Available online at www.sciencedirect.com
SCIENCE DIRECT
Neuroscience Letters 390 (2005) 139–144
Neuroscience Letters
www.elsevier.com/locate/neulet

Feature type effects in semantic memory: An event related potentials study

Giuseppe Sartori [a,∗], David Polezzi [a,b], Francesca Mameli [a,b], Luigi Lombardi [b]

[a] *Department of General Psychology, University of Padua, Via Venezia, 8, 35100 Padova, Italy*
[b] *Department of Cognitive Sciences and Education, University of Trento, Via Matteo del Ben, 5, 38068 Rovereto (TN), Italy*

Received 21 May 2005; received in revised form 15 July 2005; accepted 5 August 2005

Abstract

It is believed that the N400 elicited by concepts belonging to Living things is larger than the N400 to Non-living things. This is considered as evidence that concepts are organized, in the brain, on the basis of categories. Similarly, differential N400 to Sensory and Non-sensory semantic features is taken as evidence for a neural organisation of conceptual memory based on semantic features. We conducted a feature-verification experiment where Living and Non-living concepts are described by Sensory and Non-sensory features and were matched for Age-of-Acquisition, typicality and familiarity and finally for relevance of semantic features. Relevance is a measure of the contribution of semantic features to the "core" meaning of a concept. We found that when Relevance is low then the N400 is large. In addition, we found that when the two categories of Living and Non-living concepts are matched for relevance the seemingly category effect at the neural level disappeared. Also no difference between Sensory and Non-sensory descriptions was detected when relevance was matched. In sum, N400 does not differ between categories or feature types. Previously reported effects of semantic categories and feature type may have arisen as a consequence of the differing Relevance of concepts belonging to Living and Non-living categories.

Keywords: Semantic memory; Semantic relevance; N400

A highly controversial issue in cognitive neuroscience of semantic memory regards the format of concept representation. One highly credited theory states that concepts are represented in the brain on the basis of the content of their constituent semantic features. In this regard, one of the most frequently investigated distinctions is that between Sensory and Non-sensory features. Consider for example the concept *Dog*.[1,2] A Sensory feature may be ⟨has four legs⟩. Non-sensory features may include functional (e.g. ⟨is used for hunting⟩), associative (e.g. ⟨likes to chase cats⟩) and encyclopaedic features (e.g. ⟨may be one of many breeds ⟩).[3,4] The Sensory/Functional theory, one of the most influential explanations of semantic memory impairment, is based on the distinction between Sensory and Non-sensory semantic features, and has been used to explain the puzzling phenomenon

∗ Corresponding author.
E-mail address: giuseppe.sartori@unipd.it (G. Sartori).

[1] Concept names are printed in italics, and names of semantic features in angled brackets.

[2] Semantic features are also sometimes termed "properties" or "attributes".

[3] Throughout this paper, the term "concept" refers to a set of weighted semantic features; semantic feature is used to describe any type of statement about the concept (both Sensory and Non-sensory).

[4] Functional features are defined in different ways. Some authors use this term for features that directly refer to functions (e.g. ⟨gives milk⟩) others denote physically defined features defined by motor properties (e.g. ⟨used to cut⟩ [7]). Others have defined functional knowledge by exclusion to denote any property that is not physically defined [21]. Throughout this paper, the term "Sensory feature" is used to describe semantic features that may be perceived in any modality, whereas "Non-sensory feature" is used to describe all other types of semantic features.

0304-3940/$ – see front matter © 2005 Elsevier Ireland Ltd. All rights reserved.
doi:10.1016/j.neulet.2005.08.015

of category-specificity in semantic memory. This proposal has been enormously influential, spanning an entire area of empirical enquiry [1,2,6,7,14,16,18,22].

At neural level, it is believed that sensory experienced knowledge is stored in circumscribed brain regions, in a feature-based format, which is related to the encoding sensory channels. Functional imaging data consistent with this claim [15] have been reported and, in addition, electrophysiological investigations have shown that the N400, a negativity induced by semantic incongruity, is larger for Sensory features as compared to Non-sensory features [3]. This latter difference has been interpreted as a neurophysiological evidence of separate encoding of Sensory and Non-sensory semantic features in the brain.

