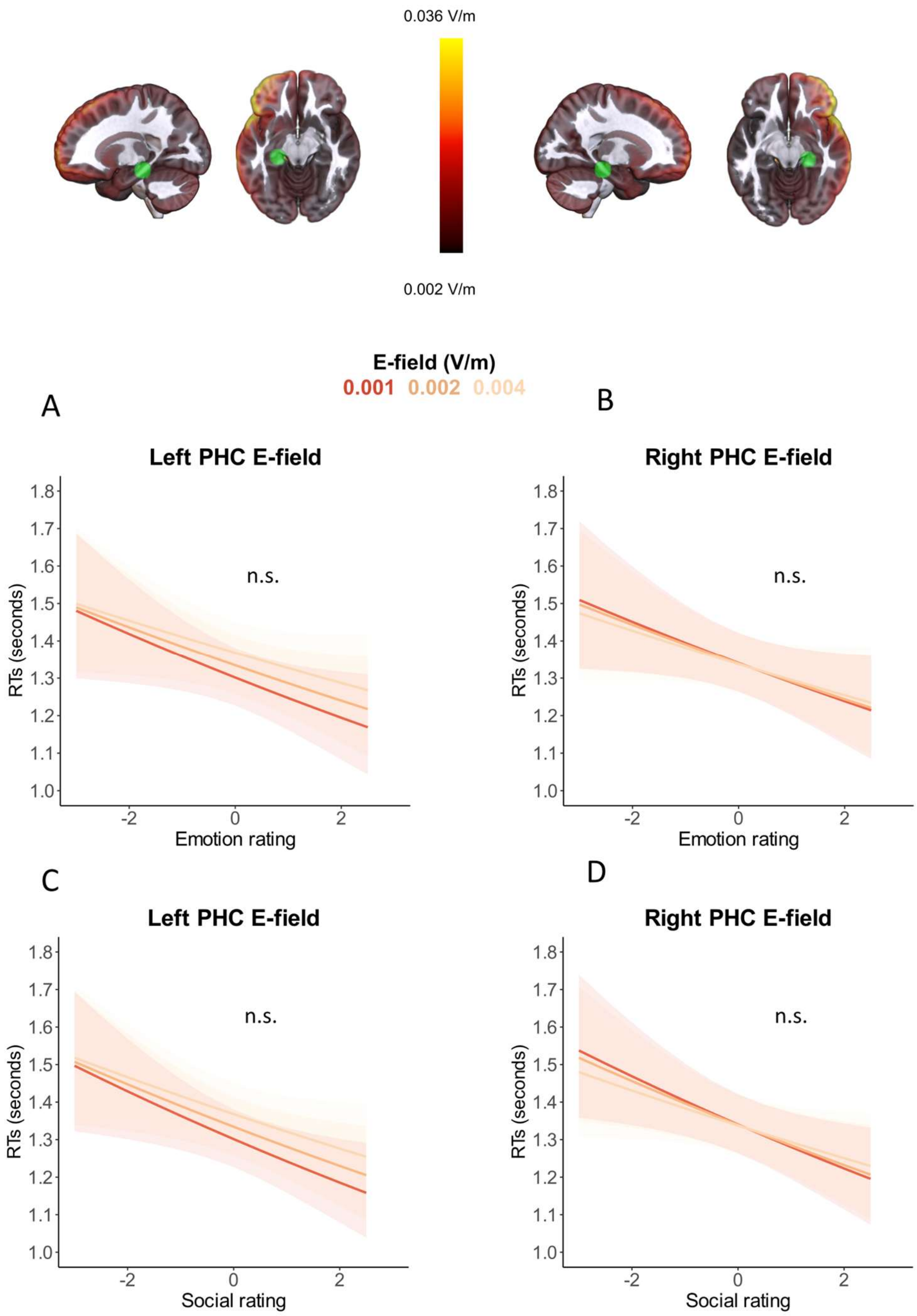
MAX: maximum, E-field: electric field. Results are shown on the centred Social and Emotion rating.

(A, C) Adjusted predictions of the interaction between the left MAX E-field on Emotion (A) and Social (C) rating. The interactions are not significant (left MAX E-field*Emotion rating: $F = 2.551$, $p = 0.110$, left MAX E-field*Social rating: $F = 2.746$, $p = 0.098$).

(B, D) Adjusted predictions of the interaction between the right MAX E-field on Emotion (B) and Social (D) rating. Both interactions are significant and show a positive trend, whereby the facilitatory effect of the Emotion and Social rating is reduced in the presence of a higher E-field in the right MAX (right MAX E-field*Emotion rating: $F = 5.168$, $p = 0.023$, right MAX E-field*Social rating: $F = 7.913$, $p = 0.005$).

Error bars represent 95% confidence intervals (CI) of the adjusted predictions. ** $p < 0.01$, * $p < 0.05$, n.s. $p > 0.05$

Figure 7-2. Interaction between PHC E-field and semantic ratings as predictors of Reaction Times of abstract triplets



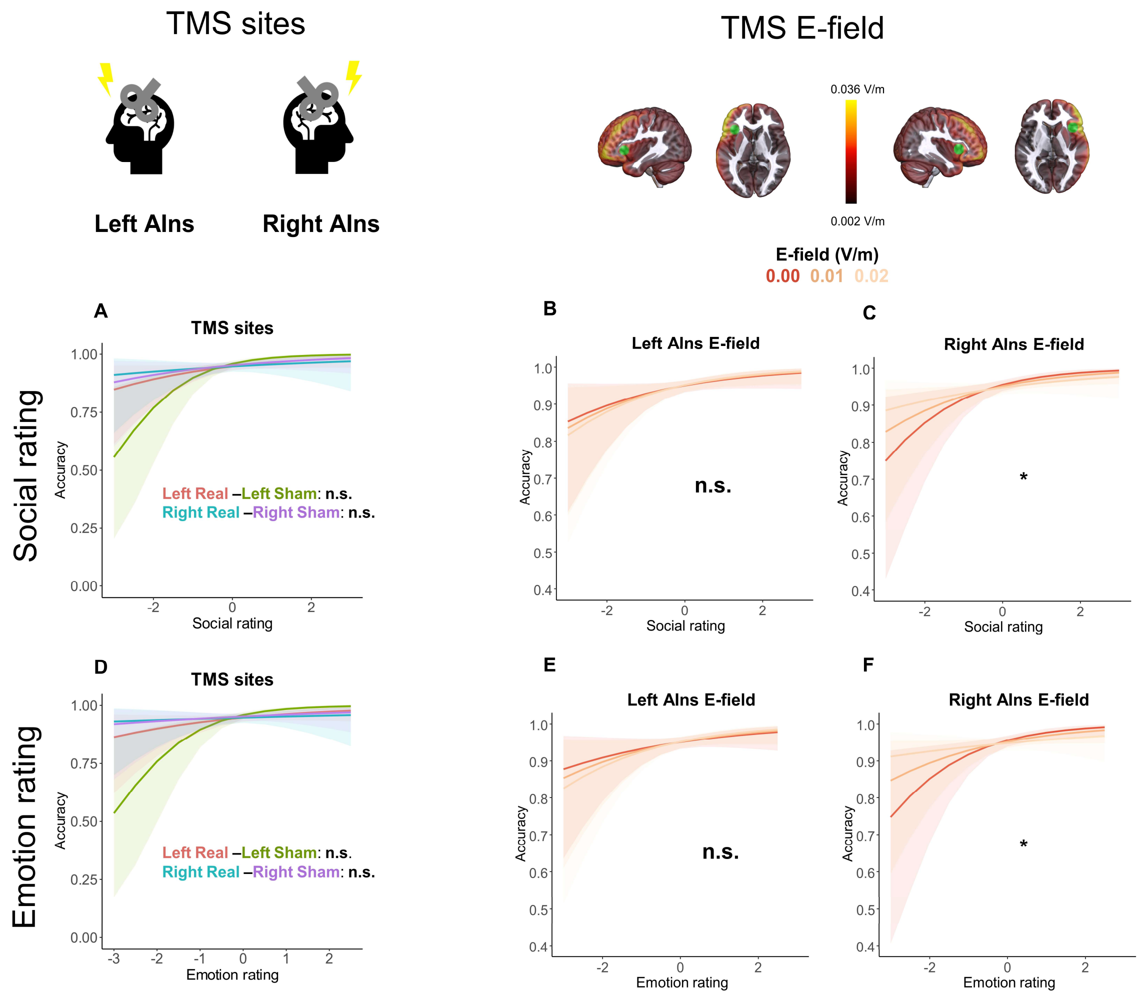
PHC: parahippocampal cortex, E-field: electric field. Results are shown on the centred Social and Emotion rating.

(A, C) Adjusted predictions of the interaction between the left PHC E-field on Emotion (A) and Social (C) rating. The interactions are not significant (left PHC E-field*Emotion rating: F value= 1.146, p = 0.284, left PHC*Social rating: F value= 1.163, p = 0.281).

(B, D) Adjusted predictions of the interaction between the right PHC E-field on Emotion (B) and Social (D) rating. Interactions are not significant (right PHC E-field*Emotion rating: F value= 0.281, p = 0.596, right PHC*Social rating: F value= 0.844, p = 0.358).

Error bars represent 95% confidence intervals (CI) of the adjusted predictions. n.s. p > 0.05

Figure 7-6. Semantic similarity task. Semantic ratings results with abstract triplets. Accuracy



AIns: Anterior Insula, E-field: electric field. Results are shown on the centred Social and Emotion rating.

