RUNNING HEAD: Embodied abstract semantics

The representation of abstract words:

Why emotion matters

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Abstract

Although much is known about the representation and processing of concrete concepts, our knowledge of what abstract semantics might be is severely limited. In this paper we first address the adequacy of the two dominant accounts (dual coding theory and the context availability model) put forward in order to explain representation and processing differences between concrete and abstract words. We find that neither proposal can account for experimental findings and that this is, at least partly, because abstract words are considered to be unrelated to experiential information in both of these accounts. We then address one particular type of experiential information, emotional content, and demonstrate that it plays a crucial role in the processing and representation of abstract concepts: statistically, abstract words are more emotionally valenced than concrete words and this accounts for a residual latency advantage for abstract words, when variables such as imageability (a construct derived from dual coding theory) and rated context availability are held constant. We conclude with a discussion of our novel hypothesis for embodied abstract semantics.

The representation of abstract word meanings: Why emotion matters

Concrete entities exist in space-time and are independent of human minds/language; abstract entities, on the other hand, do not exist in space-time but their existence depends on human minds/language (Hale, 1988). “Concreteness”, therefore, indexes a basic ontological distinction, dividing entities into these two kinds. This ontological distinction is reflected in our epistemologies, and concreteness is arguably an organizing principle of semantic knowledge. Up to the present, research into semantic and conceptual representation has focused almost exclusively on how concrete word meanings and concepts are represented and processed, to the exclusion of abstract meanings and concepts. However, the ability to communicate through language about abstract concepts, such as *courage, dignity, revenge,* lies at the heart of what it means to be human, and no theory of semantic or conceptual representation is complete without an explicit account of how abstract knowledge is acquired, represented, and processed.

In this paper we first demonstrate, combining experiments with large scale regression analyses of data from the *English Lexicon Project* (ELP, Balota et al., 2007), that the dual coding theory and the context availability hypothesis - two of the most popular accounts of differences in representation and processing between concrete and abstract words - do not exhaustively account for processing (and hence representational) differences between the two types of word meanings. In fact, once imageability and context availability (along with a large number of other lexical and sublexical variables) are controlled, there is a residual advantage for abstract word processing. We show that this advantage can be explained by differences in emotional valence between concrete and abstract words, and we discuss a new hypothesis of how the semantic system is organized with respect to the distinction between concrete and abstract concepts. Specifically, we propose that both concrete and abstract concepts bind different types of information: experiential information (sensory, motor and affective), and also linguistic information. However, concrete and abstract semantic representations differ in terms of whether sensory, motor or affective information have the greatest weight, with sensory-motor information being more preponderant for concrete concepts and affective information playing a greater role for abstract concepts. Thus, a central and novel element of this proposal is the idea that experiential information contributes to the representation of both concrete and abstract words, however, whereas sensory-motor information is statistically more important for the representation of concrete words, emotional content, a largely neglected type of experiential information in the literature on semantic representation/processing, contributes to word representation and processing, particularly for abstract concepts.

The Concreteness Effect: Dual-Coding Theory and the Context Availability Model

It has been demonstrated repeatedly, and with a variety of methodologies, that concrete words have a cognitive advantage over abstract words—an advantage, labelled the 'concreteness effect'. With respect to lexical processing, early demonstrations of a processing advantage for concrete over abstract words were provided by James (1975), Whaley (1978), and Rubin (1980). James showed that at least when low frequency words are considered, concrete words are identified as words faster than abstract words. Whaley (1978) and Rubin (1980) adopted a correlational approach, showing that there is a significant negative correlation between concreteness ratings and lexical decision reaction times for the same items. This processing advantage has since then been replicated in both lexical decision (Binder et al., 2005; Bleasdale, 1987; de Groot, 1989; Howell & Bryden, 1987; Kroll & Merves, 1986; Schwanenflugel, Harnishfeger & Stowe, 1988; Schwanenflugel & Stowe, 1989) and word naming tasks (de Groot, 1989; Schwanenflugel and Stowe, 1989).

With respect to memory for concrete and abstract words, it has been again repeatedly demonstrated that concrete words have an advantage over abstract words in both long-term and short-term memory tasks (e.g. paired-associate learning (Paivio, Yuille, & Smythe, 1966); serial recall (Allen and Hulme, 2006; Romani, McAlpine, & Martin, 2007; Walker & Hulme, 1999), free recall (Romani, McAlpine, & Martin, 2007; ter Doest & Semin, 2005), reconstruction of order (Neath, 1997); and recognition memory (Fliessbach, Weis, Klaver, Elger & Weber, 2006)).

Among the handful of proposals that have been put forward to explain the 'concreteness effect', two have been particularly influential: dual coding theory (Paivio, 1971; 1986; 1991; 2007) and the context availability model (Schwanenflugel and Shoben, 1983; Schwanenflugel, 1991). In both of these accounts, concrete word representations are assumed to be richer than abstract word representations (see also Plaut & Shallice, 1993). According to dual coding theory, concrete words are represented in two representationally distinct but functionally related systems: a verbal, linguistic system and a non-verbal, imagistic system. Abstract concepts, on the other hand, are primarily or exclusively represented in the verbal system. The cognitive advantage for words referring to concrete concepts is attributed to the fact that they have access to information from multiple systems. According to the context availability model, both concrete and abstract concepts are represented in a single verbal code and neither the representations nor the processes that operate on these representations differ for the two types of concepts. The argument here is that comprehension relies on verbal context (either supplied by the discourse or by the comprehender's own semantic memory) in order to be effective. Accessing the meaning of a word involves accessing a network of associated semantic information and the advantage for concrete words arises because they have stronger and denser associations to contextual knowledge than abstract words. These two proposals have guided research on concrete/abstract semantics; results, however, have been inconclusive. The majority of recent work is neuroscientific in nature, employing either electrophysiological or neuroimaging techniques in order to determine the neural bases of the distinction between concrete and abstract words.

