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Research report

Structural processing and category-specific deficits

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ABSTRACT

We evaluated the contribution of four structural dimensions (object parts, internal details, objects contours and variability of the representation), as a possible source of categorical processing differences and category-specific deficits. Importantly, these dimensions aggregate 22 different structural measures that have been proposed to describe the Snodgrass and Vanderwart (1980) picture set. Study 1 analysed the differences between the four dimensions across domains and categories. Study 2 investigated how these dimensions may contribute to the performance of two patients with category-specific deficits that have been reported previously in the literature (Farah et al., 1991). The results showed that living things were structurally more complex than non-living things, scoring higher in *object parts* and *object contours*. Regarding the *variability of the representation*, living things did not show much within-item diversity but did show more contour overlap and less visual similarity, the latter two qualities of living things being detrimental to object processing in a naming task. Parts, contours and variability of the representation also differentiated animals, fruits and vegetables and, to a certain degree, non-living things: animals had more parts, fruits had more object contours and non-living things had a lower variability of the representation (which was especially related to higher within-item diversity and lower contour overlap). The same three dimensions predicted patient performance. However, when structural dimensions were considered together with domain (living/non-living) and concept familiarity, only *variability of the representation* contributed significantly to patient performance.

1. Introduction

The study of brain-damaged patients exhibiting impaired knowledge for one or several categories of objects and relatively preserved knowledge for other categories has been crucial for the current understanding of conceptual organization. The first clinical observations of these category-specific deficits were reported by Nielsen in 1946 (Forde and Humphreys, 1999), and Warrington and Shallice (1984) provided the first systematic empirical study of these patients. Since then a considerable number of other cases have been described (e.g., Capitani et al., 2003; Forde and Humphreys, 1999). The notion that structural factors (and visual complexity in particular) may play an important role in the observation of category-specific deficits has been extensively discussed (e.g., Cree and McRae, 2003; Funnell and Sheridan, 1992; Mahon and Caramazza, 2009). Several authors have proposed that these category-specific deficits may be at least partially explained by differences

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related to pre-semantic or structural processing of these categories (e.g., Gerlach, 2009; Humphreys et al., 1988; Laws and Gale, 2002; Tranel et al., 1997; Turnbull and Laws, 2000). These naturally occurring structural differences would make pre-semantic processing easier for particular domains (i.e., living *vs* non-living), categories or exemplars, which in turn would be reflected in specific class advantages that could be observed both in neurological patients and in healthy subjects. For example, Cree and McRae (2003) have evaluated two structural measures as potential 'susceptibility' factors that contribute to category-specific deficits, visual similarity and visual complexity, and concluded that the latter (as indexed by number of listed features of visual and surface properties) was greater for living things, thus making items from this domain generally harder to process.

There has been considerable discussion regarding the particular structural dimensions on which domains and categories differ in real life (e.g., Coppens and Frisinger, 2005; Laws and Gale, 2002). Different authors have proposed different dimensions, especially considering the Snodgrass and Vanderwart (1980) picture set (see Table 1). However, the debate continues on which variables should be considered more adequate. The discussion is further complicated for at least two reasons. First, it is unclear what the different variables represent in terms of the underlying structural processes and dimensions, and which ones should be taken as the adequate measures of those underlying processes. Second, these variables have not been studied concurrently. As such, there is no empirical data that demonstrates precedence of one variable over another on the basis of their respective predictive power. Some authors (e.g., Funnell and Sheridan, 1992; Lloyd-Jones and Nettlemill, 2007) have shown that visual complexity is important to category-specific deficits but have not contrasted the contribution of this variable with other ones systematically. For example, in the case of Lloyd-Jones and Nettlemill (2007), the comparison included only visual complexity, decomposability and contour overlap, but many others were not evaluated (see Table 1).

Recently, Marques and Raposo (2011) analysed the underlying organization of 22 structural variables proposed in various studies for the Snodgrass and Vanderwart (1980) picture set (all variables in Table 1 with the exception of curvilinearity/rectilinearity and visual ambiguity). They performed a principal-components analysis to extract the dimensions underlying the correlations between variables and used a standard varimax rotation in order to achieve simple structure and make the pattern of loadings easier to interpret (interpretation and labeling of each component was based on component loadings of .30 or higher and considering the components where each variable had the highest salient loadings). With this procedure they found that the vast number of variables could be described more parsimoniously by a set of four underlying dimensions or components: *object parts*, *internal details*, *object contours* and *variability of the representation* (see Table 2 for a summary of the variables that most contributed to each component). The first three dimensions have a more bottom-up and uniform nature in the sense that each is composed by structural variables that index a particular structural characteristic. In contrast, the last dimension integrates various aspects of the variability of the representation of a particular picture (e.g., dog), including the extent to which this representation fares given different exemplars of the concept (i.e., within-item structural diversity; Turnbull and Laws, 2000); the extent to which the image agrees with the subject's representation of that concept (i.e., image agreement); the degree to which the visual appearance of the concept is familiar to the subject (i.e., visual familiarity; Laws and Neve, 1999); and the degree to which the image overlaps with other images from the same domain (i.e., contour overlap; Humphreys et al., 1988). All these variables imply a comparison of the picture that is being presented to an internal representation of the item in addition to other semantically related items. As such, compared with the other three structural dimensions, the variability of the representation involves a higher level of perceptual processing, is more top-down in nature, and reflects a more diverse set of structural aspects, although all are related to a common underlying representation. Within-item structural diversity seems to be a preponderant factor to the variability of the representation as it is the variable most saturated in this dimension (see Table 2), and also the only one that correlates with the other variables (respectively $r = .28$ for contour overlap, $r = .42$ for image agreement, and $r = -.39$ for visual familiarity, all

Table 1 – Variables proposed for the Snodgrass and Vanderwart (1980) picture set.