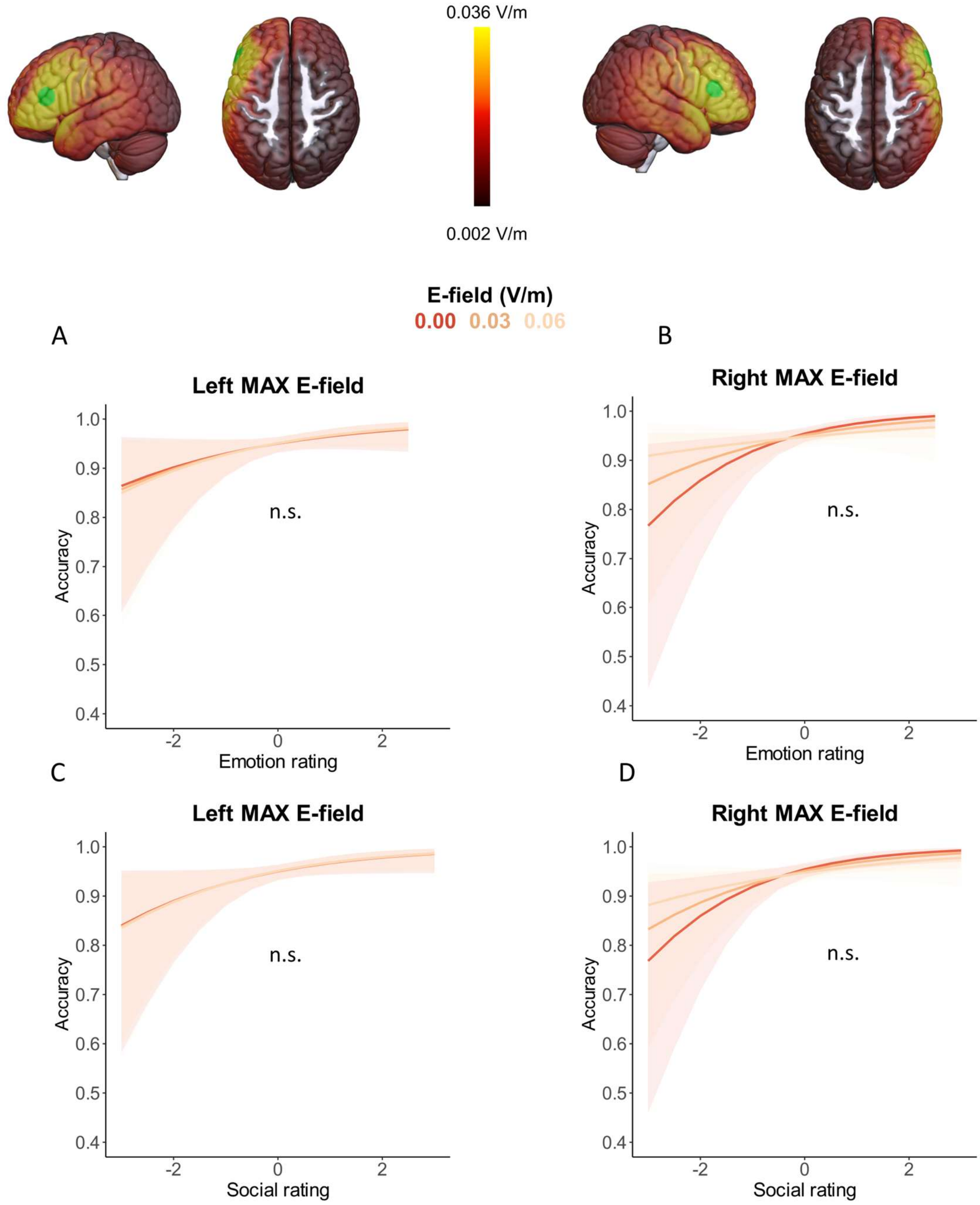
(A, D) Adjusted predictions of Accuracy following each TMS condition, transformed from logit to probability scale. The comparisons between left real-left sham and between right real-right sham were not significant. P values of the planned comparisons were corrected for multiple comparisons using Holm correction.

(B, E) Adjusted predictions of the interaction between the E-field induced in left AIns with Emotion (B) and Social (E) rating on Accuracy. The interactions are not significant.

(C, F) Adjusted predictions of the interaction between the E-field induced in right AIns with Emotion (B) and Social (E) rating on Accuracy. Both interactions are significant and show a negative trend, whereby the higher E-field in the right AIns determines the lower probability of responding correctly to triplets the higher their emotion and social rating.

Error bars represent 95% confidence intervals (CI) of the adjusted predictions. * $p < 0.05$, n.s. $p > 0.05$

Figure 7-7 Interaction between MAX E-field and semantic ratings as predictors of Accuracy of abstract triplets



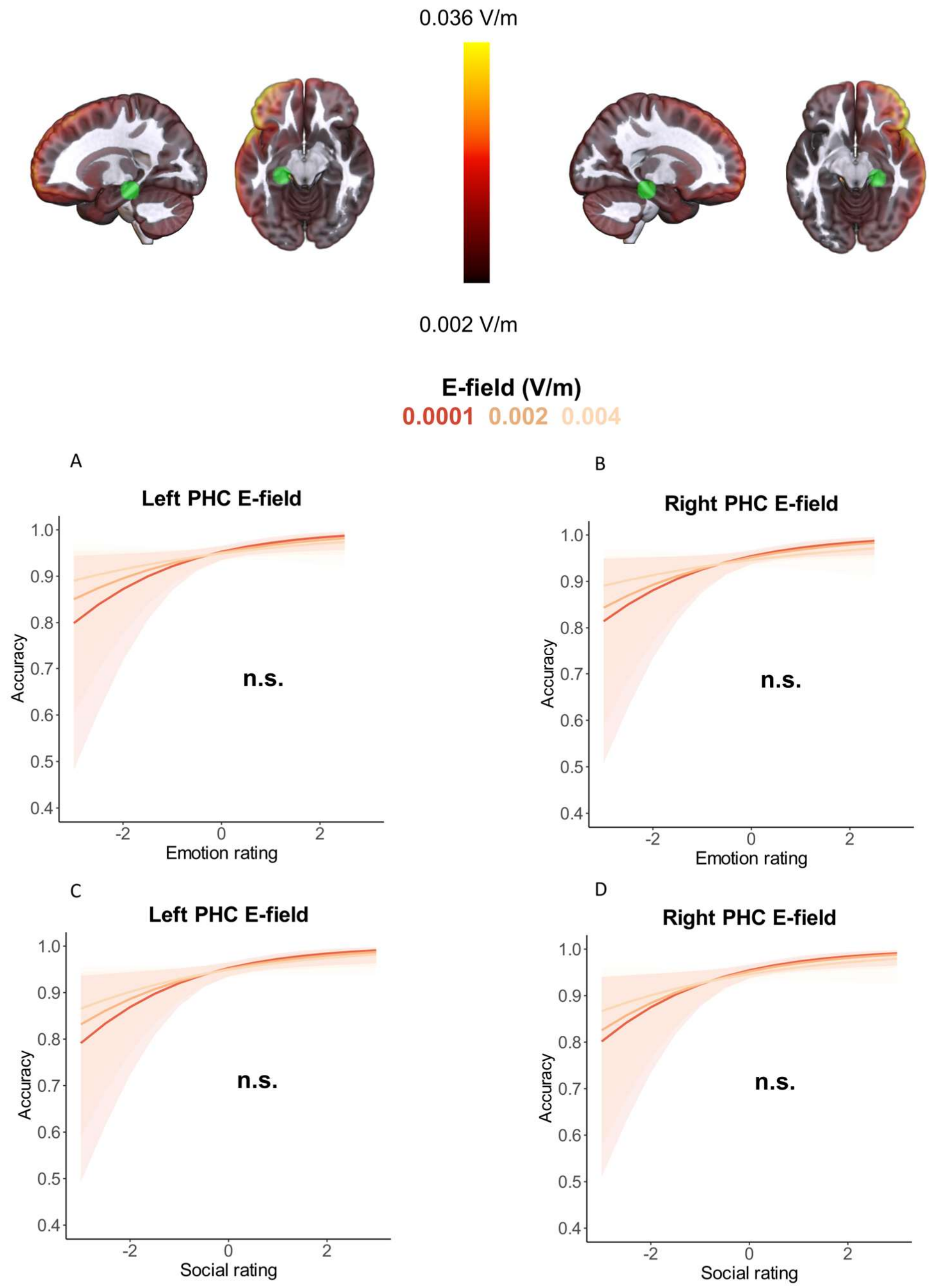
MAX: maximum, E-field: electric field. Results are shown on the centred Social and Emotion rating.

(A, C) Adjusted predictions of the interaction between the E-field induced in left MAX with Emotion (A) and Social (C) rating on Accuracy. The interactions are not significant (left MAX*Emotion rating: $X^2 = 0.054$, $p = 0.815$, left MAX* Social rating: $X^2 = 0.008$, $p = 0.927$).

(B, D) Adjusted predictions of the interaction between the E-field induced in right MAX with Emotion (B) and Social (D) rating on Accuracy. The interaction with Emotion rating is significant and shows a negative trend, whereby the higher E-field in the right MAX determines the lower probability of responding correctly to triplets the higher their emotion rating ($X^2 = 4.850$, $p = 0.028$). The interaction with Social rating is not significant ($X^2 = 3.084$, $p = 0.079$).