A series of studies using event-related potentials (ERPs) suggested combining dual-coding theory and the context availability model in explaining the concreteness effect ("context-extended dual coding theory"— Holcomb et al., 1999; West & Holcomb, 2000). ERP studies have identified two components associated with concreteness: the N400 and a late negative component peaking around 700-800 milliseconds. With respect to the first component, all relevant studies have found that concrete words elicit a larger N400 than abstract words (Holcomb et al., 1999; Kanske & Kotz, 2007; Kounios & Holcomb, 1994; Nittono et al., 2002; West & Holcomb, 2000; van Schie et al., 2005). The observation that the effect has an anterior maximum but is widely distributed across the scalp (West & Holcomb, 2000) and the failure to find any structural overlap between concreteness and visual object working memory on that component (van Schie et al., 2005) has led to the suggestion that the effect arises within a verbal semantic system that is common to both concrete and abstract words. This N400 component has been argued to reflect postlexical processing in a semantic memory system, possibly involving the integration of semantic information into higher level representations (Osterhout & Holcomb, 1995). According to the context availability model, concrete words are assumed to have stronger and denser interconnections with other concepts in semantic memory than abstract words (Schwanenflugel & Shoben, 1983). In the EEG literature, concrete words are said to activate the semantic network more extensively than abstract words and this extensive activation is reflected in an amplified N400 for concrete words. The second, later, component is assumed to reflect the contribution of mental imagery for concrete words: it is more sustained over time, peaking at around 700 or 800 ms post-stimulus. It is said to be associated with the retrieval of mental imagery associated with concrete words and thus consistent with dual coding theory. Although the imagery-related component is consistent with dual-coding claims that imagery has a late effect in processing, the greater N400 amplitude for concrete words is harder to reconcile with context availability claims. The stronger interconnections in semantic memory for concrete words according to the model lead to facilitated integration of information. The increased N400 amplitude for concrete words, however, has been interpreted as indexing difficulty in integrating appropriate information (see Kutas, Van Petten & Kluender, 2006 for a review). So the extent to which EEG data actually support the context-extended dual coding theory is questionable.

A case for a qualitative difference between concrete and abstract word meanings, thus compatible with dual-coding views, comes from neuropsychological studies where a double dissociation between concrete and abstract words has been observed. Although cases where concrete words are better preserved in the damaged/aging brain are the most frequently reported (e.g., Coltheart et al., 1980; Franklin et al., 1995; Katz & Goodglass, 1990; Martin & Saffran, 1992; Roeltgen et al., 1983; Warrington, 1975), there are cases reporting better performance on abstract over concrete words (e.g., Breedin et al., 1994; Cipolotti and Warrington, 1995; Marshall et al, 1996; Papagno et al., 2007; Reilly et al., 2007; Sirigu, Duhamel, & Poncet, 1991; Warrington, 1975; Warrington & Shallice, 1984).

In the imaging literature, although abstract word processing seems to involve activations in a more distributed network of brain regions than concrete word processing (Pexman et al., 2007), there is converging evidence that abstract word processing is associated with higher activation in left hemispheric areas that are known to be involved in semantic processing, e.g, the left inferior frontal gyrus (LIFG) (Perani et al., 1999; Jessen et al., 2000; Fiebach and Friederici, 2003; Noppeney and Price, 2004; Binder et al., 2005) and the superior temporo-lateral cortex (Mellet et al., 1998; Kiehl et al., 1999; Wise et al., 2000; Binder et al., 2005; Binder et al, 2009). With respect to greater activation for abstract over concrete words in the left inferior frontal gyrus, this finding has been interpreted as indicating more effortful retrieval of semantic information for abstract words, a finding that has been interpreted in some studies as consistent with context availability predictions. Again, however, the majority of the studies use items matched on frequency, but not on familiarity or other relevant variables. For instance, in one of the otherwise best-controlled studies in the imaging literature (Binder et al., 2005), although items were matched on frequency, we found that concrete words were significantly more familiar than abstract words (average familiarity ratings of 534 vs. 471 respectively, $t(98)=3.956$, $p<.001$). It may well be that such differences in familiarity underlie some of the effects reported in the neuroimaging literature.

When concrete words are compared to abstract words, results have been extremely variable. Although some studies have found activations of left hemispheric regions associated with higher levels of visual processing such as the left fusiform gyrus (D'Esposito et al., 1997; Mellet et al., 1998; Fiebach & Friederici, 2003; Sabsevitz et al. 2005), consistent with the dual coding prediction that concrete word meanings activate relevant imagistic information, a number of studies have failed to find any regions at all that are activated more during concrete word processing (Grossman et al., 2000; Friederici et al., 2000; Kiehl et al., 1999; Krause et al., 1999; Noppeney and Price, 2004; Perani et al., 1999; Pexman et al., 2007; Tyler et al., 2001). Some studies have found more bilateral activations during concrete word processing (Binder et al., 2005; Sabsevitz et al., 2005), while other studies have shown that there is no right hemisphere involvement in the processing of concrete words, and if anything, there are more right-hemispheric activations for abstract rather than concrete words (see Fiebach and Friederici, 2003 for a review). One of the reasons for the lack of consistency in the results may be that the concrete words used within and across studies differ in terms of their featural composition, which quite reasonably leads to activation of different brain networks in different studies or to lack of consistent areas of activation within the same study. Thus, just as the behavioral and EEG evidence reviewed above, imaging studies do not provide clear support for either dual-coding or context availability calling for new theoretical directions and further empirical investigation.