Here we report an ERP study, in accordance with an opposing theory about semantic features. According to this contrasting view, semantic features are encoded in the brain on the basis of their contribution to the meaning of a concept. A concept may have many semantic features, although those really useful in distinguishing it from closely related concepts are only a few. The information content of semantic features may be measured by semantic relevance [19,20]. Relevance is a measure of the contribution of semantic features to the "core" meaning of a concept. Elite few semantic features of high relevance are sufficient for an accurate retrieval of the target concept. In contrast, when semantic relevance is low, retrieval is inaccurate. Among all the semantic features of a concept those with high relevance are also critical in distinguishing it from other similar concepts. The following is a case in point: ⟨has a trunk⟩ is a semantic feature of very high relevance for the concept *Elephant*, because most subjects use it to define *Elephant,* whereas very few use the same feature to define other concepts. Instead ⟨Has 4 legs⟩ is a semantic feature with low relevance for the same concept, because few subjects use to define *Elephant* but do use it to define many other concepts. When a set of semantic features is presented, their overall relevance results from the sum of the individual relevance values associated with each of the semantic features. The concept with the highest summed relevance is the one that will be retrieved. For example, the three features ⟨similar to a goose⟩, ⟨lives in ponds⟩ and ⟨has a beak⟩ have topmost relevance for *Duck*, followed by *Swan*, and then by *Ostrich* (example taken from the normative data collected by Sartori and Lombardi [19][5]). The retrieved concept, given the three features, will be *Duck*, because it has the highest relevance. Hence, overall accuracy in name retrieval is poor when concepts have low relevance, and when they have many other semantically related concepts with which they may be confused. It has been shown that [20]: (i) relevance is the best predictor of naming accuracy (at least in a "naming-to-description" task) when contrasted to a number of other parameters of semantic features (dominance, distinctiveness) and of the concept (e.g. Age-of-Acquisition, familiarity and typicality), (ii) relevance is a robust measure, not significantly influenced by the number of concepts in the database or by sampling errors.

Here we will report an ERP study designed to address the issue of how semantic features are coded in the brain. In this paper we will show that: (i) low relevance descriptions have larger N400 with respect to high relevance descriptions; (ii) no effects of feature type arise when relevance is matched; (iii) no differences in N400 to differing categories of Living and Non-living concepts can be detected when relevance is matched.

Twenty-four Italian undergraduate students (age range 19–29 years; mean = 22.6, S.D. = 2.55) participated in the experiment. Nine were male and 15 female. Average education was 16.7 years. All the subjects were healthy and had normal or corrected-to-normal vision.

Every trial consisted in the sequential presentation of a verbal description of three semantic features on a computer screen (e.g. ⟨has a carriage⟩, ⟨found in the airport⟩ and ⟨found in the sky⟩) followed by the presentation of a target word (e.g. *Airplane*) after which a Yes/No response was required. The task was to indicate whether the three features correctly indexed the concept or not. Half subjects responded with their right hand using the index finger for Yes responses and the middle finger for No responses; the remaining half used the fingers in opposite order.

In regard to the experimental stimuli, they varied according to the following dimensions: (i) Category (Living versus Non-living); (ii) Relevance (High versus Low); (iii) Feature type (Sensory versus Non-sensory); (iv) Congruency (Yes versus No). A total of 80 concepts were used. For each concept four descriptions were presented (two of high relevance, one Sensory and one Non-sensory and two low relevance, again one Sensory and one Non-sensory). These 320 stimuli were followed by the target concept and required a Yes response. Target words were matched across categories (Living $n = 40$ and Non-living $n = 40$) for Age of Acquisition ($p = 0.58$), Typicality ($p = 0.90$) and Familiarity ($p = 0.60$) (norms collected by Dell'Aqua et al. [5]). Average semantic relevance for Living (2.73) did not differ from that of Non-living (2.83) ($p = 0.51$). Average semantic relevance for Sensory features (2.80) did not differ from that of Non-sensory features (2.75) ($p = 0.74$). Relevance values of the three semantic features presented sequentially to the subjects were taken from the norms collected by Sartori and Lombardi [19]. All the 320 stimuli requiring a No response had the same level of dissimilarity with the correct target as measured by standardized cosine.[6] The following is a telling example: if the correct description for the concept *Peach* is, instead, followed by *Violet* a No response is required. The cosine similarity of *Violet* with respect to *Peach* is 0.073

[5] Relevance values are derived algorithmically from a feature-listing task and are not based on subjective ratings. The computation is based on the number of times people report a given feature in defining a concept [20].