Error bars represent 95% confidence intervals (CI) of the adjusted predictions. ** $p < 0.01$, * $p < 0.05$, n.s. $p > 0.05$

Figure 7-8 Interaction between PHC E-field and semantic ratings as predictors of Accuracy of abstract triplets



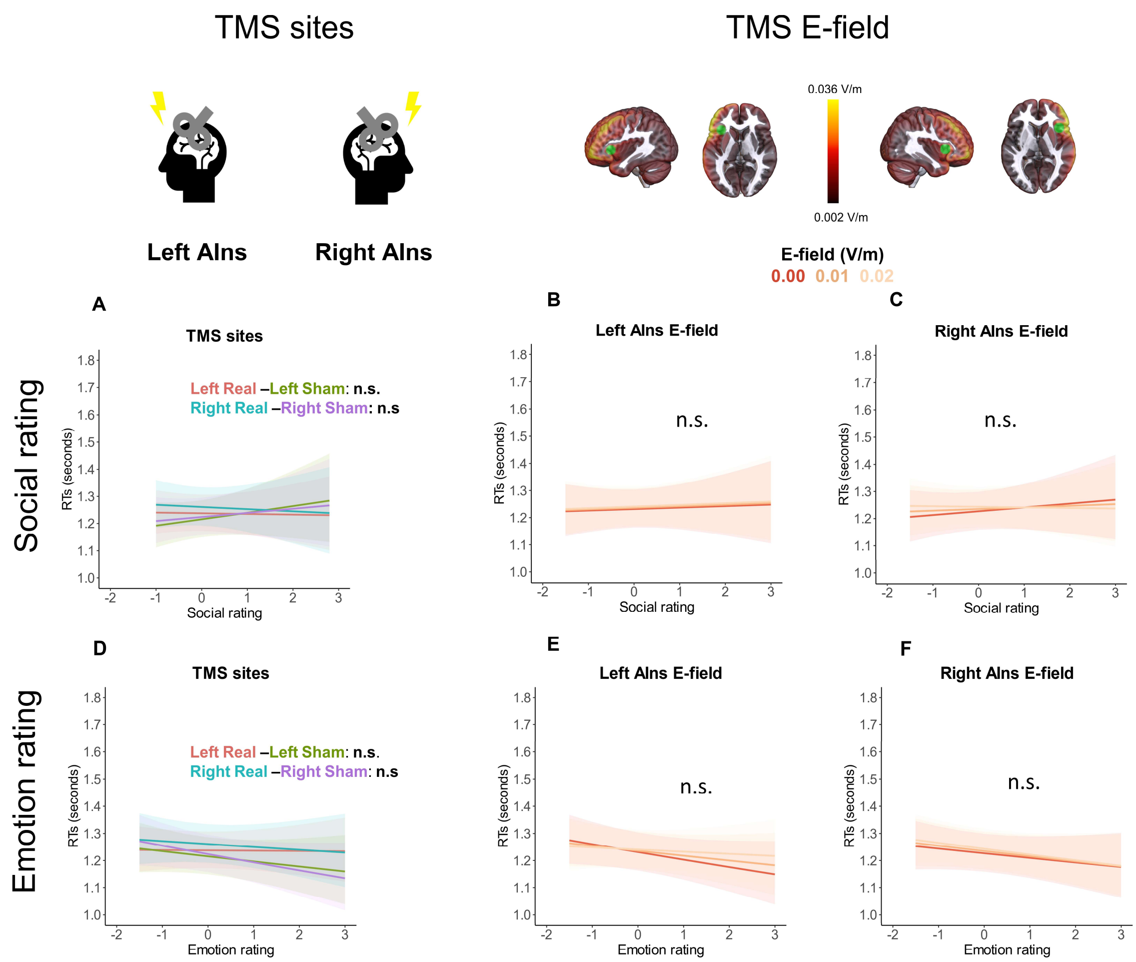
PHC: parahippocampal cortex, E-field: electric field. Results are shown on the centred Social and Emotion rating.

(A, C) Adjusted predictions of the interaction between the E-field induced in left PHC with Emotion (A) and Social (C) rating on Accuracy. The interactions are not significant (left PHC E-field*Emotion rating: $X^2 = 2.179$, $p = 0.140$, left PHC E-field*Social rating: $X^2 = 1.431$, $p = 0.232$).

(B, D) Adjusted predictions of the interaction between the E-field induced in right PHC with Emotion (B) and Social (D) rating on Accuracy. The interactions are not significant (right PHC E-field*Emotion rating: $X^2 = 1.806$, $p = 0.179$, right PHC E-field*Social rating: $X^2 = 1.336$, $p = 0.248$).

Error bars represent 95% confidence intervals (CI) of the adjusted predictions. n.s. $p > 0.05$

Figure 7-12. Semantic similarity task. Semantic ratings results with concrete triplets. RTs



AIns: Anterior Insula, E-field: electric field. Results are shown on the centred Social and Emotion rating.

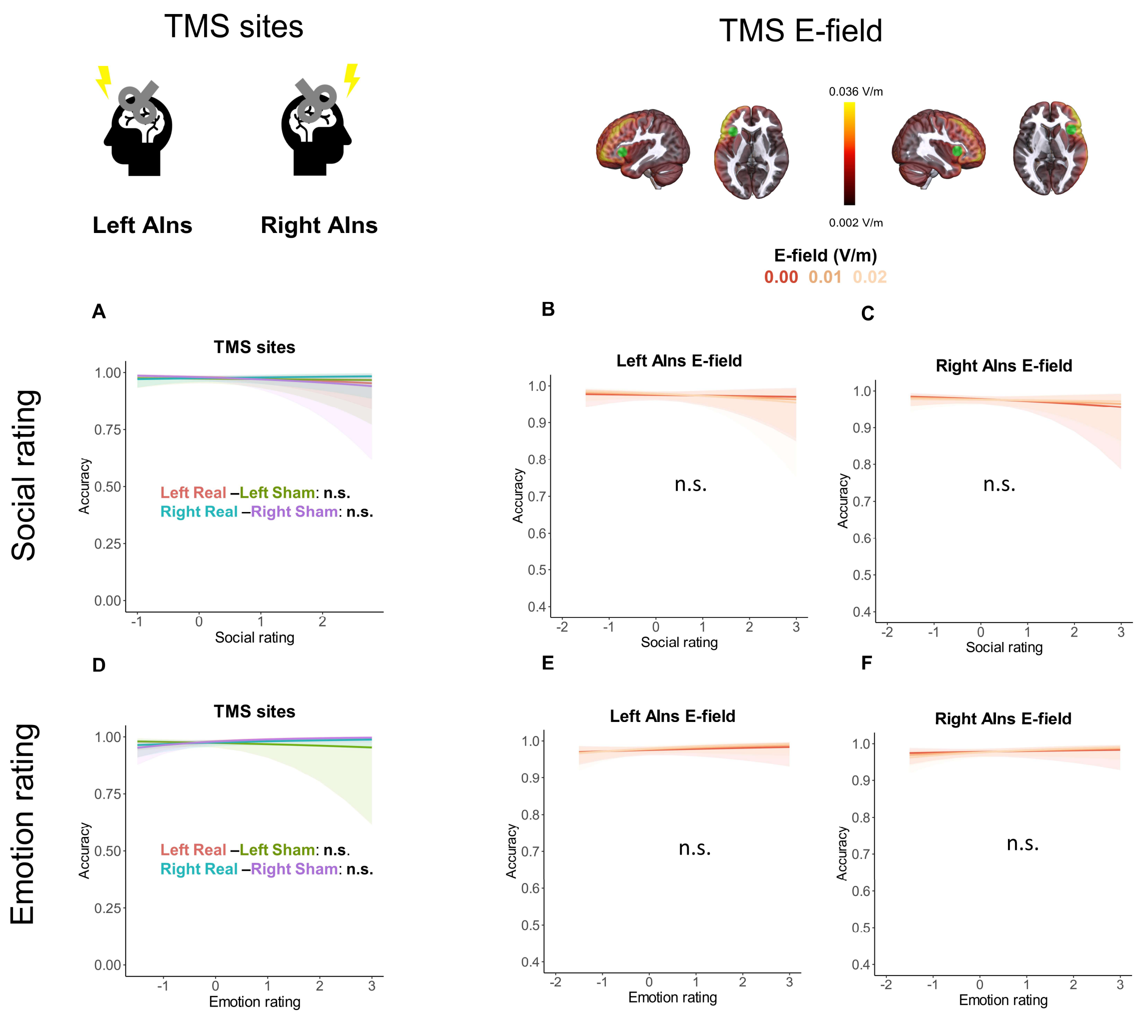
(A, D) Adjusted predictions of reaction times (RTs) following each TMS condition, shown in the response scale. The comparisons between left real-left sham and between right real-right sham were not significant, meaning the TMS condition did not significantly change the effect of social or emotion rating on the RTs for concrete triplets. P values of the planned comparisons were corrected for multiple comparisons using Holm correction.

(B, E) Adjusted predictions of the interaction between the E-field induced in left AIns on Social (B) and Emotion (E) rating. The interactions are not significant, meaning the magnitude of the E-field inside left AIns did not significantly change the effect of social or emotion rating on the RTs for concrete triplets.

(C, F) Adjusted predictions of the interaction between the E-field induced in right AIns with Emotion (B) and Social (E) rating. Interactions are not significant, meaning the magnitude of the E-field inside right AIns did not significantly change the effect of social or emotion rating on the RTs for concrete triplets.

Error bars represent 95% confidence intervals (CI) of the adjusted predictions. ** $p < 0.01$, * $p < 0.05$, n.s. $p > 0.05$

Figure 7-16. Semantic similarity task. Semantic ratings results with concrete triplets. Accuracy



AIns: Anterior Insula, E-field: electric field. Results are shown on the centred Social and Emotion rating.

(A, D) Adjusted predictions of Accuracy following each TMS condition, transformed from logit to probability scale. The comparisons between left real-left sham and between right real-right sham were not significant, meaning the TMS condition did not significantly change the effect of social or emotion rating on the accuracy for concrete triplets. P values of the planned comparisons were corrected for multiple comparisons using Holm correction.

(B, E) Adjusted predictions of the interaction between the E-field induced in left AIns with Emotion (B) and Social (E) rating on Accuracy. The interactions are not significant, meaning the magnitude of the E-field inside left AIns did not significantly change the effect of social or emotion rating on the accuracy for concrete triplets

(C, F) Adjusted predictions of the interaction between the E-field induced in right AIns with Emotion (B) and Social (E) rating on Accuracy. Interactions are not significant, meaning the magnitude of the

E-field inside right AIns did not significantly change the effect of social or emotion rating on the accuracy for concrete triplets.