Variables	Reference
Complexity	Forsythe et al., 2008
Contour overlap	Humphreys et al., 1988
Curvature variability coarse	Kurbat, 1997
Curvature variability fine	Kurbat, 1997
Curvilinearity/rectilinearity	Tranel et al., 1997
Decomposability	Lloyd-Jones and Nettlemill, 2007
Euclidean overlap category	Laws and Gale, 2002
Euclidean overlap general	Laws and Gale, 2002
Image agreement	Snodgrass and Vanderwart, 1980
Inter-pixel correlation	Laws and Gale, 2002
Number of concavities coarse	Kurbat, 1997
Number of concavities fine	Kurbat, 1997
Proportion of black line	Laws and Gale, 2002
Proportion of concave contour coarse	Kurbat, 1997
Proportion of concave contour fine	Kurbat, 1997
Proportion of convex contour coarse	Kurbat, 1997
Proportion of convex contour fine	Kurbat, 1997
Proportion of internal details	Kurbat, 1997
Proportion of straight contour coarse	Kurbat, 1997
Proportion of straight contour fine	Kurbat, 1997
Visual ambiguity	Tranel et al., 1997
Visual complexity	Snodgrass and Vanderwart, 1980
Visual familiarity	Laws and Neve, 1999
Within-item structural diversity	Turnbull and Laws, 2000

Note: references refer to the study that first proposed the measure.

Table 2 – Structural dimensions, contributing variables and respective loadings (in parenthesis) from Marques and Raposo (2011).

Object parts	Internal details	Object contours	Variability of the representation
Proportion of concave contour coarse (.95)	Inter-pixel correlation (−.95)	Proportion of convex contour coarse (.94)	Within-item structural diversity (.90)
Number of concavities coarse (.93)	Euclidean overlap general (.90)	Proportion of convex contour fine (.94)	Image agreement (.57)
Proportion of concave contour fine (.92)	Proportion of black line (.90)	Proportion of straight contour fine (−.84)	Visual familiarity (−.51)
Number of concavities fine (.91)	Complexity (.84)	Proportion of straight contour coarse (−.71)	Contour overlap (.37)

$n = 212$, $p < .01$; other correlations from −.03 to .09 and ns). This means that, for the set of items, a concept with a lesser degree of within-item structural diversity (higher values for the variable) will probably present greater contour overlap with other members of the category, greater image agreement but less visual familiarity.

The four dimensions, object parts, internal details, object contours and variability of the representation, accounted for 76% of the variance, providing a simpler account of the structural variables underlying the Snodgrass and Vanderwart (1980) picture set. The analysis also provided aggregated factor scores for each picture on each of the four dimensions. With subsequent analyses, Marques and Raposo (2011) showed that *variability of the representation* and *internal details* were the most relevant structural predictors of naming latencies in previously published studies of object decision (Magnié et al., 2003) and picture naming with healthy adults under no deadline conditions (Alario et al., 2004; Barry et al., 1997; Bonin et al., 2002; Nishimoto et al., 2005; Snodgrass and Yuditsky, 1996). However the studies did not evaluate or discuss whether these structural dimensions differ across between domains or categories of objects, nor did they assess their possible contribution to patient performance in general and to category-specific deficits in particular.

The present study builds on this organization of structural dimensions and explores whether it relates to the categorical organization of semantic memory and the performance of patients with category-specific deficits in picture naming tasks. It is important to note that the dimensions studied here are extracted from a particular picture set (Snodgrass and Vanderwart, 1980). Consequently, the structural properties of the real objects corresponding to the different pictures will include other dimensions (e.g., colour, tri-dimensionality) and other values for the dimensions studied here. Nevertheless, this picture set has been used in the large majority of studies reporting category-specific deficits (90% of all category-specific studies according to Laws and Gale, 2002; see also Capitani et al., 2003) or discussing the contribution of structural dimensions to these deficits (e.g., Gerlach, 2009; Humphreys and Forde, 2001; Humphreys et al., 1988; Kurbat, 1997; Laws and Gale, 2002; Laws et al., 2002; Laws and Hunter, 2006; Laws and Neve, 1999; Lloyd-Jones and Nettlemill, 2007; Tranel et al., 1997; Turnbull and Laws, 2000). As such, studying the structural dimensions that underlie the Snodgrass and Vanderwart (1980) picture set is important in the context of the debate about category-specific deficits.

Here we present two studies. Study 1 investigates the differences in these structural dimensions across different domains and categories and Study 2 explores how these dimensions may have contributed to the performance of two patients with reported category-specific deficits.

2. Study 1

In this first study we analysed how the four structural dimensions reported by Marques and Raposo (2011) relate to the domains and categories that have been associated with category-specific deficits. At a more general level, two domains have been contrasted, living things and non-living things or artefacts. These domains have been analysed including or excluding the categories of body parts and musical instruments, which some authors have reported to be impaired or spared along with their non-natural domain (i.e., body parts associated to non-living things and musical instruments associated to living things; e.g., Hillis and Caramazza, 1991; Sachett and Humphreys, 1992; and Warrington and McCarthy, 1987, for body parts; Gainotti and Silveri, 1996, Warrington and Shallice, 1984, for musical instruments). More recently, research has focused on a tripartite domain distinction considering animals, fruits and vegetables, and non-living things (Cree and McRae, 2003; Mahon and Caramazza, 2009). As such, we examined the differences between the two domain distinctions (e.g., living *vs* non-living; animals *vs* fruits and vegetables *vs* non-living) considering the four structural dimensions previously described. Given the more composite and diverse nature of the "variability of the representation" dimension we further examined the differences between classes for the four variables that were more strongly related to this dimension (i.e., within-item structural diversity, image agreement, visual familiarity and contour overlap).

2.1. *Method*

2.1.1. *Variables and cases*

The study included the four structural dimensions obtained in Marques and Raposo (2011) and the variables composing variability of the representation (within-item structural diversity, image agreement, visual familiarity and contour overlap), considering the original paper in which they were reported (see Table 1). We used as cases the items of the

Snodgrass and Vanderwart set for which we have data on the dimensions and variables ($n = 212$). These cases were further classified considering the different classes of items (list of items and classifications is given in the Appendix).