[6] Standardized cosine is a popular measure of similarity between vectors of semantic features. Matching cosine similarity guarantees that the foils are equally dissimilar to the target.

and this value was similar in all No responses (range 0.069–0.076).

Instructions were presented to the subject on a computer screen. In a trial a blank screen was displayed for 300 ms. Next appeared the first word of the concept description. Every word of a trial was presented sequentially for 300 ms with 200 ms of separation between one word and the following one. The target word was displayed after a random interval ranging between 0 and 1000 ms after the final word of the sentence. The total 640 trials were presented in a single session in two blocks, which lasted about 50 min with YES and NO responses randomly intermixed.

Scalp voltages were collected using a 64-channel ElectroCap. The electrocap consists of 59 sintered Ag/AgCL electrodes. A frontal electrode (AFZ) was connected to the ground, and the vertex electrode was used as reference. Electrode impedance has been kept under 10 kΩ for all recordings. Ocular movements have been monitored trough four electrodes fixed close to the eyes: two for vertical movements and two for the horizontal movements. Scalp voltage were continuously recorded, digitised by a computer at a sampling rate of 1000 Hz, and stored on the hard disk for off-line analysis. Electrical signals were amplified with Synamps amplifier (high pass = 0.10 Hz, 24-dB/octave attenuation; low pass = 1000 Hz, 24-dB/octave attenuation; 50 Hz notch filter). The signal was recorded in all the scalp's areas (frontal, temporal, parietal, and occipital) and filtered using a low pass filter for 30 Hz, 24-dB/octave attenuation. The continuous EEG was segmented in epochs starting 100 ms before target onset and lasting until 1500 ms after its onset. The epochs were aligned to the 100 ms baseline before the onset of the target. EEG epochs were examined, and all trials contaminated with ocular or movements artefacts were discarded. Approximately, 5% of the trials were excluded from the average because of ocular and movements artefacts. Consequently, the reference channel has been replaced with an average-reference. This procedure allows computing the mean signal recorded in all active channels and then using this mean signal as reference. This step has been necessary because the N400 has its maximum amplitude in the centre-parietal areas