Error bars represent 95% confidence intervals (CI) of the adjusted predictions. n.s. $p > 0.05$

Tables

Table 3-1. Single-subject MNI MAX PEAKS

Left MAX		
x	y	z
-57	31	16
-51	25	41
-59	24	21
-43	29	48
-58	33	8
-55	40	0
58	28	8
-55	34	-4
-58	20	29
-60	17	10
-58	32	8
-57	33	6
-53	39	14
-56	36	12
-52	43	16
-55	29	24
-57	35	11
-58	57	24

Right MAX		
x	y	z
54	19	38
58	27	20
56	30	26
61	21	19
55	38	13
61	21	17
57	31	12
58	31	12
58	28	13
56	36	0
58	29	18
61	20	17
59	28	7
58	33	10
53	41	18
60	21	19
58	29	21
54	59	20

-57	34	4		55	36	18
-52	22	43		61	21	15
-56	35	14		58	30	23
-57	33	4		57	35	15
-57	35	4		58	31	8
-59	27	7		58	31	17
-58	32	5		55	38	4
AVERAGE				AVERAGE		
-51.20	32.12	14.92		57.48	30.56	16

MNI coordinates of E-field maximum peak (MAX E-field) during left and right TMS, for each subject.

Table 2-1. E-field in left Anterior Insula as predictor of Interoceptive accuracy.

Model results

	Chisq	*Df*	*p-value*
(Intercept)	0.487	1	0.485
Left AIns MagnE E-field	0.050	1	0.823
Heart rate	**7.635**	**1**	**0.006**

Mixed-effects model results of TMS E-field in left AIns as predictors of interoceptive accuracy. Significant effects are written in bold.

Chisq: Chi-squared statistic, Df: degrees of freedom

Table 4-1. Interaction between semantic ratings and E-field in left Anterior Insula as predictors of Reaction times of Abstract triplets.

Model results

	Sum.Sq	*Mean.Sq*	*NumDF*	*DenDF*	*F.value*	*p-value*
Left AIns E-field	**0.331**	**0.331**	**1**	**4523.185**	**5.602**	**0.018**
Emotion_rating	0.222	0.222	1	103.405	3.751	0.055

Social_rating	**0.312**	**0.312**	**1**	**103.486**	**5.281**	**0.024**
semantic similarity similars	**0.321**	**0.321**	**1**	**103.627**	**5.427**	**0.022**
semantic similarity distants	0.000	0.000	1	104.848	0.001	0.972
triplet length	**0.768**	**0.768**	**1**	**103.146**	**12.989**	**0.000**
Left AIns E-field:Emotion_rating	0.197	0.197	1	4514.340	3.337	0.068
Left AIns E-field:Social_rating	**0.263**	**0.263**	**1**	**4513.293**	**4.450**	**0.035**

Mixed-effects model results of TMS E-field in left AIns and semantic ratings as predictors of (log-transformed) reaction times to abstract triplets, where the last two rows represent the interaction between the magnitude of the E-field inside left AIns and respectively emotion and social rating. Significant effects are written in bold.

Sum.Sq: Sum of squares, Mean.Sq: Sum of squares / degrees of freedom, NumDF: Degrees of freedom, DenDF: Denominator degrees of Freedom

Figure 6-1. Interaction between category and TMS site as predictors of Reaction Times.

Model results

	Sum.Sq	*Mean.Sq*	*NumDF*	*DenDF*	*F.value*	*p-value*
TMS site	**1.177**	**0.392**	**3**	**8169.676**	**6.994**	**0.000**
category	**1.102**	**0.551**	**2**	**176.689**	**9.817**	**0.000**
semantic similarity similars	**0.578**	**0.578**	**1**	**176.618**	**10.294**	**0.002**
semantic similarity distants	0.028	0.028	1	177.715	0.493	0.484
triplet length	**0.322**	**0.322**	**1**	**176.367**	**5.745**	**0.018**
TMS site:category	0.093	0.015	6	8170.305	0.276	0.948

Planned comparisons

contrast	*estimate*	*SE*	*df*	*t.ratio*	*p-value*
Emotion Left Real - Left Sham	1.014	0.013	8205.338	1.112	0.475
Social Left Real - Left Sham	1.018	0.013	8198.664	1.385	0.475
Object Left Real - Left Sham	1.018	0.013	8198.395	1.411	0.475
Emotion Right Real - Right Sham	1.026	0.013	8180.070	1.978	0.192
Social Right Real - Right Sham	1.029	0.013	8179.276	2.279	0.123
Object Right Real - Right Sham	1.030	0.013	8179.980	2.318	0.123

Mixed-effect regression model results of TMS site and category as predictors of (log-transformed) reaction times, and planned comparisons between ipsilateral real and sham stimulations, showing for each semantic category the difference in average between right real and right sham TMS conditions, and between left real and left sham TMS conditions. Significant results are written in bold.

Sum.Sq: Sum of squares, Mean.Sq: Sum of squares / degrees of freedom, NumDF, df: Degrees of freedom, DenDF: Denominator degrees of Freedom, estimate: estimated value of the contrast, SE: standard error, t.ratio: test statistic

Figure 6-2. Interaction between category and E-field in left Anterior Insula as predictors of Reaction times.

Model results

	Sum.Sq	*Mean.Sq*	*NumDF*	*DenDF*	*F.value*	*p-value*
Left AIns E-field	**0.413**	**0.413**	**1**	**7845.968**	**7.352**	**0.007**
category	**1.106**	**0.553**	**2**	**176.786**	**9.858**	**0.000**
semantic similarity similars	**0.541**	**0.541**	**1**	**176.630**	**9.649**	**0.002**
semantic similarity distants	0.015	0.015	1	177.888	0.267	0.606
triplet length	**0.317**	**0.317**	**1**	**176.471**	**5.649**	**0.019**
Left AIns E-field:category	0.117	0.059	2	7839.937	1.044	0.352

Planned comparisons

contrast	*estimate*	*SE*	*df*	*t.ratio*	*p-value*
Emotion - Social	0.714	0.723	7846.604	0.988	0.647
Emotion - Objects	1.009	0.715	7846.158	1.411	0.475
Social - Objects	0.295	0.711	7841.947	0.414	0.679

Mixed-effect regression model results of TMS E-field in left AIns and category as predictors of (log-transformed) reaction times, and planned comparisons to test for differences in the effects of E-field in left AIns between categories. Significant results are written in bold.

Sum.Sq: Sum of squares, Mean.Sq: Sum of squares / degrees of freedom, NumDF, df: Degrees of freedom, DenDF: Denominator degrees of Freedom, estimate: estimated value of the contrast, SE: standard error, t.ratio: test statistics

Figure 6-3. Interaction between category and E-field in right Anterior Insula as predictors of Reaction times.

Model results

	Sum.Sq	*Mean.Sq*	*NumDF*	*DenDF*	*F.value*	*p-value*
Right AIns E-field	0.056	0.056	1	7837.694	1.001	0.317
category	**1.108**	**0.554**	**2**	**176.776**	**9.865**	**0.000**
semantic similarity similars	**0.550**	**0.550**	**1**	**176.605**	**9.797**	**0.002**
semantic similarity distants	0.015	0.015	1	177.894	0.261	0.610
triplet length	**0.317**	**0.317**	**1**	**176.468**	**5.642**	**0.019**
Right AIns E-field:category	0.230	0.115	2	7830.225	2.047	0.129

Planned comparisons

contrast	*estimate*	*SE*	*df*	*t.ratio*	*p-value*
Emotion - Social	-1.100	0.628	7836.549	-1.751	0.232
Emotion - Objects	-1.104	0.625	7835.156	-1.768	0.232
Social - Objects	-0.004	0.618	7834.162	-0.006	0.995

Mixed-effect regression model results of TMS E-field in right AIns and category as predictors of (log-transformed) reaction times, and planned comparisons to test for differences in the effects of E-field in right AIns between categories. Significant results are written in bold.

Sum.Sq: Sum of squares, Mean.Sq: Sum of squares / degrees of freedom, NumDF, df: Degrees of freedom, DenDF: Denominator degrees of Freedom, estimate: estimated value of the contrast, SE: standard error, t.ratio: test statistic

Figure 6-6. Interaction between category and TMS site as predictors of Accuracy.

Model results

	Chisq	*Df*	*p-value*
(Intercept)	**492.904**	**1**	**0.000**
TMS site	0.772	3	0.856
category	**19.246**	**2**	**0.000**
semantic similarity similars	**11.371**	**1**	**0.001**
semantic similarity distants	2.874	1	0.090
triplet length	0.756	1	0.385
TMS site:category	4.971	6	0.548

Planned comparisons

contrast	*odds.ratio*	*SE*	*z.ratio*	*p-value*
Emotion Left Real - Left Sham	0.858	0.169	-0.781	1.000
Social Left Real - Left Sham	0.807	0.170	-1.016	1.000
Object Left Real - Left Sham	1.307	0.359	0.975	1.000
Emotion Right Real - Right Sham	1.027	0.189	0.143	1.000
Social Right Real - Right Sham	0.868	0.188	-0.654	1.000
Object Right Real - Right Sham	0.833	0.229	-0.664	1.000

Mixed-effects logistic regression model results of TMS site and category as predictors of accuracy, and planned comparisons between ipsilateral real and sham stimulations, for each semantic category. Significant results are written in bold.

Chisq: Chi-squared statistic, Df: degrees of freedom, SE: standard error, z.ratio: test statistic

Figure 6-7. Interaction between category and E-field in right Anterior Insula as predictors of Accuracy.