2.1.2. Data analysis

The factor scores for each item on the four structural dimensions were taken from Marques and Raposo (2011). These scores were computed by first converting measured structural variables (see Table 1) into z scores with means of zero and standard deviations of one. Then, for each item, the factor score of a given dimension or component was calculated as the sum of all its z scores (one for each variable), each multiplied by the corresponding variable loading (or weight) on that particular component. Within-item structural diversity values corresponded to a five point rating scale to the extent that a given real-world item may be considered to have similar representations to other items with the same name (with 1 reflecting high and 5 reflecting low structural diversity), image agreement values correspond to a five point rating scale on the extent to which each picture provides a good match to the subject's representation of the corresponding item (with 1 denoting low and 5 denoting high agreement), visual familiarity values correspond to five point rating scale on the extent to which the visual appearance of a given concept is familiar to the subject (5 indicating high familiarity) and contour overlap corresponds to the percentage of overlap in contour between a given picture and of the other pictures from the same taxonomic category.

As all comparisons systematically violated the assumptions of parametric tests (i.e., homogeneity of variances), analyses were performed using Mann–Whitney U tests (for two independent samples) or Kruskal–Wallis tests (for multiple independent samples), considering a statistical level of $p < .05$. For the Kruskal–Wallis analyses, significant main effects were further analysed using Mann–Whitney U tests with corrections for multiple comparisons (i.e., Bonferroni correction, $.05/3 = p \leq .017$).

2.2. Results and discussion

Regarding the more general domain distinction (living = 75, non-living = 137) the analyses showed significant differences between domains for object parts ($U = 2530$, $p < .05$), object contours ($U = 2744$, $p < .05$), and variability of the representation ($U = 2691$, $p < .05$), but no differences for internal details ($U = 4975$, ns). In all of the significant comparisons, living things had significantly higher scores than non-living things. These results indicate that living things have more information or are more complex in terms of objects parts and contours but may require a lesser degree of top-down processing, at least considering within-item structural diversity which is lower for living things (the higher the variability of their representation, the lower the within-item structural diversity). Moreover, the same results were obtained when the same analyses were performed excluding musical instruments and body part items (living = 69, non-living = 126).

Regarding the tripartite domain distinction (animals = 44, fruits and vegetables = 24, non-living things = 137), Kruskal–Wallis tests revealed a main effect of domain for object parts [$H(2) = 81.55$, $p < .05$], object contours [$H(2) = 34.21$, $p < .05$], and variability of the representation [$H(2) = 37.99$, $p < .05$], but not for internal details [$H(2) = .12$, ns]. Differences between the three domains on the four structural dimensions are presented in Fig. 1 (scale is z-score + 3 so that all items have positive values and can be more easily compared).

As is clear from Fig. 1 and was confirmed by statistical analysis, in the case of object parts, animals present significantly more parts than both fruits and vegetables and non-living things (respectively, $U = 73$, $p \leq .017$ for animals *vs* fruits/vegetables; and $U = 363$, $p \leq .017$, for animals *vs* non-living things), with no difference between the latter ($U = 1488$, ns). As for object contours, all differences were significant, with fruits and vegetables having more contours ($U = 247$, $p \leq .017$, for fruits/vegetables *vs* animals; $U = 610$, $p \leq .017$, for fruits/vegetables *vs* non-living things) followed by animals and non-living things ($U = 247$, $p \leq .017$, for animals *vs* non-living things). Finally, regarding the variability of the representation, both animals and fruit and vegetables present higher scores (so less within-item diversity) than non-living things (respectively, $U = 634$, $p \leq .017$ for fruits/vegetables *vs* non-living things; and $U = 1652$, $p \leq .017$, for animals *vs* non-living things).

Considering that the number of exemplars of non-living things ($n = 137$) is much larger (and diverse) than that of animals ($n = 44$) and fruits and vegetables ($n = 24$) it could be argued an unbalanced number of items by domain is responsible for the results. To evaluate this possibility, we reanalysed this tripartite distinction considering only tools and utensils ($n = 75$), which have been discussed many times as the most representative category of non-living things (Mahon and Caramazza, 2009). Importantly, the same results were generally obtained as for the non-living domain with only one exception (see Appendix for more details), as a small main effect of domain for internal details [$H(2) = 7.58$, $p < .05$] was observed. This main effect corresponded to a significant difference between tools and utensils and animals ($U = 1194$, $p \leq .017$). Therefore, with the possible exception of this latter variable, differences between domains are unlikely to be due to the unbalanced number of items.

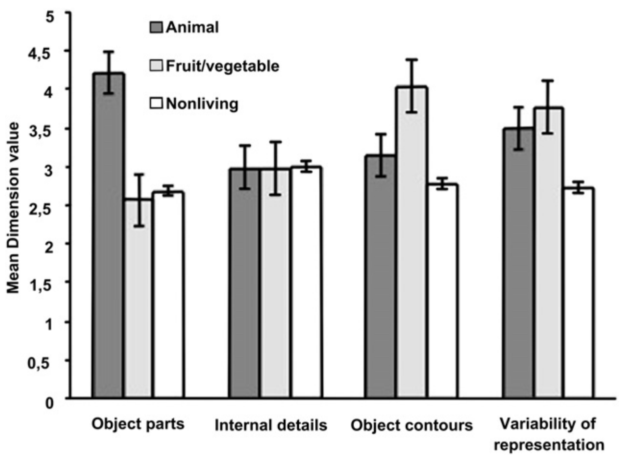

Fig. 1 – Mean values on the four structural dimensions by domain (scale is z-score + 3). Bars represent standard error of the mean.

We further explored the differences between domains in terms of the variability of the representation. For the more general domain distinction (living $= 75$; non-living $= 137$) the analyses showed significant differences between domains for within-item structural diversity ($U = 1844$, $p < .05$), visual familiarity ($U = 4038$, $p < .05$) and contour overlap ($U = 2792$, $p < .05$) but not for image agreement ($U = 4726$, ns). Living things did not show as much within-item structural diversity or visual familiarity, but showed more contour overlap relative to non-living things. Moreover, the same results were obtained when the same analyses were performed excluding musical instruments and body part items (living $= 69$; non-living $= 126$).