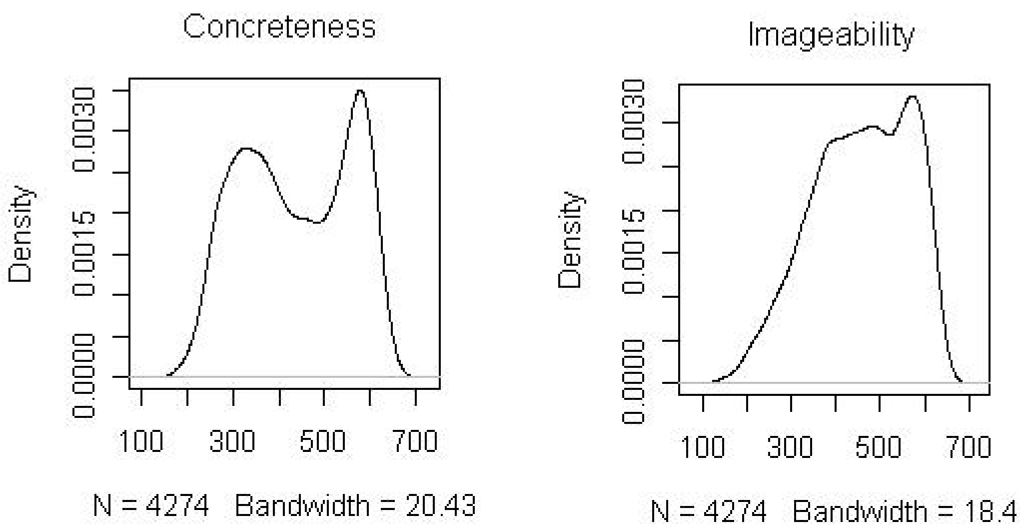
The Concreteness Effect: Testing Dual-Coding Theory and the Context-Availability Hypothesis

In the literature, it is invariably assumed that the psycholinguistic constructs of concreteness and imageability tap into the same underlying theoretical construct, i.e., the ontological distinction between concrete, spatiotemporally-bound concepts and abstract, non-spatiotemporally bound concepts. After all, when nothing else is taken into account, imageability ratings explain more than 72% of the variance in concreteness ratings, and up to now the variance that is not explained by imageability has been considered to be pure noise, due perhaps to the imprecise nature of subjective norms. This general assumption is illustrated in the following quote: “Although imageability and concreteness are technically different psycholinguistic constructs, the correlation between these variables is so strong that many authors use the terms interchangeably. Here we make the same assumption of synonymy between imageability and concreteness in terms of theory (i.e., concreteness effects = imageability effects).” (Reilly and Kean, 2007: 158). In fact, concreteness and imageability ratings have been used interchangeably in most of the recent literature in the field (e.g. Binder et al., 2005; Richardson, 2003; Fliessbach et al., 2006; Giesbrecht et al., 2004). However, concreteness and imageability tap into, at least partially, different aspects of semantic representations if native speaker intuitions about them are taken seriously: our analyses of ratings for more than

4,000 words in the MRC Psycholinguistic Database show that the frequency distribution of concreteness ratings is bimodal, with two distinct modes for abstract and concrete words (see also Cartwright & Nickerson, 1979; Nelson & Schreiber, 1992), while the distribution of imageability ratings is unimodal (Figure 1). In other words, concreteness ratings capture the categorical ontological distinction between concrete and abstract words (and their underlying conceptual representations), while imageability ratings index a graded property that is meant to capture the differential association of words with sensory (primarily visual) properties.

Moreover, from a theoretical point of view, imageability ratings are a proxy for concreteness only in the dual-coding theory, not, for example, in the Context Availability hypothesis because only the former explains differences between concrete and abstract words in terms of whether (and to what extent) the non verbal imagistic system is engaged (Reily and Kean, 2007; Fliessbach, Weis, Klaver, Elger, & Weber, 2006). According to the Context Availability hypothesis, however, imageability would not exhaust the differences between concrete and abstract words which, instead, arise as a consequence of different degrees of richness of semantic representation within a verbal system.

Figure 1. Density plots for concreteness and imageability ratings for 4,274 words from the MRC Psycholinguistic Database. Using the dip test (Hartigan & Hartigan, 1985) we rejected the hypothesis of unimodality for the concreteness distribution (dip = .0244, p<. 001) but not for the imageability distribution (dip = .0058, n.s.).



One approach to test both hypotheses is to manipulate concreteness while controlling for both imageability and context availability. Both dual-coding and context availability theories predict that concreteness effects will not be observed under these conditions.

Experiment 1

In this experiment, we contrast morphologically simple abstract and concrete words that have been matched for imageability and context availability (as well as a host of other noise variables).

Method

Participants. Fifty-eight native English speakers (32 female; mean age: 28.69 ± 9.96) participated and were paid at a rate of £6 per hour. Three participants were replaced because of a high number of timed-out responses in their data.

Materials and design. Forty concrete and 40 abstract monomorphemic words were selected (the full item list appears in Appendix I). The items differed on concreteness, but were matched pairwise on 12 lexical and sublexical variables, including rated context availability (see Table 1). Imageability, familiarity, and age of acquisition ratings were obtained from the MRC Psycholinguistic Database (Coltheart, 1981). Items were also matched in length (in number of letters, phonemes, and syllables) and number of meanings (in terms of number of synsets in which a word appears in WordNet; Fellbaum, 1998). Frequency, orthographic neighbourhood density, mean frequency of orthographic neighbours, and mean positional bigram frequency were taken from the English Lexicon Project (ELP; Balota et al., 2007). Finally, we obtained context availability ratings by asking 47 native English speakers to rate words on a 7-point Likert scale according to how easy it is to come up with a particular context or circumstance in which they might appear. The instructions to participants were identical to those used by Schwanenflugel et al. (1989), with the exception of some of the examples given in order to anchor the ratings which differed between the studies. We obtained these norms for 650 words (each word was rated by 22 or 25 speakers). See Table 1 for details and Appendix I for a full list of items used in the experiment.