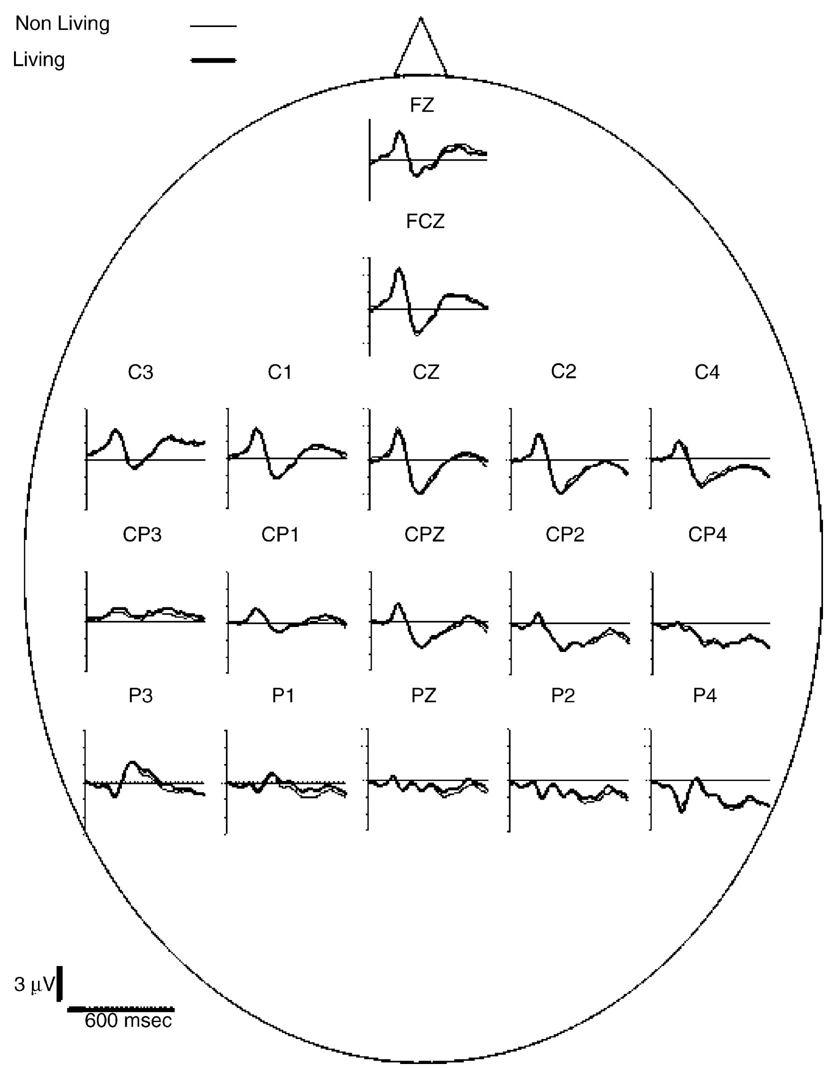

Fig. 1. Grand average ERPs in response to descriptions of Living and Non-living concepts. No difference in the N400 windows at any site.

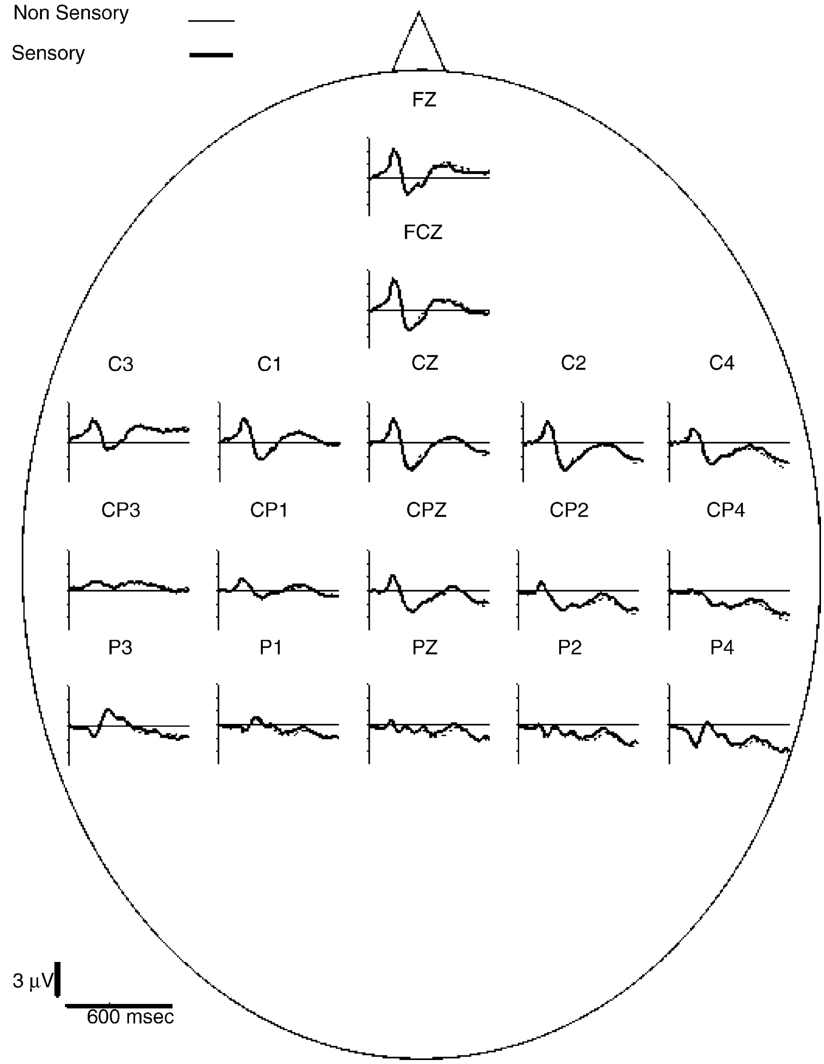

Fig. 2. Grand average ERPs in response to descriptions of Sensory and Non-sensory concepts. No difference in the N400 windows at any site.

[12], close to vertex. In accordance with the literature [12], the N400 peak was defined as the negative deflection in the time range between 300 and 500 ms after target onset.