Regarding the tripartite domain distinction (animals $= 44$, fruits and vegetables $= 24$, non-living things $= 137$), Kruskal–Wallis tests revealed a main effect of domain for the four structural dimensions, respectively, within-item structural diversity [$H(2) = 63.80$, $p < .05$], image agreement [$H(2) = 7.51$, $p < .05$], visual familiarity [$H(2) = 29.07$, $p < .05$] and contour overlap [$H(2) = 38.14$, $p < .05$]. In the first case, non-living things presented significantly more within-item structural diversity than both animals and fruits and vegetables (respectively, $U = 1209$, $p \leq .017$ for animals *vs* non-living things; and $U = 345$, $p \leq .017$, for fruits/vegetables *vs* non-living things), with no difference between the latter ($U = 400$, ns). In the second case, fruits and vegetables presented higher image agreement than animals ($U = 307$, $p \leq .017$) and all other differences were non significant (respectively, $U = 2874$, ns, for animals *vs* non-living things; and $U = 1154$, ns, for fruits/vegetables *vs* non-living things). For visual familiarity, animals were significantly less familiar than both non-living things and fruits and vegetables (respectively, $U = 1542$, $p \leq .017$ for animals *vs* non-living things; and $U = 215$, $p \leq .017$, for animals *vs* fruits/vegetables), with no difference between the latter ($U = 1394$, ns). Finally, non-living things presented significantly less contour overlap than both animals and fruits and vegetables (respectively, $U = 1556$, $p \leq .017$ for animals *vs* non-living things; and $U = 706$, $p \leq .017$, for fruits/vegetables *vs* non-living things), with no difference between the latter ($U = 400$, ns).

The results for within-item structural diversity and for contour overlap are in accord with previous studies that showed that non-living things present higher within-item diversity (Turnbull and Laws, 2000) but lower contour overlap than living things (Humphreys et al., 1988). In the case of image agreement, the present results show that the subjects' representation of fruits and vegetables agree with their depictions in the Snodgrass and Vanderwart (1980) picture set in comparison with those of animals and non-living things. This may be associated with the fact that fruits and vegetables have a lesser degree of within-item diversity. Importantly, however, it has been argued that subjects may be more familiar with the appearance of living things than of non-living things since the former are less structurally diverse and are thus more visually predictable (Laws and Neve, 1999). For the set of items studied, this does not seem to be the case for animals which stand out as less visually familiar than both non-living items and than fruits and vegetables. Moreover, when we reanalysed this tripartite distinction considering only tools and utensils ($n = 75$), similar results were obtained with the exception of image agreement, for which no domain differences were found (see Appendix for more details).

These results show that, depending on the hierarchical level on which analyses are run, some dimensions or variables may be more salient than others in explaining the structural differences between domains and categories. At the more general level, there seems to be a processing disadvantage for living things, which are more complex in terms of object parts and contours but that may be compensated by a lesser degree of top-down processing as related to the variability of the representation, in particular to a lesser degree of within-item diversity and higher image agreement. However, other multiple top-down aspects related to the variability of the representation, such as the familiarity with the visual appearance of the item or confusability as related to contour overlap may again be more favourable to non-living items.

These differences are further discriminated when we consider the more specific categories and items that are included in these domains. Specifically, we found that animals are more complex in terms of object parts, fruits and vegetables are more complex in terms of object contours, while non-living things have lower scores in the dimension variability of the representation, which seem to reflect both higher degree of within-item diversity and lesser degree of contour overlap in comparison with animals and fruits and vegetables. Moreover, other aspects of the variability of the representation (i.e., image agreement and visual familiarity) particularly distinguish fruits and vegetables from animals.

These differences become even more complex when we plot the mean values for more specific categories (e.g., birds, body parts, fruits, insects, furniture, vehicles) on each of the four structural dimensions against the item's value for the same dimensions, similarly to what Laws and Gale (2002) did for more specific structural variables (see online Supplementary materials).

As it can be observed from the figures, no single dimension fully discriminates the larger domains considered. Object parts are the dimension that better allows discrimination of animals (especially the categories of insects, four legged animals and birds) from other domains, whereas object contours allow better discrimination of fruits and vegetables, confirming the previous statistical analyses. Other than that and, for all dimensions, while some categories seem to cluster by larger domains, others do not. Moreover, within each category we can also observe some variation that is larger for some categories than others, again depending on the particular structural dimension considered.

One important question that stems from Study 1 concerns the possible impact that these structural differences at the domain and category level may have on the performance of brain-damaged patients. Can they contribute to the current explanations of the cases of category impairment observed in the literature? What is their relative importance to other semantic and lexical variables? We explored these questions in Study 2.

3. Study 2

In the second study we analysed the predictive power of the four structural dimensions reported by Marques and Raposo

(2011) in explaining the performance of two visual agnosia patients presenting a category-specific impairment for living things. Patients LH and MB were originally reported by Farah et al. (1991) and later reanalysed by Kurbat (1997) in terms of the contribution of different structural and lexical variables to patient naming performance (i.e., proportion of correct responses to each item) using the Snodgrass and Vanderwart (1980) picture set. In both analyses some variables were significant predictors of both patients' performance (e.g., familiarity in Farah et al., 1991), while others were only significant for one patient (e.g., curvature variability for LH in Kurbat, 1997) or not significant at all. Importantly, both studies showed that the living/non-living distinction was a highly significant predictor of performance for both patients even with the other variables included in the analysis. Moreover, the impact of the structural variables included in those analyses was smaller in comparison to the living/non-living distinction.

In the present study, we reanalysed these data (published in Kurbat, 1997), considering the four structural dimensions reported by Marques and Raposo (2011).

3.1. *Method*

3.1.1. *Variables and cases*

The study included the four structural dimensions previously described as possible predictors of the performance of the two patients, LH and MB. The cases correspond to the different items of the Snodgrass and Vanderwart (1980) set for which we have data on the four structural dimensions and on naming performance ($n = 212$), corresponding to the proportion of correct naming on four to six separate occasions (for more details see Farah et al., 1991).

3.1.2. *Data analysis*

We computed simultaneous multiple regressions separately for each patient using the four structural predictors as the independent variables and patients' performance (i.e., proportion correct responses) as the dependent variable. Additional multiple regressions were performed with other structural, and lexical-semantic variables as independent variables to further evaluate the predictive power of the original four structural dimensions to patient performance.