We also selected 40 concrete and 40 abstract words matched with the experimental items in terms of concreteness to serve as the basis for creating the pseudowords for the experiment. We created pseudowords by altering a single letter in one of these words. We made an effort to select pseudowords with only one orthographic neighbour (the intended real word). In cases in which that was not possible (for all 3-letter and some of the 4-letter words), the intended word was the most frequent among the set of orthographic neighbours of the nonword. The resulting pseudowords were matched pairwise with the experimental items in terms of length and mean positional bigram frequency.

Table 1. Item information for Experiment 1 (averages and standard deviations). The numbers reported here are based on 38 items per condition (two were excluded on the basis of low accuracy; see Results).

	Abstract	Concrete
Concreteness	345 (40)	552 (44)
Context availability	568 (46)	566 (52)
Imageability	500 (42)	505 (35)
Familiarity	504 (70)	505 (67)
Age of acquisition	385 (40)	390 (103)
Log frequency	9.02 (1.44)	9.03 (1.62)
Number of letters	5.55 (1.20)	5.63 (1.28)
Number of phonemes	4.71 (1.33)	4.55 (1.27)
Number of syllables	1.68 (0.57)	1.68 (0.70)
Mean positional bigram freq.	1491 (959)	1595 (943)
Num. ortho. neighbors	2.63 (3.90)	2.84 (4.02)
Mean neighbour freq.	4.86 (3.93)	4.26 (4.13)
Number of synsets	5.16 (3.25)	6.50 (6.86)

Procedure. Participants were tested individually. Each trial began with a fixation cross presented in the middle of the screen for 400 milliseconds, followed by presentation of the string for 2000 milliseconds or until a response was given (whichever was earlier). Participants were instructed to respond as quickly and accurately as possible using a serial response box. After response or time-out, the screen went blank and participants were instructed to press the space bar to continue with the next trial. Ten practice items were first presented, followed by the 320 words and nonwords presented in a different random order for each participant.

Results

In the analysis of reaction times, we excluded from analysis all responses faster than 200 milliseconds and slower than 2000 milliseconds (0.84% of the data). For two concrete words, accuracy rates did not differ from chance. We excluded these items from further analysis as well as their paired abstract items. We also removed outliers by excluding from analysis reaction times 2.5 standard deviations above the mean per condition for each participant (2.04% of the data). Mean latencies can be found in Table 2. The analyses reported were carried out on correct responses only.

Table 2. Reaction times and accuracy rates (standard deviations in parentheses) for Experiment 1.

	High concreteness	Low concreteness	Nonwords
RTs (in ms)	590 (99)	568 (88)	682 (140)
Accuracy Rates (%)	95.48 (4.92)	96.59 (3.66)	94.19 (4.78)

Abstract words were recognized as words faster than concrete words ($M_{abstract}$=568ms; $M_{concrete}$=590ms). This difference was significant both by participants ($F1(1, 57)=23.327$, $p<.001$) and by items ($F2(1, 37)=5.447$, $p<.05$). In the analysis of accuracy, there was a numerical advantage for abstract over concrete words ($M_{abstract}$=96.59%; $M_{concrete}$=95.48%), but the effect was not statistically reliable ($F1(1, 57)=3.166$, $p=.08$; $F2<1$).

<u>Discussion</u>

<u>In this experiment we found that abstract words are processed faster than concrete words. This finding forces us</u> to reject the dual coding and context availability hypotheses as stated above, since we found differences between the concrete and abstract conditions that were matched for

imageability and context availability. In order to further assess the generalizability of the effect, given that in contrast to previous work we found an advantage for abstract words, below we report the results of large-scale regression analyses on lexical decision data from the English Lexicon Project (ELP; Balota et al., 2007).

Regression Analyses I (903 words)

In this set of analyses, we used context availability norms from Clark and Paivio (2004), who collected ratings for 925 words. We also included concreteness, imageability, and a number of variables that have been identified as relevant for visual word recognition: number of letters, mean positional bigram frequency, orthographic neighbourhood density (the latter two from the ELP), number of morphemes, log frequency (based on the Hyperspace Analogue to Language frequency counts as reported in the ELP), and age of acquisition (from the merged Bristol and MRC norms—Stadthagen-Gonzalez and Davis, 2006). We also coded each word according to whether its grammatical class is ambiguous or not. We did not include familiarity in this analysis due to the high correlation with context availability (.93 and .80 for the two sets of familiarity ratings reported in Clark and Paivio, 2004).

The analyses reported below were carried out on 903 items for which lexical decision reaction times (averaged across multiple subjects) and accuracy data were available in the ELP. We tested whether concreteness explains any of the variance in the data after the effects of imageability, context availability and other lexical and sublexical variables are removed. For the reaction time analyses, we logarithmically transformed the by-item mean reaction times and then fitted an ordinary least squares linear regression model on the transformed data. For the accuracy analysis, we used maximum likelihood estimation models.