Model results

	Chisq	*Df*	*p-value*
(Intercept)	**474.911**	**1**	**0.000**
Right AIns E-field	2.365	1	0.124

category	**19.796**	**2**	**0.000**
semantic similarity similars	**12.586**	**1**	**0.000**
semantic similarity distants	3.514	1	0.061
triplet length	1.023	1	0.312
Right AIns E-field:category	1.814	2	0.404

Planned comparisons

contrast	*estimate*	*SE*	*z.ratio*	*p-value*
Emotion - Social	-12.904	9.611	-1.343	0.538
Emotion - Objects	-4.523	11.333	-0.399	0.957
Social - Objects	8.381	11.828	0.709	0.957

Mixed-effect logistic regression model results of TMS E-field in right AIns and category as predictors of accuracy, and planned comparisons to test for differences in the effects of E-field in right AIns between categories, showing the differences in the slope of the E-field effect on accuracy across categories. Significant results are written in bold.

Chisq: Chi-squared statistic, Df: degrees of freedom, estimate: estimated value of the contrast, SE: standard error, z.ratio: test statistic

Figure 6-8. Interaction between category and E-field in left Anterior Insula as predictors of Accuracy.

Model results

	Chisq	*Df*	*p-value*
(Intercept)	**474.879**	**1**	**0.000**
Left AIns E-field	0.636	1	0.425
category	**19.969**	**2**	**0.000**
semantic similarity similars	**12.580**	**1**	**0.000**
semantic similarity distants	3.442	1	0.064
triplet length	1.020	1	0.313
Left AIns E-field:category	1.208	2	0.547

Planned comparisons

contrast	*estimate*	*SE*	*z.ratio*	*p-value*
Emotion - Social	10.921	11.129	0.981	0.979
Emotion - Objects	-1.143	12.997	-0.088	0.979
Social - Objects	-12.064	13.552	-0.890	0.979

Mixed-effect logistic regression model results of TMS E-field in left AIns and category as predictors of accuracy, and planned comparisons to test for differences in the effects of E-field in left AIns between categories, showing the differences in the slope of the E-field effect on accuracy across categories. Significant effects are written in bold.

Chisq: Chi-squared statistic, Df: degrees of freedom, estimate: estimated value of the contrast, SE: standard error, z.ratio: test statistic

Figure 7-3. Interaction between semantic ratings and TMS site as predictors of Accuracy of Abstract triplets.

Model results

	Chisq	*Df*	*p-value*
(Intercept)	**351.527**	**1**	**0.000**
Emotion rating	3.323	1	0.068
Social rating	**5.109**	**1**	**0.024**
TMS site	3.545	3	0.315
semantic similarity similars	**7.846**	**1**	**0.005**
semantic similarity distants	3.411	1	0.065
triplet length	0.017	1	0.896
Emotion rating:TMS site	**10.404**	**3**	**0.015**
Social rating:TMS site	**8.131**	**3**	**0.043**

Planned comparisons

Emotion rating and TMS site

contrast	*estimate*	*SE*	*z.ratio*	*p-value*
Left Real – Left Sham	-0.653	0.308	-2.119	0.068
Right Real – Right Sham	-0.090	0.296	-0.305	0.760

Social rating and TMS site

contrast	*estimate*	*SE*	*z.ratio*	*p-value*
Left Real – Left Sham	-0.583	0.293	-1.988	0.094
Right Real – Right Sham	-0.148	0.282	-0.525	0.600

Mixed-effects logistic regression model results of TMS site and semantic ratings as predictors of accuracy, and planned comparisons between ipsilateral real and sham stimulations, showing the difference in the average slope of emotion and social scores effect between right real and right sham TMS conditions, and between left real and left sham TMS conditions. Significant results are written in bold.

Chisq: Chi-squared statistic, Df: degrees of freedom, estimate: estimated value of the contrast, SE: standard error, z.ratio: test statistic

Figure 7-4. Interaction between semantic ratings and E-field in right Anterior Insula as predictors of Accuracy of Abstract triplets.

Model results

	Chisq	*Df*	*p-value*
(Intercept)	**340.264**	**1**	**0.000**
Right AIns E-field	2.547	1	0.111
Emotion rating	**3.508**	**1**	**0.061**
Social rating	**5.039**	**1**	**0.025**
semantic similarity similars	**9.313**	**1**	**0.002**
semantic similarity distants	**4.237**	**1**	**0.040**
triplet length	0.032	1	0.859
Right AIns E-field:Emotion rating	**6.132**	**1**	**0.013**
Right AIns E-field:Social rating	**4.252**	**1**	**0.039**

Mixed-effects logistic regression model results of TMS E-field in right AIns and semantic ratings as predictors of accuracy, where the last two rows represent the interaction between the magnitude of the E-field inside right AIns and respectively emotion and social rating. Significant effects are written in bold.

Chisq: Chi-squared statistic, Df: degrees of freedom

Figure 7-5. Interaction between semantic ratings and E-field in left Anterior Insula as predictors of Accuracy of Abstract triplets.

Model results

	Chisq	*Df*	*p-value*
(Intercept)	**341.337**	**1**	**0.000**
Left AIns E-field	0.052	1	0.820
Emotion rating	3.191	1	0.074
Social rating	**4.662**	**1**	**0.031**
semantic similarity similars	**9.228**	**1**	**0.002**
semantic similarity distants	**4.285**	**1**	**0.038**
triplet length	0.042	1	0.837
Left AIns E-field:Emotion rating	0.463	1	0.496
Left AIns E-field:Social rating	0.232	1	0.630

Mixed-effects logistic regression model results of TMS E-field in left AIns and semantic ratings as predictors of accuracy, where the last two rows represent the interaction between the magnitude of the E-field inside left AIns and respectively emotion and social rating. Significant effects are written in bold.

Chisq: Chi-squared statistic, Df: degrees of freedom

Figure 7-9. Interaction between TMS site and semantic ratings as predictors of Reaction times of Concrete triplets.

Model results

	Sum.Sq	*Mean.Sq*	*NumDF*	*DenDF*	*F.value*	*p value*
Emotion_rating	0.045	0.045	1	58.444	0.898	0.347
Social_rating	0.006	0.006	1	58.676	0.113	0.738
TMS_session	**0.548**	**0.183**	**3**	**2795.148**	**3.682**	**0.012**
semantic similarity similars	0.166	0.166	1	58.742	3.346	0.072
semantic similarity distants	0.068	0.068	1	58.772	1.373	0.246
triplet length	0.059	0.059	1	58.946	1.194	0.279
Emotion_rating:TMS_session	0.150	0.050	3	2793.051	1.010	0.387
Social_rating:TMS_session	0.127	0.042	3	2794.523	0.853	0.465

Planned comparisons

Emotion ratings and TMS site

contrast	*estimate*	*SE*	*df*	*t.ratio*	*p.value*
Left Real-Left Sham	0.015	0.015	2806.852	1.009	0.500
Right Real-Right Sham	0.017	0.015	2802.993	1.151	0.500

Social ratings and TMS site

contrast	*estimate*	*SE*	*df*	*t.ratio*	*p.value*
Left Real-Left Sham	-0.022	0.019	2812.013	-1.161	0.492
Right Real -Right Sham	-0.019	0.018	2801.795	-1.009	0.492

Mixed-effect regression model results of TMS site and semantic ratings as predictors of (log-transformed) reaction times to concrete triplets, and planned comparisons between ipsilateral real and sham stimulations, showing the difference in the average slope of emotion and social scores effect between right real and right sham TMS conditions, and between left real and left sham TMS conditions. Significant results are written in bold.

Sum.Sq: Sum of squares, Mean.Sq: Sum of squares / degrees of freedom, NumDF, df: Degrees of freedom, DenDF: Denominator degrees of Freedom, estimate: estimated value of the contrast, SE: standard error, t.ratio: test statistics

Figure 7-10. Interaction between semantic ratings and E-field in right Anterior Insula as predictors of Reaction times of Concrete triplets.

Model summary

	Sum.Sq	*Mean.Sq*	*NumDF*	*DenDF*	*F.value*	*p value*
Right AIns E-field	0.128	0.128	1	2686.189	2.581	0.108
Emotion_rating	0.049	0.049	1	58.422	0.985	0.325
Social_rating	0.003	0.003	1	58.633	0.068	0.795
semantic similarity similars	0.147	0.147	1	58.696	2.954	0.091
semantic similarity distants	0.060	0.060	1	58.703	1.204	0.277
triplet length	0.059	0.059	1	58.916	1.196	0.278
Right AIns E-field: Emotion_rating	0.001	0.001	1	2678.569	0.021	0.884
Right AIns E-field:Social_rating	0.099	0.099	1	2678.088	1.987	0.159

Mixed-effect regression model results of TMS E-field in right AIns and semantic ratings as predictors of (log-transformed) reaction times to concrete triplets, where the last two rows represent the interaction between the magnitude of the E-field inside right AIns and respectively emotion and social rating. Significant effects are written in bold.

Sum.Sq: Sum of squares, Mean.Sq: Sum of squares / degrees of freedom, NumDF: Degrees of freedom, DenDF: Denominator degrees of Freedom

Figure 7-11. Interaction between semantic ratings and E-field in left Anterior Insula as predictors of Reaction times of Concrete triplets.

	Sum.Sq	Mean.Sq	NumDF	DenDF	F.value	p value
Left AIns E-field	0.031	0.031	1	2688.058	0.633	0.426
Emotion_rating	0.050	0.050	1	58.416	1.000	0.321
Social_rating	0.003	0.003	1	58.635	0.070	0.792
semantic similarity similars	0.146	0.146	1	58.696	2.937	0.092
semantic similarity distants	0.059	0.059	1	58.710	1.191	0.280
triplet length	0.059	0.059	1	58.915	1.177	0.282
Left AIns E-field:Emotion_rating	0.093	0.093	1	2680.186	1.878	0.171
Left AIns E-field:Social_rating	0.000	0.000	1	2682.959	0.010	0.921

Mixed-effect regression model results of TMS E-field in left AIns and semantic ratings as predictors of (log-transformed) reaction times to concrete triplets, where the last two rows represent the interaction between the magnitude of the E-field inside left AIns and respectively emotion and social rating. Significant effects are written in bold.