3.2. *Results and discussion*

Patients' performance for living, non-living and the tripartite domain distinction (i.e., animal, fruits and vegetables, non-living things) is presented in Table 3. As it was originally described and is also valid for this data subset, both patients presented a clear deficit for living things, which in the case of LH was especially salient for animals.

Table 3 – Patients' performance (proportion correct) by domain (living, non-living, animals, fruits/vegetables), calculated from Kurbat (1997).

	Living ($n = 75$)	Non-living ($n = 137$)	Animals ($n = 45$)	Fruits and vegetables ($n = 24$)
Patient LH	49.33	84.37	38.67	63.33
Patient MB	28.55	78.28	19.67	31.52

The results of the multiple regressions are presented in Table 4.[1] As it is clearly demonstrated in the table, variability of the representation is the main predictor of performance across patients, followed by object parts and object contours. However, while the results show that structural dimensions directly influence patients' performance, the contribution of lexical-semantic variables should also be taken into account, since structural components explain only part of the observed variance (28% for MB and 16% for LH). This was confirmed when we introduced domain (living = 0, non-living = 1) and concept familiarity (1–5 ratings on the extent to which to which you come in contact with or think about the concept from Snodgrass and Vanderwart, 1980; 5 indicates very familiar) as predictors (similarly to Farah et al., 1991; Kurbat, 1997).[2] Now, for both patients, the percentage of explained variance increased ($R^2 = .27$, $F = 12.35$, $p < .01$, for LH; and $R^2 = .45$, $F = 28.11$, $p < .01$, for MB). For MB, variability of the representation remained as the only significant structural predictor, along with domain and concept familiarity ($\beta = -.13$, standard error of beta – $SE\beta = .06$, $t = -2.07$, $p < .05$ for variability of the representation, $\beta = -.37$, $SE\beta = .07$, $t = -5.19$, $p < .01$ for domain and $\beta = .36$, $SE\beta = .06$, $t = 5.62$, $p < .01$ for concept familiarity). For LH only domain and concept familiarity remained significant predictors ($\beta = -.29$, $SE\beta = .08$, $t = -3.48$, $p < .01$ for domain and $\beta = .28$, $SE\beta = .07$, $t = 3.80$, $p < .01$ for concept familiarity).[3]

Considering the nature of the dimension of the variability of the representation and the fact that it remained the only significant predictor of patient performance when domain and concept familiarity were added (in the case of MB), we further explored the predictive power of its components. For this purpose we ran a multiple regression analysis with the four structural variables of this dimension together with domain and concept familiarity (see Table 5).

Again, for both patients, the percentage of explained variance increased in relation to the analysis run with the larger structural dimensions, suggesting that the role of the

[1] As data for the four structural variables corresponds to factor scores calculated considering the results of a principal components analysis with varimax rotation, they constitute totally independent predictors (i.e., the four predictor variables obtained present zero correlation in terms of their factor scores) and multicollinearity is completely avoided.

[2] We only included these two lexical-semantic variables, as all others (e.g., linguistic frequency, age-of-acquisition) implied significant reductions in number of items due to missing values on the particular variables. In addition to the relations established between the structural dimensions and domain in Study 1, both object parts ($r = -.38$, $p < .01$) and variability of the representation ($r = -.43$, $p < .01$) correlated with concept familiarity (but not internal details, $r = -.12$, ns, or object contours, $r = -.09$, ns).

[3] For the analysis with domain and concept familiarity, diagnostics for collinearity considered both variance inflation factors (values from 1.00 to 1.87; values should not be higher than 6) and tolerance values (.53–1.00; values close to 0 indicate extreme collinearity and values close to 1 indicate independency) for the predictors, but these and other indexes suggest no problems of multicollinearity (Maruyama, 1998).

Table 4 – Multiple regression analysis with proportion of correct naming of patients LH and MB as dependent variables and the four components as independent variables. Values of Rs, beta coefficients (β), standard error of beta (SEβ), t-test (t) and significance (p) for the independent variables for each patient (n = 212).

	β	SEβ	t	p
Patient LH				
Object parts	−.23	.06	−3.64	.0004
Internal details	−.02	.06	−.30	.77
Object contours	−.14	.06	−2.13	.03
Variability of the representation	−.30	.06	−4.75	.000004
Multiple R^2	.16			
F value	10.13			.000001
Patient MB				
Object parts	−.22	.06	−3.82	.0002
Internal details	−.07	.06	−1.26	.21
Object contours	−.22	.06	−3.71	.0003
Variability of the representation	−.42	.06	−7.19	.000001
Multiple R^2	.28			
F value	20.46			.000001

variability of the representation to patient performance may be best understood considering its different aspects separately. However, the best structural predictors varied from one patient to the other (visual familiarity and image agreement for LH, and within-item structural diversity for MB), with only domain remaining a significant predictor in both cases. Moreover, some effects are marginally significant (e.g., visual familiarity, image agreement in the case of MB), and thus more power may highlight contributions from other variables.

Table 5 – Multiple regression analysis with proportion of correct naming of patients LH and MB as dependent variables and domain, concept familiarity and the four components of variability of the representation as independent variables. Values of Rs, beta coefficients (β), standard error of beta (SEβ), t-test (t) and significance (p) for the independent variables for each patient (n = 212).

	β	SEβ	t	p
Patient LH				
Within-item structural diversity	−.08	.09	−.89	.37
Image agreement	.14	.07	1.99	.05
Visual familiarity	.18	.08	2.23	.03
Contour overlap	−.08	.06	−1.21	.23
Domain	−.28	.07	−3.82	.0002
Concept familiarity	.14	.08	1.64	.10
Multiple R^2	.31			
F value	15.07			.000001
Patient MB				
Within-item structural diversity	−.16	.08	−2.08	.04
Image agreement	.11	.06	1.74	.08
Visual familiarity	.13	.07	1.89	.06
Contour overlap	−.10	.06	−1.72	.09
Domain	−.32	.06	−4.91	.000002
Concept familiarity	.24	.07	3.24	.001
Multiple R^2	.47			
F value	30.09			.000001

Note: tolerance values (.44 to .83) and variance inflation (1.20–2.27) do not indicate collinearity problems. Concept familiarity correlated with within-item diversity ($r = -.42$, $p < .01$), visual familiarity ($r = .65$, $p < .01$) and contour overlap ($r = -.17$, $p < .05$) but not image agreement ($r = .10$, ns).