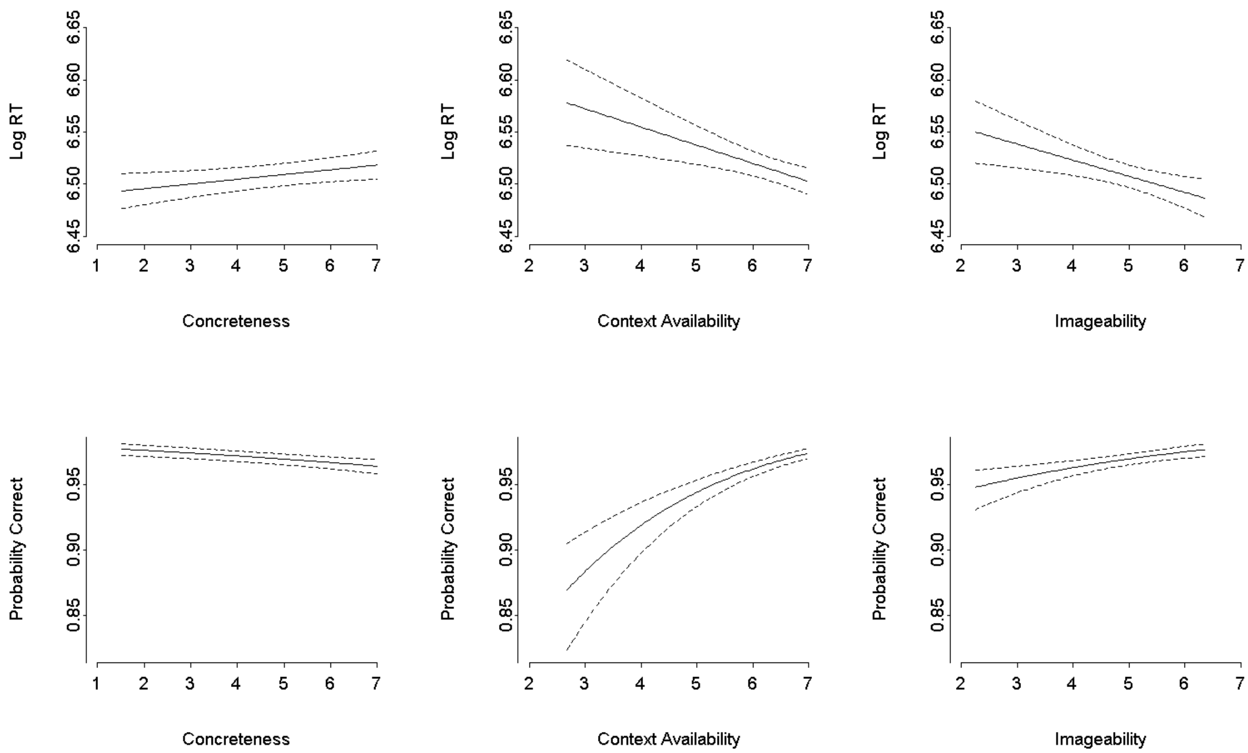
Latencies. In this and all subsequent regression analyses on latencies, the procedure is as follows: We first fit a linear regression model including all the predictors. In all models, the relationship between latencies and the predictors is modelled as a linear combination of the relevant correlation co-efficients. When fitting the linear model, we relax the assumption of linearity when considering the relationship between *each individual predictor* and the dependent variable. In order to model nonlinear relationships between individual predictors and the dependent variable, we used restricted cubic splines (Harrell, 2001). Cubic splines are piecewise polynomials used in curve fitting such that the relationship between a predictor and a dependent variable (X) is modelled by placing polynomials within intervals of X and connecting the polynomials across different intervals of X (Harrell, 2001). These intervals are called knots—and in our analyses we used the minimum number of knots necessary in order to model nonlinearities. *Restricted* cubic splines are spline functions that are constrained to be linear at the tails—that is, before the first and after the last knot; the motivation for constraining the function to be linear at the tails is that cubic splines provide poor fit at the tails.

After fitting the initial model, we take out outliers (following the procedure in Baayen et al., 2006). We then refit the model and use a bootstrap validation procedure (Harrell, 2001) to determine to what extent our model overfits the data. We include a fast backward elimination algorithm in the validation procedure, to eliminate non-explanatory variables. We then refit the model, excluding non-explanatory variables. The results we report are from this final refitted model.

3.10% of the data were removed as outliers. Model optimism (an estimate of the degree of overfitting) was very low (0.29%). Although context availability had a significant facilitatory effect on latencies ($F(1, 863) = 10.30$, $p < .01$), concreteness continued to have a significant inhibitory effect ($F(1,863) = 5.51$, $p < .05$)—final model $R^2 = 71.70\%$. The effect of imageability was also significant ($F(1,863) = 8.72$, $p < .01$). The partial effects of these predictors are plotted in Figure 1.

Accuracy rates. All three variables of interest predicted probability of a correct response, consistent with the response latency data (context availability: $\chi^2 = 105.13$ df=1, $p < .001$; concreteness: $\chi^2 = 21.08$, df=1, $p < .001$; imageability $\chi^2 = 12.82$, df=1, $p < .001$)—see Figure 2 for the partial effects. The results of these analyses show, with a much larger set of items than the one used in Experiment 1, that concreteness has a small but significant effect on latencies and accuracy rates to the advantage of abstract words, when imageability and context availability are partialled out.

Figure 2. Plots of the partial effects of Concreteness, Context Availability, and Imageability in Regression Analyses I (Upper panels: Log RT; Lower panels: Accuracy) Dashed lines indicate 95% confidence intervals. The effects are adjusted to the median of all other continuous predictors and to class ambiguous words.



In the following regression analyses we provide a final test of dual coding, assessing the generalizability of these results for an even larger set of words from the ELP (achieved by leaving out context availability).