A first ANOVA was performed on average voltage of the time window 300–500 ms after target onset. Category (Living versus Non-living), Relevance (High versus Low), Feature Type (Sensory versus Non-sensory), Congruency (Yes versus No) and Midline (FPZ, FZ, FCZ, CZ, CPZ, PZ, POZ, OZ) were the within-subject factors. In this analysis we observed a significant effect of the Midline factor ($F(7,161) = 15.24$; $p < 0.001$) and, as reported in previous studies [11,12], the maximum N400 effect (i.e. the difference in N400 amplitude between congruent and incongruent targets [10]) was detected in CZ, CPZ and PZ. Hence, we repeated the same analysis using CZ, CPZ and PZ as levels of the Midline factor, which was not significant ($F(2,46) = 1.10$; $p = 0.34$) and did not interact with any other factor. The N400 did not differ between Categories ($F(1,23) = 1.76$; $p = 0.20$) and, except for the interaction with Feature Type, no other effect involving Category was significant. More specifically, the interaction between Category and Congruency was not significant ($F(1,23) = 2.89$; $p = 0.10$). The N400 did not show any significant difference ($F(1,23) = 1.25$; $p = 0.28$) between Feature Type and, no other interaction with Feature Type was significant. Particularly, interaction of Feature Type by Congruency was not significant ($F(1,23) = 0.46$; $p = 0.50$). The N400 to low relevance was larger than to high relevance semantic features ($F(1,23) = 29.81$; $p < 0.001$). Given that the N400 indexes semantic incongruity [12], the differing effect to high and low relevance shows that low relevance descriptions index with more difficulty the target concept and this is consistent with previous behavioural observations.[7] The significant interaction between Relevance and Congruency ($F(1,23) = 9.04$; $p < 0.01$) indicates that the N400 is larger for

[7] Confronting concepts with their high relevance descriptions is accurate and fast. In contrast, confronting concepts with their low relevance descriptions is harder, yielding inaccurate and slow responses. The semantic incongruity that gives rise to the N400 is therefore characteristic of low relevance descriptions.

incongruent high relevance descriptions as compared with congruent high relevance descriptions. There was no difference between congruent and incongruent low relevance descriptions. Finally, the interactions between Category and Relevance ($F(1,23) = 0.30$; $p = 0.59$) and between Feature Type and Relevance ($F(1,23) = 2.11$; $p = 0.16$) were not significant.

A similar analysis was conducted using Category (Living versus Non-living), Relevance (High versus Low), Feature Type (Sensory versus Non-sensory), Congruency (Yes versus No) and Laterality (CP3, CP1, CPZ, CP2, CP4) as within-subjects factors. The absence of any Category effect ($F(1,23) = 1.79$; $p = 0.194$), a strong Relevance effect ($F(1,23) = 33.16$; $p < 0.001$) and also a strong Congruency effect ($F(1,23) = 28.34$; $p < 0.001$) were confirmed. Furthermore the significant interaction between Congruency and Laterality ($F(4,92) = 4.79$; $p < 0.001$) indexes a larger N400 on the right hemisphere sites, a result that was reported before many times [13].

The N400 amplitude to Sensory descriptions did not differ from that of Non-sensory descriptions ($F(1,23) = 0.47$; $p = 0.51$). This result clearly indicates that when semantic relevance is matched among feature types any previously reported difference in ERPs disappears [3].

Previous electrophysiological investigations using the N400 indicated both a Category effect with larger N400 for Living (as compared to Non-living [8,11,23]) and a feature type effect with larger N400 for Sensory semantic features (as compared to Non-sensory [3]). This pattern of results leaded to contrasting interpretations. On one side, different ERPs between categories seemed to parallel behavioural dissociations between Living and Non-living. This was interpreted as supporting the view that categories were organising principles at neural level [2]. On the other side, the different ERPs between feature types (Sensory versus Non-sensory) was also considered as evidence for an organising principle based on featural content (e.g. [14]) (Figs. 1–3).

Our data show that these may be spurious results due to the lack of control over a parameter of semantic features that greatly affects concept retrieval: semantic relevance. In fact, given that lower semantic relevance is characteristic of Living and of Sensory features [19], and given that lower relevance