It should be noted that some of the variance explained by domain may be shared by some of the structural dimensions that have been shown to interact with the living and non-living domains as Study 1 points out. Our results, together with Farah et al. (1991) and Kurbat (1997), clearly show that the category-specific deficit observed for these patients has a contribution from both structural and lexical-semantic variables and also that domain is an important dimension to be further considered.

4. General discussion

In the present study we explored the differences among structural variables between domains and categories and how these differences impact on the performance of patients with category-specific deficits. In particular, we addressed these questions by taking into account the four structural dimensions identified by Marques and Raposo (2011) for the Snodgrass and Vanderwart (1980) picture set, which have been used in the majority of studies demonstrating category-specific impairments in object naming.

Regarding the structural differences between domains, the results showed that living things are structurally more complex than non-living things, with more object parts and more object contours. Domains also differed in terms of variability of the representation with further analysis showing that living things were not so diverse across items, and were not so visually familiar, but they do demonstrate greater contour overlap than non-living things.

The same three overall structural dimensions also differentiated between animals, fruits and vegetables and, to a certain degree, non-living things: animals were particularly distinguishable for having more parts, fruits and vegetables for having more object contours and non-living things for having lower scores on the variability of the representation (and also tools and utensils when only this subset of non-living things is considered). A more detailed analysis of this last dimension showed that this corresponded to the fact that non-living things had greater within-item structural diversity but less contour overlap. The first aspect may be detrimental for naming non-living things as the specific object to name will be more difficult to predict from its visual characteristics (i.e., due to the greater diversity in representing these items). In contrast, low contour overlap may be more advantageous to naming, as each object will be easier to distinguish from other category members (see also Laws and Neve, 1999, for a similar argument).

Differences in the structural dimensions were additionally found at more specific category levels (e.g., birds, fruits, insects, furniture, vehicles). Thus, it is plausible that category-specific impairments reported with this picture set are partially related to naturally occurring categorical differences at the structural level.

In agreement with this view, we found that at the structural level, the variability of the representation was the most important dimension contributing to the two cases of impairment for living things, while the contribution of other bottom-up structural dimensions seems to be related or subsumed to the living/non-living distinction. However, this does not mean that accounts based exclusively in bottom-up visual characteristics (e.g., Gale and Laws, 2006) can be ruled out as possible explanations for some category-specific cases of impairment.

Further analysis showed that the different aspects of the variability of the representation were differentially important for the two cases analysed (i.e., visual familiarity for patient LH but within-item diversity for patient MB). This is an important result, as it shows that even at a pre-semantic level, different factors may contribute to an apparently similar category-specific deficit (living things impairment in this case).

This can be explained by the fact that category-specific deficits can occur at different stages in the object recognition process (Capitani et al., 2003; Humphreys and Riddoch, 2003; Humphreys et al., 1988; Farah et al., 1991), as well as the fact that patients presenting similar cognitive dissociations may present with lesions in different sites (Farah et al., 1991; Kurbat, 1997). As such, it is possible that for these cases the deficit has both a structural and a semantic origin but that for other cases of impairment, other structural dimensions and/or lexical-semantic variables turn out to be more important to performance.

The larger impact of top-down modulation (i.e., related to variability of the representation) on patient performance is strengthened by previous findings showing that this dimension also influences naming latencies for this picture set in healthy subjects (Marques and Raposo, 2011). Interestingly, internal details, the other dimension reported in that study to influence performance in standard picture naming did not differentiate domains nor did it explain the two cases of impairment for living things. This suggests that internal details have a more general effect on processing speed than on response accuracy and may be less relevant in differentiating larger domains and categories. However, this is not the case for all patients with category-specific deficits. For example, Riddoch and Humphreys (2004) described two patients with simultanagnosia whose naming performance was particularly impaired when ‘internal details’ were critical to the identification of the items. It is thus possible that, under certain conditions, this dimension also contributes significantly to differentiating categories.

Together, these studies suggest that different structural dimensions may influence different aspects of object recognition performance, although both the study by Marques and Raposo (2011) and the present study seem to show that the overall impact of structural variables on final naming performance is small. Moreover, the present study extends this result to patient naming performance, further showing that the contribution of structural variables is also smaller in comparison with other lexical-semantic variables, and in particular with the object domain. This latter variable thus remains an important dimension to be considered in explaining category-specific deficits.

At a more general level, this is in accord with previous studies showing that structural dimensions interact with other stimuli characteristics as well as tasks and tasks demands (e.g., Coppens and Frisinger, 2005; Gale et al., 2006; Kiefer, 2001; Gerlach, 2009; Laws and Neve, 1999; Låg, 2001). In particular, the differential contribution of the structural dimensions in terms of task demands could be understood in the framework of the recent PACE (i.e., pre-semantic account of category effects) model (Gerlach, 2009). The PACE tries to account for the way in which category effects are affected by different task parameters (the degree of perceptual differentiation called for), stimulus characteristics (whether stimuli are presented as silhouettes, full line drawings, or fragmented forms), stimulus presentation (stimulus exposure duration and position) as well as interactions between these parameters. As such, the contribution of the structural dimensions considered here may be envisaged by taking into account these task parameters.

As previously stated, the structural dimensions studied here were extracted from a particular picture set (Snodgrass and Vanderwart, 1980) of black-and-white line drawings, where many of the visual details of the depicted objects may have been left out. Still, this picture set has been used in the large majority of studies reporting category-specific deficits (Laws and Gale, 2002). For this reason, the conclusions reached here are certainly relevant for other cases of impairment using this same picture set.

The present results show that for these patients, the deficits observed may be in part related to naturally occurring differences between categories, in particular related to top-down modulation requirements related to different aspects of the variability of the representation. Studies with other patients, tasks and picture sets will inform us about the generalizability of these effects.