Sum.Sq: Sum of squares, Mean.Sq: Sum of squares / degrees of freedom, NumDF: Degrees of freedom, DenDF: Denominator degrees of Freedom

Figure 7-13. Interaction between TMS site and semantic ratings as predictors of Accuracy of Concrete triplets.

Model summary

	Chisq	*Df*	*p value*
(Intercept)	302.847	1	0.000
Emotion_rating	2.410	1	0.121
Social_rating	0.453	1	0.501

TMS_session	1.477	3	0.688
semantic similarity similars	3.355	1	0.067
semantic similarity distants	0.040	1	0.841
triplet length	2.520	1	0.112
Emotion_rating:TMS_session	5.212	3	0.157
Social_rating:TMS_session	1.452	3	0.693

Planned comparisons

Emotion ratings and TMS site

contrast	*estimate*	*SE*	*z.ratio*	*p.value*
Left Real-Left Sham	0.802	0.439	1.826	0.136
Right Real-Right Sham	-0.337	0.455	-0.742	0.458

Social ratings and TMS site

contrast	*estimate*	*SE*	*z.ratio*	*p.value*
Left Real-Left Sham	-0.242	0.482	-0.502	0.616
Right Real-Right Sham	0.546	0.501	1.089	0.552

Mixed-effects logistic regression model results of TMS site and semantic ratings as predictors of accuracy to concrete triplets, and planned comparisons between ipsilateral real and sham stimulations, showing the difference in the average slope of emotion and social scores effect between right real and right sham TMS conditions, and between left real and left sham TMS conditions. Significant results are written in bold.

Chisq: Chi-squared statistic, Df: degrees of freedom, estimate: estimated value of the contrast, SE: standard error, z.ratio: test statistic

Figure 7-14. Interaction between semantic ratings and E-field in right Anterior Insula as predictors of Accuracy of Concrete triplets.

	Chisq	*Df*	*p value*
(Intercept)	296.364	1	0.000
Right AIns E-field	0.153	1	0.696
Emotion_rating	0.899	1	0.343

Social_rating	0.259	1	0.611
semantic similarity similars	2.963	1	0.085
semantic similarity distants	0.036	1	0.849
triplet length	3.389	1	0.066
Right AIns E-field:Emotion_rating	0.710	1	0.400
Right AIns E-field:Social_rating	0.292	1	0.589

Mixed-effect logistic regression model results of TMS E-field in right AIns and semantic ratings as predictors of accuracy to concrete triplets, where the last two rows represent the interaction between the magnitude of the E-field inside right AIns and respectively emotion and social rating. Significant effects are written in bold.

Chisq: Chi-squared statistic, Df: degrees of freedom

Figure 7-15. Interaction between semantic ratings and E-field in left Anterior Insula as predictors of Accuracy of Concrete triplets.

	Chisq	*Df*	*p value*
(Intercept)	295.956	1	0.000
Left AIns E-field	0.448	1	0.503
Emotion_rating	0.958	1	0.328
Social_rating	0.276	1	0.599
semantic similarity similars	2.952	1	0.086
semantic similarity distants	0.030	1	0.862
triplet length	3.314	1	0.069
Left AIns E-field:Emotion_rating	0.125	1	0.723
Left AIns E-field:Social_rating	0.059	1	0.809

Mixed-effects logistic regression model results of TMS E-field in left AIns and semantic ratings as predictors of accuracy to concrete triplets, where the last two rows represent the interaction between the magnitude of the E-field inside left AIns and respectively emotion and social rating. Significant effects are written in bold.

Chisq: Chi-squared statistic, Df: degrees of freedom

Table 8.1 Three-way interaction between semantic ratings, E-field in right Anterior Insula and sex as predictors of Reaction Times of Abstract triplets

	Sum.Sq	*Mean.Sq*	*NumDF*	*DenDF*	*F.value*	*P value*
Right AIns E-field	0,020	0,020	1	4524,692	0,343	0,558
Emotion_rating	**0,291**	**0,291**	**1**	**112,388**	**4,933**	**0,028**
Social_rating	**0,393**	**0,393**	**1**	**112,960**	**6,647**	**0,011**
sex	0,164	0,164	1	23,990	2,771	0,109
semantic similarity similars	**0,330**	**0,330**	**1**	**103,637**	**5,584**	**0,020**
semantic similarity distants	0,000	0,000	1	104,863	0,002	0,967
triplet length	**0,764**	**0,764**	**1**	**103,191**	**12,932**	**0,000**
Right AIns E-field:Emotion_rating	**0,276**	**0,276**	**1**	**4518,075**	**4,675**	**0,031**
Right AIns E-field:Social_rating	**0,468**	**0,468**	**1**	**4517,240**	**7,925**	**0,005**
Right AIns E-field:sex	0,017	0,017	1	4543,124	0,296	0,586
Emotion_rating:sex	0,123	0,123	1	4506,050	2,090	0,148
Social_rating:sex	0,123	0,123	1	4506,805	2,082	0,149
Right AIns E-field:Emotion_rating:sex	0,001	0,001	1	4521,120	0,010	0,919
Right AIns E-field:Social_rating:sex	0,010	0,010	1	4521,356	0,165	0,685

Mixed-effect regression model results of TMS E-field in right AIns and semantic ratings and sex as predictors of (log-transformed) reaction times to abstract triplets, where the last two rows represent the interaction between sex, the magnitude of the E-field inside right AIns, and respectively emotion and social rating. Significant effects are written in bold.

Sum.Sq: Sum of squares, Mean.Sq: Sum of squares / degrees of freedom, NumDF: Degrees of freedom, DenDF: Denominator degrees of Freedom

Table 8.2 Three-way interaction between semantic ratings, E-field in left Anterior Insula and sex as predictors of Reaction Times of Abstract triplets

	Sum.Sq	*Mean.Sq*	*NumDF*	*DenDF*	*F.value*	*P value*
Left AIns E-field	**0,359**	**0,359**	**1**	**4524,398**	**6,070**	**0,014**
Emotion_rating	**0,290**	**0,290**	**1**	**112,480**	**4,906**	**0,029**
Social_rating	**0,391**	**0,391**	**1**	**113,104**	**6,623**	**0,011**
sex	0,158	0,158	1	24,000	2,668	0,115
semantic similarity similars	**0,320**	**0,320**	**1**	**103,651**	**5,414**	**0,022**
semantic similarity distants	0,000	0,000	1	104,872	0,002	0,966

triplet length	**0,765**	**0,765**	**1**	**103,171**	**12,942**	**0,000**
Left AIns E-field:Emotion_rating	0,054	0,054	1	4516,359	0,906	0,341
Left AIns E-field:Social_rating	0,079	0,079	1	4514,607	1,343	0,246
Left AIns E-field:sex	0,038	0,038	1	4518,623	0,649	0,420
Emotion_rating:sex	0,122	0,122	1	4506,168	2,060	0,151
Social_rating:sex	0,119	0,119	1	4506,922	2,022	0,155
Left AIns E-field:Emotion_rating:sex	0,095	0,095	1	4507,910	1,615	0,204
Left AIns E-field:Social_rating:sex	0,108	0,108	1	4507,645	1,824	0,177

Mixed-effect regression model results of TMS E-field in left AIns and semantic ratings and sex as predictors of (log-transformed) reaction times to abstract triplets, where the last two rows represent the interaction between sex, the magnitude of the E-field inside left AIns, and respectively emotion and social rating. Significant effects are written in bold.

Sum.Sq: Sum of squares, Mean.Sq: Sum of squares / degrees of freedom, NumDF: Degrees of freedom, DenDF: Denominator degrees of Freedom

Figure 8.3. Interaction between semantic ratings, E-field in right Anterior Insula and sex as predictors of Accuracy of Abstract triplets.

	Chisq	*Df*	*P value*
(Intercept)	340,382	1	0,000
Right AIns E-field	2,368	1	0,124
Emotion_rating	**5,402**	**1**	**0,020**
Social_rating	**6,185**	**1**	**0,013**
sex	**4,457**	**1**	**0,035**
semantic similarity similars	**9,394**	**1**	**0,002**
semantic similarity distants	**4,242**	**1**	**0,039**
triplet length	0,031	1	0,860
Right AIns E-field:Emotion_rating	**4,948**	**1**	**0,026**
Right AIns E-field:Social_rating	2,888	1	0,089
Right AIns E-field:sex	0,155	1	0,694
Emotion_rating:sex	2,979	1	0,084
Social_rating:sex	1,254	1	0,263
Right AIns E-field:Emotion_rating:sex	0,023	1	0,881

Right AIns E-field:Social_rating:sex	0,056	1	0,812

Mixed-effect logistic regression model results of TMS E-field in right AIns and semantic ratings and sex as predictors of accuracy to abstract triplets, where the last two rows represent the interaction between sex, the magnitude of the E-field inside right AIns and respectively emotion and social rating. Significant effects are written in bold.

Chisq: Chi-squared statistic, Df: degrees of freedom

Figure 8.4. Interaction between semantic ratings, E-field in left Anterior Insula and sex as predictors of Accuracy of Abstract triplets.