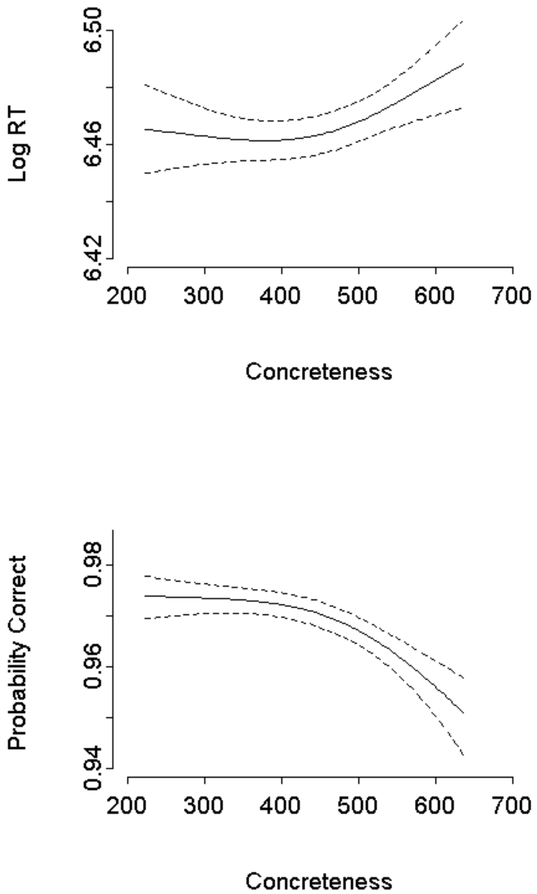
Regression Analyses II (2,330 words)

We used the same predictors in these analyses as in Regression Analyses I, excluding context availability. We also included familiarity (from the MRC Psycholinguistic Database) and part of speech. Again we fit separate models for lexical decision latencies and accuracy.

Latencies. 1.63% of the data were outliers and were removed. The validation procedure showed that model optimism was minimal (0.38%), confirming that our model was reliable. Both variables of interest were significant predictors of latencies (concreteness: $F(1, 2276) = 4.32$, $p < .05$; imageability: $F(2, 2276) = 3.75$, $p < .05$; nonlinear $F(1, 2274) = 4.47$, $p < .05$)—final model R^2 = 69.65%. Plots of the partial effects of the two predictors, which enable direct comparison of effect sizes, appear in Figure 3. For concreteness, slower response times are observed for the most concrete words, while for imageability, faster response times are observed for the most imageable words.

Accuracy. Both variables significantly predict correct responses (concreteness: χ^2=44.57, df=2, p<.001; nonlinear χ^2=11.64, p<.001; imageability; χ^2=28.24, df=2, p<.001; nonlinear χ^2=18.54, p<.001). Plots of the partial effects of these predictors can be found in Figure 3. Concreteness predicts greatest accuracy for abstract words, with a nonlinear decrease in accuracy with higher concreteness ratings. Imageability, on the other hand, predicts greatest accuracy for highly imageable words, while for low imageability words (in the 200-400 range) the effect of imageability levels off to similar accuracy rates.

Figure 3. Plots of the partial effects of Imageability and Concreteness in Regression Analyses II (upper panels: latencies; lower panels: accuracy). Dashed lines indicate 95% confidence intervals. The effects are adjusted to the median of all other continuous predictors and to nouns and class ambiguous words.



Note that the zero-order correlation between concreteness and latency in this word set is negative (r=-.22), while in the analyses above we found a positive slope for concreteness. Cases in which the coefficient of a predictor variable reverses in sign when entered in a regression model have been associated with the phenomenon of enhancement (McFatter, 1979; Bollen, 1989; Shrout and

Bollinger, 2003; Friedman and Wall, 2005)[1]. According to our hypothesis that differences in concreteness are not exhausted by differences in imageability, we assume that the coefficient for concreteness in this model represents the direct effect of concreteness, when the indirect effect of concreteness (through imageability) is held constant. Because the interpretation of such effects in linear regression has been a matter of debate, we provide a detailed theoretical overview as well as a formal specification of the theoretical model we assume underlies our data in Appendix II.

Thus, to summarise, we have presented here decisive evidence that neither dual coding nor context availability provide a full account of the representational and processing differences between concrete and abstract words.

The Abstractness Effect: The Role of Affect

Altarriba et al. (1999) were the first to note that affective association (and in particular valence of words, namely whether words have positive, negative or neutral connotation) may be confounded with, or rather interact with, concreteness. These authors proposed that instead of treating concreteness as a dichotomous variable (concrete vs. abstract), it should be treated as a trichotomy (concrete vs. abstract vs. emotion words). This proposal was motivated by the finding that concrete, abstract, and words denoting emotional states consistently received different concreteness, imageability and context availability ratings: although emotion words were rated as more abstract than other abstract words, they were higher in imageability and context availability than other

[1] Many thanks to Harald Baayen for bringing this phenomenon to our attention.

abstract words (and lower than concrete words.[2] On the basis of these findings, Altarriba et al. (1999) cautioned against including emotion words within the group of abstract words when concreteness effects are investigated, as their inclusion would be a confound. If we consider the items we used in Experiment 1 (reported in Appendix I), it appears indeed that our abstract words may have more affective associations than the concrete words (although importantly, only a few refer directly to emotions, and the pattern of results does not change if they are removed from the analysis), leading to the possibility that the abstractness effect we observed there may be mediated by the confounding between concreteness and affective association (see also Altarriba and Bauer, 2004).