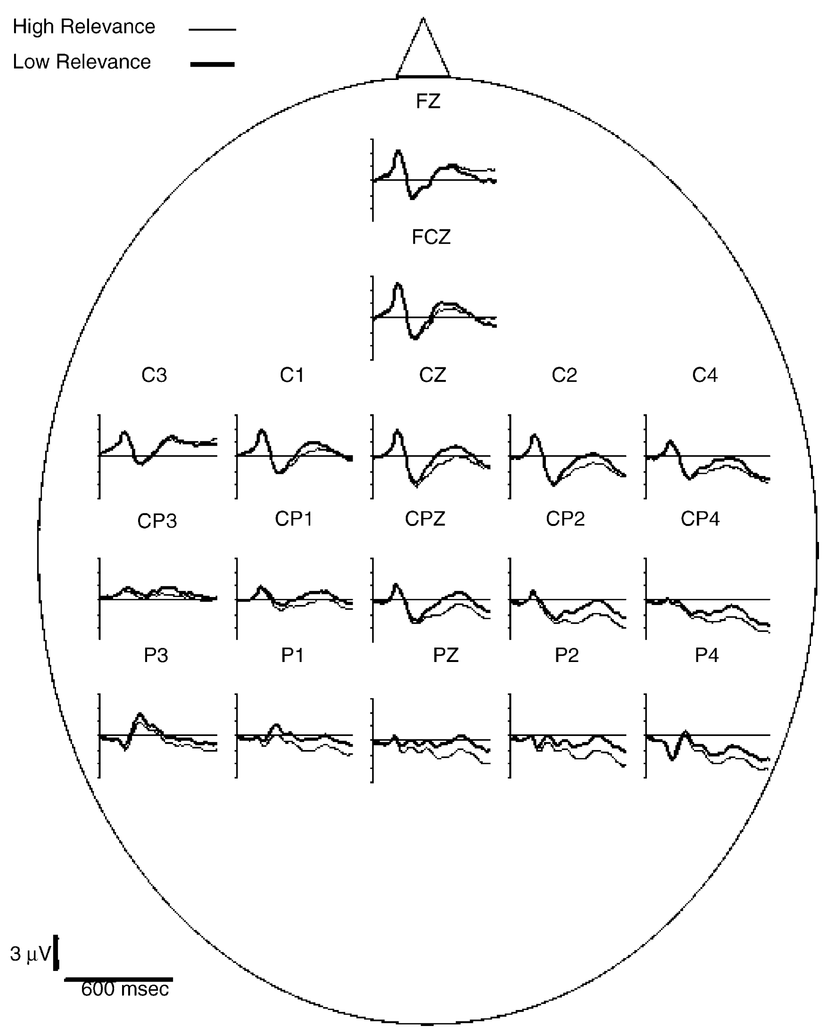

Fig. 3. ERPs to High Relevance as compared to Low Relevance concept descriptions. Negativity is larger to Low Relevance descriptions.

shows up in larger N400, then larger N400 are expected for these two types of items if relevance is not controlled. In contrast, when relevance is matched, any category or feature type effect should vanish; and this is what we found. At neural level, we showed that relevance matched categories had similar N400 and that relevance matched feature types had also similar N400. In other words, no difference between Living and Non-living and between Sensory and Non-sensory descriptions may be found when relevance is matched. These results confirmed the view that the previously reported dissociations observed using ERPs could be spurious.

In our view, the larger N400 for Living [11] and for Sensory features [3] may not be genuine effects if we consider that: (i) low relevance semantic features elicit larger N400 and (ii) Living items have, on average, many Sensory features of lower relevance as compared to Non-living [19]. Therefore, any uncontrolled set of stimuli is likely to result in larger, spurious N400 for items belonging to the Living category and in larger N400 for Sensory descriptions.

These results increase credibility to the general claim that the organising principles of conceptual representation in the brain are semantic features rather than categories (see also [17]). Aside from a clear relevance effect, also the absence of any category effect is in accord with this view. With regard to semantic features, we present results at neural level that parallel those previously reported at behavioural level [19]. Taken together our results seem to indicate that semantic features may not be organised on the basis of their content (Sensory versus Non-sensory) but rather on the basis of their importance in facilitating concept retrieval. Relevance, an effective index of this importance, may account for many effects previously believed to characterise the organisation at neural level. Instead, feature content per se does not affect ERPs. Our data raise the possibility that it is the importance of semantic features (relevance), which is the basis of behavioural and neural effects of category and feature types that were previously reported. In sum, this investigation adds credibility to the sceptic views on category-specificity as researchers are looking more closely at criteria used in defining the phenomenon. In fact, credibility of semantic memory dissociations, at behavioural level, is reduced by a number of methodological problems concerning the methods through which dissociations are established [4]. Experimental approaches to the neural basis of semantic memory are just beginning to control the effect of such variables on processing requirements after a period in which the only variable manipulated was category (see [9]).