	Chisq	*Df*	*P value*
(Intercept)	343,300	1	0,000
Left AIns E-field	1,555	1	0,212
Emotion_rating	**5,309**	**1**	**0,021**
Social_rating	**6,019**	**1**	**0,014**
sex	**4,807**	**1**	**0,028**
semantic similarity similars	**9,465**	**1**	**0,002**
semantic similarity distants	**4,250**	**1**	**0,039**
triplet length	0,038	1	0,846
Left AIns E-field:Emotion_rating	2,532	1	0,112
Left AIns E-field:Social_rating	1,529	1	0,216
Left AIns E-field:sex	2,728	1	0,099
Emotion_rating:sex	3,563	1	0,059
Social_rating:sex	1,582	1	0,208
Left AIns E-field:Emotion_rating:sex	3,220	1	0,073
Left AIns E-field:Social_rating:sex	2,083	1	0,149

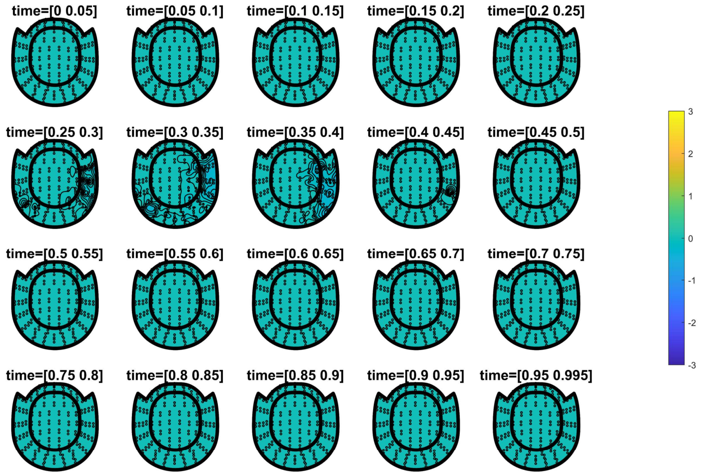
Mixed-effect logistic regression model results of TMS E-field in left AIns and semantic ratings and sex as predictors of accuracy to abstract triplets, where the last two rows represent the interaction between sex, the magnitude of the E-field inside left AIns and respectively emotion and social rating. Significant effects are written in bold.

Chisq: Chi-squared statistic, Df: degrees of freedom

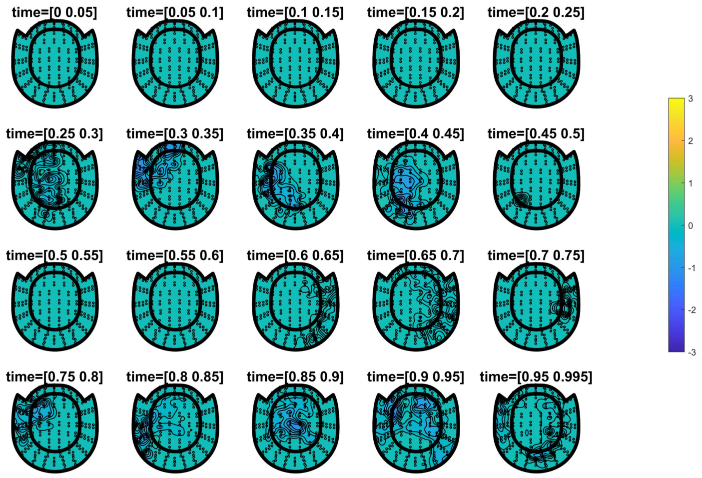
APPENDIX 3. CHAPTER 4 SUPPLEMENTARY MATERIALS

Concreteness

CONCRETE CONCEPTS



ABSTRACT CONCEPTS



ALL CONCEPTS

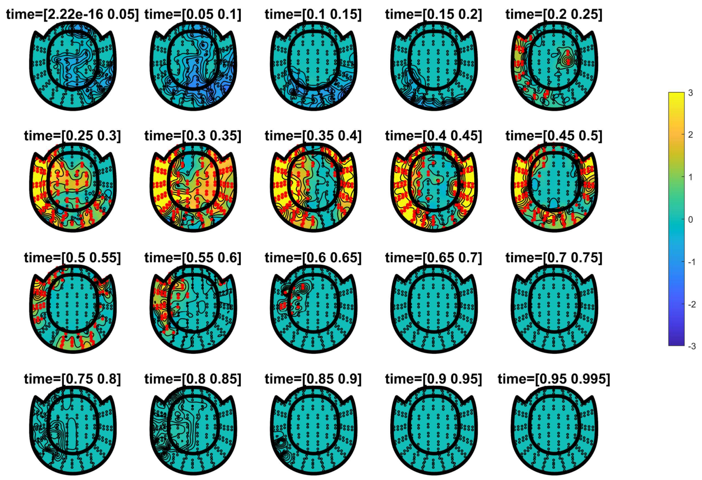
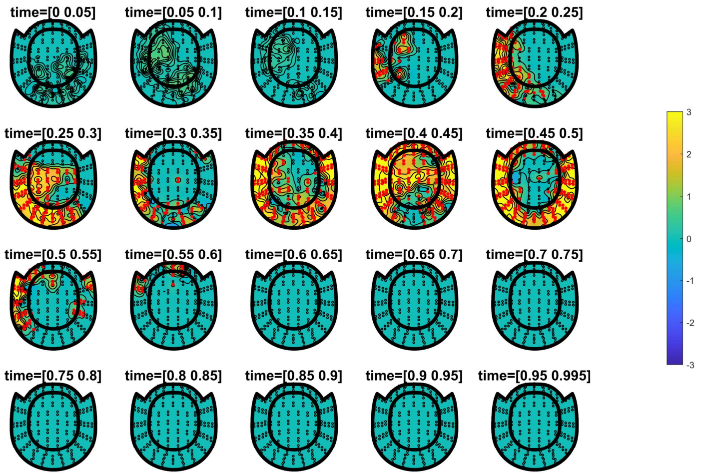


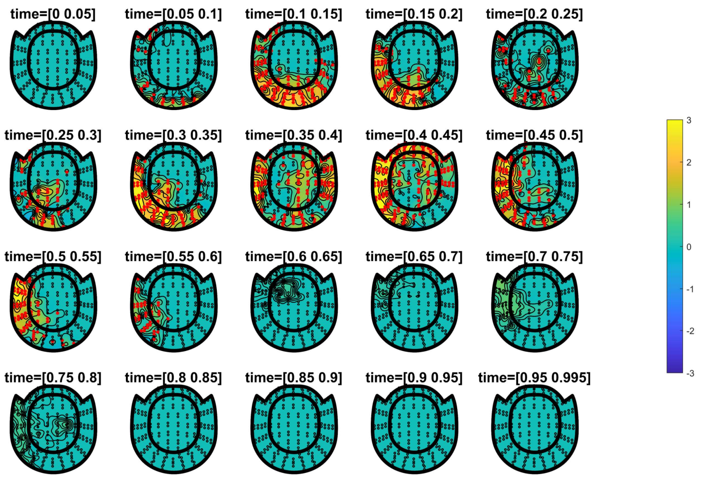
Figure S1. Simple correlation RSA of the Concreteness model with concrete, abstract and all words. Time-resolved sensor-level topographies of cluster-based permutation test z-values, averaged within each time interval, of RSA results between Concreteness model RDM and concrete (top), abstract (middle) and all (bottom) words MEG RDMs. Colours represent z-values. Sensors highlighted in red indicate channels belonging to a significant cluster ($z > 1.6449$) in any time point within the corresponding 50-ms time interval.

Glove

CONCRETE CONCEPTS



ABSTRACT CONCEPTS



ALL CONCEPTS

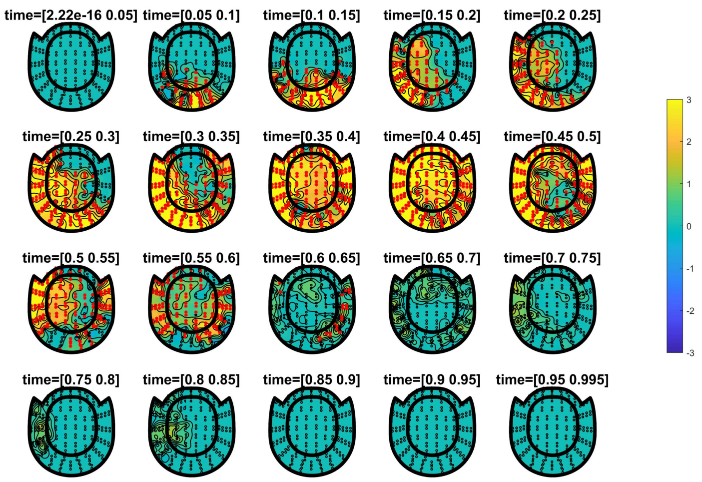


Figure S2. Simple correlation RSA of the Glove model with concrete, abstract and all words. Time-resolved sensor-level topographies of cluster-based permutation test z-values, averaged within each time interval, of RSA results between Glove model RDM and concrete (top), abstract (middle) and all (bottom) words MEG RDMs. Colours represent z-values. Sensors highlighted in red indicate channels belonging to a significant cluster ($z > 1.6449$) in any time point within the corresponding 50-ms time interval.