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Appendix. Names of target items by category

Birds: Chicken, Duck, Eagle, Ostrich, Owl, Peacock, Penguin, Rooster, Swan.
Body parts: Arm, Ear, Eye, Hair, Heart, Lips.
Buildings: Barn, Church, Fence, House, Windmill, Window.
Clothes: Belt, Blouse, Boot, Cap, Coat, Dress, Glove, Hat, Jacket, Pants, Shirt, Shoe, Skirt, Sock, Sweater, Tie, Vest.
Four-legged animals: Alligator, Bear, Camel, Cat, Cow, Deer, Dog, Donkey, Elephant, Fox, Frog, Giraffe, Goat, Gorilla, Horse, Kangaroo, Leopard, Lion, Monkey, Mouse, Pig, Rabbit, Raccoon, Rhinoceros, Sheep, Skunk, Squirrel, Tiger.
Fruits: Apple, Banana, Cherry, Grapes, Lemon, Orange, Peach, Peanut, Pear, Pineapple, Strawberry, Watermelon.
Furniture: Ashtray, Bed, Chair, Clock, Couch, Desk, Door, Doorknob, Dresser, Record player, Rocking chair, Stool, Table, Telephone, Television, Vase.
Insects: Ant, Bee, Beetle, Butterfly, Caterpillar, Fly, Grasshopper, Spider.

Kitchen utensils: Bottle, Bowl, Broom, Clothespin, Cup, Fork, Frying pan, Glass, Iron, Ironing board, Kettle, Knife, Pitcher, Pot, Refrigerator, Rolling pin, Saltshaker, Spoon, Stove, Toaster.
Musical instruments: Accordion, Bell, Drum, Flute, French horn, Guitar, Harp, Piano, Trumpet, Violin, Whistle.
Manipulable objects: Basket, Book, Box, Button, Brush, Candle, Chain, Cigar, Cigarette, Comb, Glasses, Gun, Hanger, Key, Lamp, Light bulb, Light switch, Lock, Nail file, Necklace, Pen, Pencil, Pipe, Plug, Ring, Spool of thread, Suitcase, Thimble, Toothbrush, Umbrella, Watch, Watering can.
Tools: Axe, Chisel, Hammer, Ladder, Nail, Nut, Paintbrush, Pliers, Ruler, Saw, Scissors, Screw, Screwdriver, Wrench.
Toys: Ball, Balloon, Baseball bat, Doll, Football, Kite, Roller skate, Swing, Top.
Vegetables: Artichoke, Asparagus, Carrot, Celery, Corn, Lettuce, Mushroom, Onion, Pepper, Potato, Pumpkin, Tomato.
Vehicles: Airplane, Baby carriage, Bicycle, Bus, Car, Helicopter, Motorcycle, Sailboat, Sled, Train, Truck, Wagon.

Appendix. Analyses of tripartite domain differences with tools

The analysis of differences (Kruskal–Wallis tests) between structural dimensions for the tripartite domain distinction of animals ($n = 44$), fruits and vegetables ($n = 24$) and tools and utensils ($n = 75$) showed a main effect of domain for object parts [$H(2) = 74.39$, $p < .05$], internal details [$H(2) = 7.58$, $p < .05$], object contours [$H(2) = 25.21$, $p < .05$], and variability of the representation [$H(2) = 15.12$, $p < .05$]. Further analysis of these effects using Mann–Whitney U tests with corrections for multiple comparisons (i.e., Bonferroni correction, $.05/3 = p \leq .017$) showed that: tools and utensils presented significantly less parts than animals ($U = 155$, $p \leq .017$) but not than fruits and vegetables ($U = 856$, ns); tools and utensils presented less internal details than animals ($U = 1194$, $p \leq .017$), but not than fruits and vegetables ($U = 712$, ns); tools and utensils presented less object contours than animals ($U = 1178$, $p \leq .017$) and than fruits and vegetables ($U = 368$, $p \leq .017$); and tools and utensils presented lower scores than animals ($U = 1206$, $p \leq .017$) and than fruit and vegetables ($U = 476$, $p \leq .017$) for variability of the representation.

The analysis of differences between structural variables of variability of the representation (Kruskal–Wallis tests) for the tripartite domain distinction of animals ($n = 44$), fruits and vegetables ($n = 24$) and tools and utensils ($n = 75$) showed a main effect of domain for within-item structural diversity [$H(2) = 41.09$, $p < .05$], visual familiarity [$H(2) = 28.29$, $p < .05$] and contour overlap [$H(2) = 17.06$, $p < .05$] but not for image agreement [$H(2) = 9.75$, ns]. Further analysis of these effects using Mann–Whitney U tests with corrections for multiple comparisons (i.e., Bonferroni correction, $.05/3 = p \leq .017$) showed that: tools and utensils presented significantly more within-item diversity than fruits and vegetables ($U = 233$, $p \leq .017$) and than animals ($U = 805$, $p \leq .017$); tools and utensils were more visual familiar than animals ($U = 796$, $p \leq .017$) but not than fruits and vegetables ($U = 774$, ns); and tools and utensils presented less contour overlap than animals ($U = 1120$, $p \leq .017$) and than fruits and vegetables ($U = 487$, $p \leq .017$).

Supplementary material

Supplementary data related to this article can be found online at doi:10.1016/j.cortex.2011.10.006.

REFERENCES

Alario F-X, Ferrand L, Laganaro M, New B, Frauenfelder UH, and Segui J. Predictors of picture naming speed. *Behavior Research Methods, Instruments, & Computers*, 36(1): 140–155, 2004.

Barry C, Morrison CM, and Ellis AW. Naming the Snodgrass and Vanderwart pictures: Effects of age of acquisition, frequency and name agreement. *Quarterly Journal of Experimental Psychology A*, 50(3): 560–585, 1997.

Bonin P, Chalard M, Méot A, and Fayol M. The determinants of spoken and written picture naming latencies. *British Journal of Psychology*, 93(Pt 1): 89–114, 2002.

Capitani E, Laiacona M, Mahon BZ, and Caramazza A. What are the facts of semantic category-specific deficits? A critical review of the clinical evidence. *Cognitive Neuropsychology*, 20(3/4/5/6): 307–326, 2003.