References

[1] S.F. Cappa, D. Perani, T. Schnur, M. Tettamanti, F. Fazio, The effects of semantic category and knowledge type on lexical-semantic access: a PET study, Neuroimage 8 (1998) 350–359.

[2] A. Caramazza, J.R. Shelton, Domain-specific knowledge systems in the brain, J. Cogn. Neurosci. 10 (1998) 1–34.

[3] M. Coltheart, L. Inglis, L. Cupples, P. Michie, A. Bates, B. Budd, A semantic subsystem of visual attributes, Neurocase 4 (1998) 353–370.

[4] G.S. Cree, K. McRae, Analyzing the factors underlying the structure and computation of the meaning of chipmunk, cherry, chisel, and cello (and many other such concrete nouns), J. Exp. Psychol.: Gen. 132 (2003) 163–201.

[5] R. Dell'Acqua, L. Lotto, R. Job, Naming time and standardized norms for the Italian PD/DPSS of 266 pictures: direct comparisons with American, English, French, and Spanish published databases, Behav. Res. Methods Instrum. Comput. 32 (2000) 588–612.

[6] J.T. Devlin, C.J. Moore, C.J. Mummery, M.L. Gorno-Tempini, J.A. Phillips, U. Noppeney, R.S.J. Frackowiak, K.J. Friston, C.J. Price, Anatomic constraints on cognitive theories of category specificity, Neuroimage 15 (2002) 675–685.

[7] M.J. Farah, J.L. McClelland, A computational model of semantic memory impairment: modality specificity and emergent category specificity, J. Exp. Psychol.: Gen. 120 (1991) 339–357.

[8] K.D. Federmeier, M. Kutas, A rose by any other name: long-term memory structure and sentence processing, J. Mem. Lang. 41 (1999) 469–495.

[9] J. Joseph, Functional neuroimaging studies of category specificity in object recognition: a critical review and meta-analysis, Cogn. Affect. Behav. Neurosci. 1 (2001) 119–136.

[10] M. Kiang, M. Kutas, Association of schizotypy with semantic processing differences: an event-related brain potentials study, Schizophr. Res. (2005) 329–342.

[11] M. Kiefer, Perceptual and semantic source of category-specific effects: event-related potentials during picture and word categorization, Mem. Cogn. 29 (2001) 100–116.

[12] M. Kutas, K.D. Federmeier, Electrophysiology reveals semantic memory use in language comprehension, Trends Cogn. Sci. 4 (2000) 463–470.

[13] M. Kutas, S.A. Hillyard, Reading senseless sentences: brain potentials reflect semantic incongruity, Science 297 (1980) 203–205.

[14] A. Martin, L.L. Chao, Semantic memory and the brain: structure and processes, Curr. Opin. Neurobiol. 11 (2001) 194–201.

[15] A. Martin, C.L. Wiggs, L.G. Ungerleider, J.V. Haxby, Neural correlates of category-specific knowledge, Nature 379 (1996) 649–652.

[16] R. McCarthy, E.K. Warrington, Category specificity in an agrammatic patient: the relative impairment of verb retrieval and comprehension, Neuropsychologia 23 (1985) 709–727.

[17] C.J. Mummery, T. Shallice, C.J. Price, Dual-process model in semantic priming: a functional imaging perspective, Neuroimage 9 (1999) 516–525.

[18] E. Saffran, The organization of semantic memory: in support of a distributed model, Brain Lang. 71 (2000) 204–212.

[19] G. Sartori, L. Lombardi, Semantic relevance and semantic disorders, J. Cogn. Neurosci. 16 (2004) 439–452.

[20] G. Sartori, L. Lombardi, L. Mattiuzzi, Semantic relevance best predicts normal and abnormal name retrieval, Neuropsychologia (2005) 754–770.

[21] S.L. Thompson-Schill, G.K. Aguirre, M. Desposito, M.J. Farah, A neural basis for category and modality specificity of semantic knowledge, Neuropsychologia 37 (1999) 671–676.

[22] E.K. Warrington, T. Shallice, Category specific semantic impairments, Brain 107 (1999) 829–854.

[23] T. Yano, M. Kaga, Semantic category discrimination and N400, Psychol. Rep. 87 (2000) 415–422.