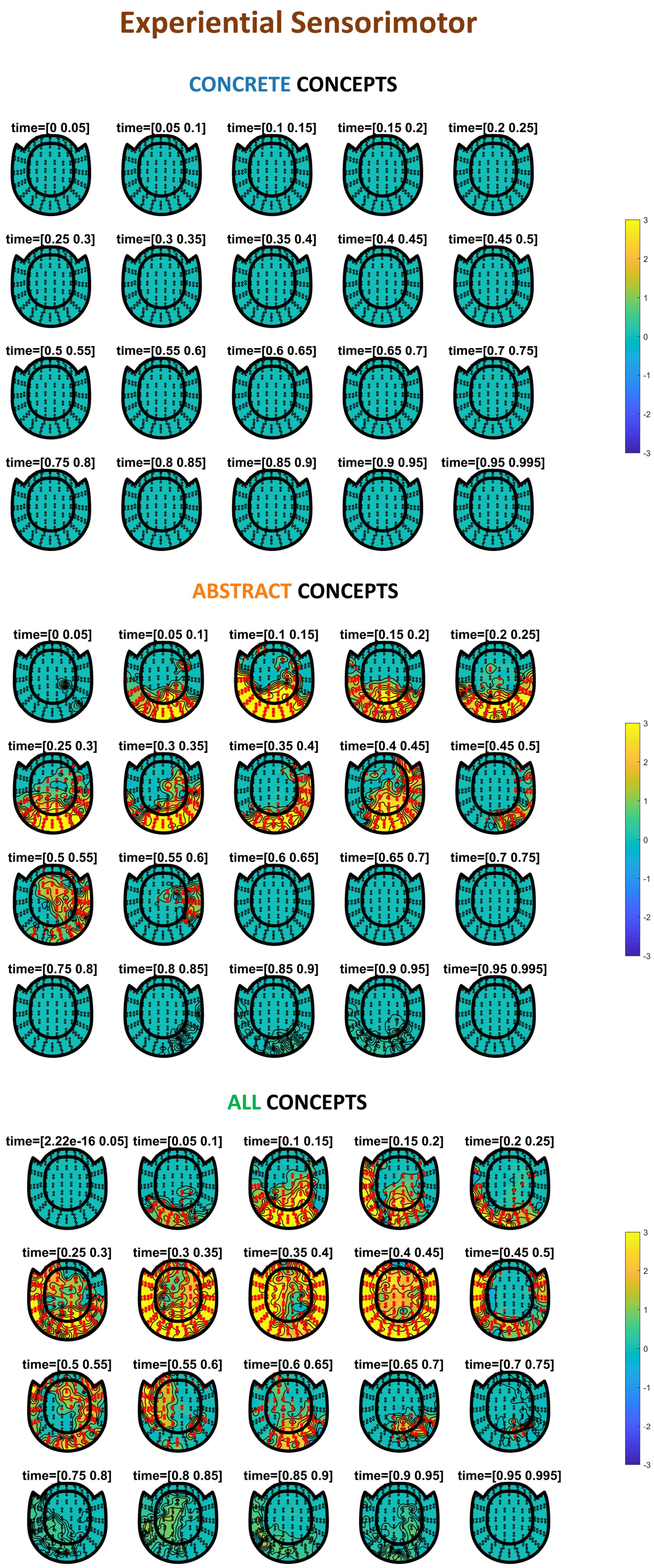


Figure S3. Simple correlation RSA of the Experiential Sensorimotor model with concrete, abstract and all words. Time-resolved sensor-level topographies of cluster-based permutation test z-values, averaged within each time interval, of RSA results between Experiential Sensorimotor model RDM and concrete (top), abstract (middle) and all (bottom) words MEG RDMs. Colours represent z-values. Sensors highlighted in red indicate channels belonging to a significant cluster ($z > 1.6449$) in any time point within the corresponding 50-ms time interval.

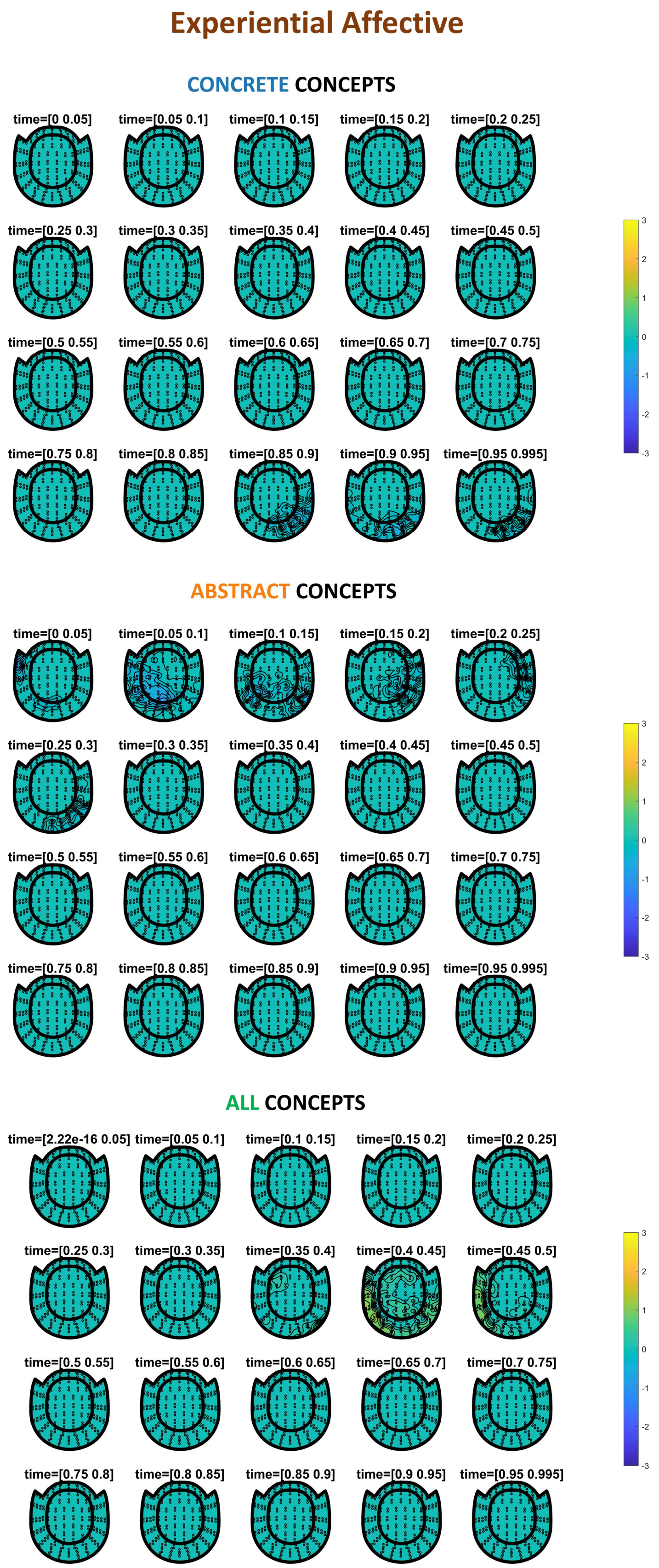


Figure S4. Simple correlation RSA of the Experiential Affective model with concrete, abstract and all words. Time-resolved sensor-level topographies of cluster-based permutation test z-values, averaged within each time interval, of RSA results between Experiential Affective model RDM and concrete (top), abstract (middle) and all (bottom) words MEG RDMs. Colours represent z-values. Sensors highlighted in red indicate channels belonging to a significant cluster ($z > 1.6449$) in any time point within the corresponding 50-ms time interval.

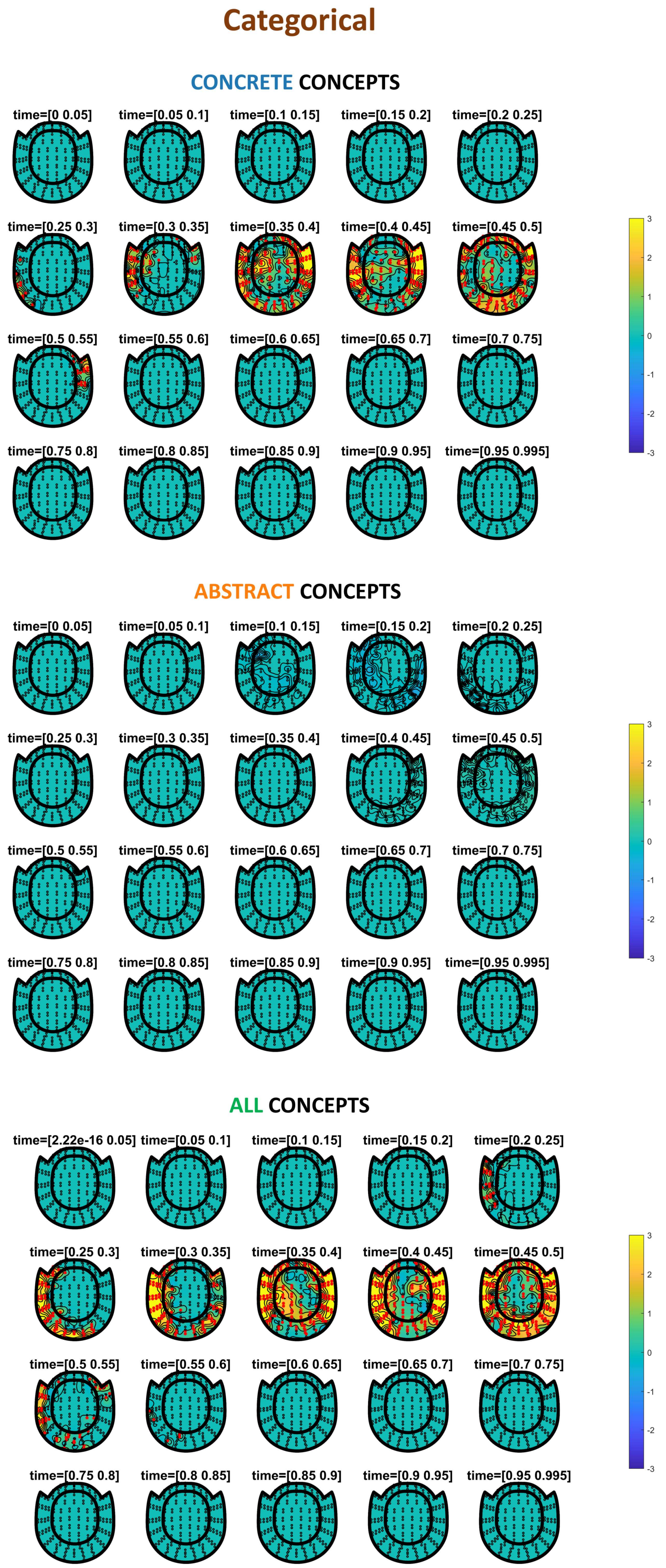


Figure S5. Simple correlation RSA of the Categorical model with concrete, abstract and all words. Time-resolved sensor-level topographies of cluster-based permutation test z-values, averaged within each time interval, of RSA results between Categorical model RDM and concrete (top), abstract (middle) and all (bottom) words MEG RDMs. Colours represent z-values. Sensors highlighted in red indicate channels belonging to a significant cluster ($z > 1.6449$) in any time point within the corresponding 50-ms time interval.