Coppens P and Frisinger D. Category-specific naming effect in non-brain-damaged individuals. *Brain and Language*, 94(1): 61–71, 2005.

Cree GS and McRae K. Analyzing the factors underlying the structure and computation of the meaning of chipmunk, cherry, chisel, cheese, and cello (and many other such concrete nouns). *Journal of Experimental Psychology: General*, 132(2): 163–201, 2003.

Farah M, McMullen P, and Meyer M. Can the recognition of living things be selectively impaired? *Neuropsychologia*, 29(2): 185–193, 1991.

Forde EME and Humphreys GW. Category-specific recognition impairments: A review of important case studies and influential theories. *Aphasiology*, 13(3): 169–193, 1999.

Forsythe A, Mulhern G, and Sawey M. Confounds in pictorial sets: The role of complexity and familiarity in basic-level picture processing. *Behavior Research Methods*, 40(1): 116–129, 2008.

Funnell E and Sheridan J. Categories of knowledge: Unfamiliar aspects of living and nonliving things. *Cognitive Neuropsychology*, 9(2): 135–153, 1992.

Gainotti G and Silveri MC. Cognitive and anatomical locus of lesion in a patient with a category-specific impairment for living beings. *Cognitive Neuropsychology*, 13(3): 357–389, 1996.

Gale TM and Laws K. Category-specificity can emerge from bottom-up visual characteristics: Evidence from a modular neural network. *Brain and Cognition*, 61(3): 269–279, 2006.

Gale TM, Laws K, and Foley K. Crowded and sparse domains in object recognition: Consequences for categorization and naming. *Brain and Cognition*, 60(2): 139–145, 2006.

Gerlach C. Category-specificity in visual object recognition. *Cognition*, 111(3): 281–301, 2009.

Hillis AE and Caramazza A. Category-specific naming and comprehension impairment: A double dissociation. *Brain and Language*, 114(Pt 5): 2081–2084, 1991.

Humphreys GW and Forde EME. Hierarchies, similarity, and interactivity in object recognition: "Category-specific" neuropsychological deficits. *Behavioral and Brain Sciences*, 24: 453–509, 2001.

Humphreys GW and Riddoch MJ. A case series analysis of "category-specific" deficits of living things: The HIT account. *Cognitive Neuropsychology*, 20(3-6): 263–306, 2003.
Humphreys GW, Riddoch MJ, and Quinlan PT. Cascade processes in picture identification. *Cognitive Neuropsychology*, 5(1): 67–104, 1988.
Kiefer M. Perceptual and semantic sources of category-specific effects: Event-related potentials during picture and word categorization. *Memory and Cognition*, 29(1): 100–116, 2001.
Kurbat MA. Can the recognition of living things really be selectively impaired? *Neuropsychologia*, 35(6): 813–827, 1997.
Låg T. Category-specific effects in object identification: What is 'normal'? *Cortex*, 41(6): 833–841, 2001.
Laws KR and Gale TM. Category-specific naming and the 'visual' characteristics of line drawn stimuli. *Cortex*, 38(1): 7–21, 2002.
Laws KR, Gale TM, Frank R, and Davey N. Visual similarity is greater for line drawings of nonliving than living things: The importance of musical instruments and body parts. *Brain & Cognition*, 48(2–3): 421–424, 2002.
Laws KR and Hunter MZ. The impact of colour, spatial resolution, and presentation speed on category naming. *Brain & Cognition*, 62(2): 89–97, 2006.
Laws KR and Neve C. A 'normal' category-specific advantage for naming living things. *Neuropsychologia*, 37(11): 1263–1269, 1999.
Lloyd-Jones TJ and Nettlemill M. Sources of error in picture naming under time pressure. *Memory and Cognition*, 35(4): 816–836, 2007.
Magnié MN, Besson M, Poncet M, and Dolisi C. The Snodgrass and Vanderwart set revisited: Norms for object manipulability and for pictorial ambiguity of objects, chimeric objects and nonobjects. *Journal of Clinical and Experimental Neuropsychology*, 25(4): 521–560, 2003.
Mahon BZ and Caramazza A. Concepts and categories: A cognitive neuropsychological perspective. *Annual Review of Psychology*, 60: 27–51, 2009.
Marques JF and Raposo A. Structural dimensions of object pictures: Organization and relation to object decision and naming. *Visual Cognition*, 19(6): 705–729, 2011.
Maruyama GM. *Basics of Structural Equation Modeling*. Thousand Oaks: Sage, 1998.
Nishimoto T, Miyawaki K, Ueda T, Une Y, and Takahashi M. Japanese normative set of 359 pictures. *Behavior Research Methods*, 37(3): 398–416, 2005.
Riddoch MJ and Humphreys GW. Object identification in simultanagnosia: When wholes are not the sum of their parts. *Cognitive Neuropsychology*, 21(2): 423–441, 2004.
Sachett C and Humphreys GW. Calling a squirrel a squirrel but a canoe a wigwam: A category-specific deficit for artifactual objects and body parts. *Cognitive Neuropsychology*, 9(1): 73–86, 1992.
Snodgrass JG and Yuditsky T. Naming times for the Snodgrass and Vanderwart pictures. *Behavior Research Methods, Instruments, & Computers*, 28(4): 516–536, 1996.
Snodgrass JG and Vanderwart M. A standardized set of 260 pictures: Norms for name agreement, image agreement, familiarity, and visual complexity. *Journal of Experimental Psychology: Human Learning and Memory*, 6(2): 174–215, 1980.
Tranel D, Logan CG, Frank RJ, and Damasio AR. Explaining category-related effects in the retrieval of conceptual and lexical knowledge for concrete entities: Operationalization and analysis of factors. *Neuropsychologia*, 35(10): 1329–1339, 1997.
Turnbull OH and Laws KR. Loss of stored knowledge of object structure: Implications for 'category-specific' deficits. *Cognitive Neuropsychology*, 17(4): 365–389, 2000.
Warrington EK and McCarthy RA. Categories of knowledge: Further fractionations and an attempted integration. *Brain*, 110(Pt 5): 1273–1296, 1987.
Warrington EK and Shallice T. Category-specific semantic impairments. *Brain*, 107(Pt 3): 829–853, 1984.