In previous related work (also combining carefully controlled experiments with regression analyses of ELP data), we have found that words with affective associations (regardless of whether they referred to positive or negative emotions) are processed faster than neutral words (Kousta et al., 2009). Ratings of affective association were obtained by merging the ANEW database (Bradley & Lang, 1999) with normative data we collected for an additional 1,200 words using the same instructions and procedure as in the original database (see Kousta et al., for details)[3]. These findings by Kousta et al (2009) are important because the processing advantage for words with affective associations provides a straightforward account of the abstractness effect: abstract words have a processing advantage over concrete words because abstract words tend to be more emotionally loaded. Importantly, Kousta et al (2009) showed that the processing advantage is not limited to

[2] See also Altarriba and Bauer (2004 Experiment 1): in a free recall test, higher recall rates were observed for emotion words than for either concrete or abstract words.

[3] We prefer to talk about affective associations, namely, considering valence and arousal together, rather than distinguishing between the two here. This is because, first, in all of our studies conducted to date, valence has the largest effect, but arousal also has a modest role. Second, although there are neuroanatomical and theoretical reasons to distinguish between the two constructs (e.g., Lewis et al., 2007), there is no clear rationale to expect dissociations between them for abstract words.

words referring to emotions but also extends to other words with affective associations. Thus, these results suggest that affective association should be considered as a continuous variable spanning across words of all types (rather than a variable identifying the special category of emotion words, as originally hypothesized by Altarriba et al., 1999; but see also Altarriba, 2008 for a discussion concerning bilingualism). Note here, that the processing advantage for both positive and negative words reported by Kousta et al (2009) goes against evidence indicating that differences are observed between positive and negative words (e.g., advantage for positive words over negative words in immediate serial recall, greater for concrete words than for abstract words: Tse & Altarriba, 2009; or inhibition of negative words: e.g., Estes & Adelman, 2008). This discrepancy is addressed in Kousta et al (2009) who show that in many instances, differences in results can be attributed to less stringent criteria for item selection, or as in the case of Estes and Adelman (2008), due to sampling differences for valence (see Kousta et al., 2009, p. 474 and p. 478 for details).[4]

In order to make the link between abstract words and affective associations explicit, we first need evidence that abstract words tend to have more affective associations than concrete words. Initial evidence in this direction is provided by Kousta, et al (submitted) who showed that for a set of 1,446 words, valence ratings significantly predict concreteness ratings, even after imageability is taken into account. In other words, the more valenced a word is, the more abstract it tends to be, whereas the more neutral a word is, the more concrete it tends to be. In an fMRI study using items similar to those we used in Experiment 1, Kousta et al further showed that for abstract words, ratings of affective association predicted modulation of BOLD signal in rostral anterior cingulate cortex, an

[4] Although the study by Tse & Altarriba (2009) is not discussed by Kousta et al., a similar point can be made as the authors did not control for age of acquisition, which varies by valence and concreteness (for concrete words, those that are positively valenced tend to be acquired earlier than neutral or negative words; for abstract words, those that are positively or negatively valenced tend to be acquired earlier than neutral words).

area associated with emotional processing on the basis of anatomical, physiological and imaging results (see Bush et al, 2000). Taken together, these findings provide the motivation for exploring abstractness effects in terms of words' emotional content.

The Abstractness Effect: Testing the Role of Affective Associations

In Experiments 2 and 3 below, we directly test whether differences in affective associations can account for the abstractness effect. In Experiment 2 we used neutral words (arbitrarily defined as those words whose mean valence ratings ranged between 4.25 and 5.75 on a 9-point scale, where 1=negative; 5=neutral; and 9=positive), but which spanned the entire range of the concreteness and imageability scales. In Experiment 3, instead we selected familiar words spanning the whole range of valence (and arousal) ratings, both concrete and abstract.

If the abstractness effect we observed in Experiment 1 and Regression Analyses I and II can be accounted for in terms of differences in affective associations between abstract and concrete words, it should not be found in Experiment 2; and it should be present in Experiment 3 when affective associations (both valence and arousal) are not entered in the regression model but should be eliminated once affective associations are entered in the model.

Experiment 2

Method

Participants. Forty-six undergraduate psychology students (30 women and 16 men, mean age = 23.9) participated in the experiment and received monetary compensation of £10.

Materials and design. 774 words with valence ratings ranging between 4.25 and 5.75 (mean = 5.11±0.39) were chosen for this experiment.[5] Their concreteness ratings ranged from 217 to 646 (mean = 481±112); imageability from 143 to 659 (mean = 475±106); familiarity from 126 to 643 (mean = 476±88); age of acquisition from 164 to 700 (mean = 413±124); length from 3 to 14 letters (mean = 6.26±2.32); and log frequency (HAL) from 2.71 to 12.99 (mean = 8.41±1.85). 774 pronounceable non-words were created changing one letter in random position within real words. Pseudowords were matched to the experimental items in terms of length and bigram frequency (using WordGen, Duyck et al., 2004). A single presentation list was generated for the experiment. The data were analyzed using linear regression models (procedures as in Regressions I and II, except that in Experiments 2 and 3 we did not average reaction times across subjects, but instead analyzed trial-level data) including the following predictors: familiarity, length, log frequency, age of acquisition, orthographic neighbours, bigram frequency, part of speech, number of morphemes in addition to concreteness, imageability and valence.

Procedure. The procedure was the same as in Experiment 1.

Results.

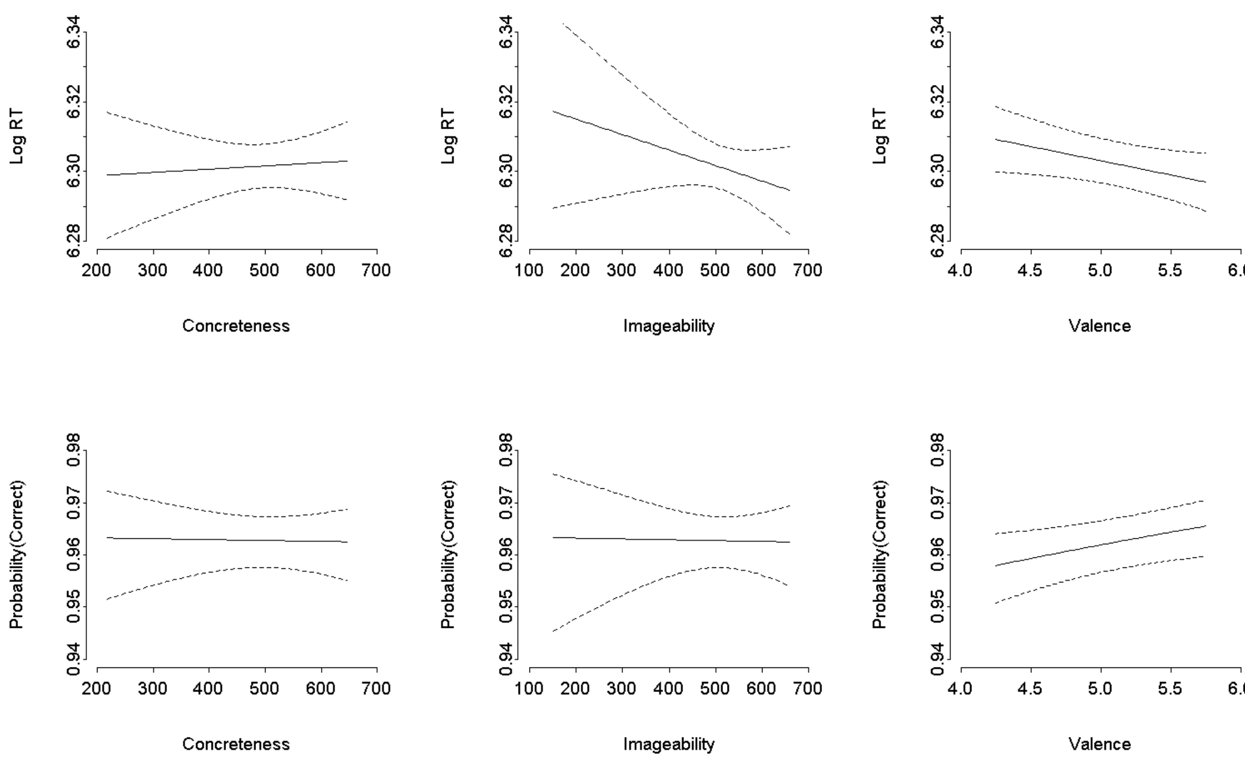
Latencies. Analyses were only conducted on those 706 words for which age of acquisition data were available. We additionally excluded 35 words for which accuracy was less than 60% correct across subjects. Finally, we excluded from analyses all responses faster than 200ms and slower than 2000ms, as well as reaction times more than three standard deviations from the mean for each participant (2.4% of the data). An additional 2.35% of data points were excluded as outliers (as in Regressions I and II). In the analysis of reaction times (using the predictors listed above),

[5] Words on the more negative end of this interval include *golf, chop, transfer*; words on the more positive end of this

concreteness and imageability were not significant predictors (concreteness: $\underline{F}(1,29413) = .09$, $\underline{p} = .76$; imageability: $\underline{F}(1,29413) = 1.37$, $\underline{p} = .24$)—final model $\underline{R}^2 = 9.54\%$[6]. Despite valence ratings being limited to a very restricted range (4.25 – 5.75) this predictor was significant ($\underline{F}(1,29413) = 3.85$, $\underline{p} < .05$) (Figure 4, upper panels).

Accuracy. Concreteness was not a significant predictor ($\chi^2 = 0.01$ df=1, $\underline{p} = .91$), nor was imageability ($\chi^2 = 0.01$ df=1, $\underline{p} = .94$), while valence was significant ($\chi^2 = 4.88$ df=1, $\underline{p} <$ 05). (Figure 4, lower panels).

Figure 4. Plots of the partial effects of Concreteness, Imageability and Valence in Experiment 2. Above: reaction times; below: accuracy. Dashed lines indicate 95% confidence intervals.



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interval include *post, menu, theme*.

[6] The substantial decrease in amount of variance explained in Experiments 2 and 3 compared to Regressions I and II arises because, in the Regressions, reaction time data was averaged across subjects. In the Experiments the models were fit to trial-level data.

Discussion.

No abstractness effect was observed in this experiment using neutral words, thus supporting the suggestion that the apparent abstractness advantage in Experiment 1 and Regressions I and II is due to a confounding effect of valence. By reducing the range of valence in the item set (while retaining the full range of concreteness and imageability) we were able to eliminate any abstractness effect. A further, unexpected result from this study is the finding of a significant effect of valence even for the subtle extent of variation among "neutral" words, a result further underscoring the graded (rather than categorical) nature of valence effects.

Experiment 3

In order to seek converging evidence with the results of Experiment 2, in this final Experiment we chose a set of items to cover the full range of emotional valence and arousal, allowing other variables to vary freely, following the same logic as above. Because so many items had to be excluded from Experiment 2 due to low accuracy, and because words rated low in imageability often also tend to be particularly low in familiarity, we were also more selective in choosing items: picking only words with average or high familiarity, and which yielded accurate lexical decisions in the English Lexicon Project.

Method

Participants. Forty-seven native English speakers (33 female; mean age: 20.34 ± 4.59) participated as part of a class requirement.

Materials and design. 480 words were chosen from the set of items for which valence, arousal, concreteness, age of acquisition and other such variables were available, but not including any items with low familiarity (i.e. ratings below 350 on the 100-700 scale), or lexical decision accuracy less than 70% correct in the ELP. We started by including 111 words from Kousta et al (2009) (37 neutral, 37 positive, and 37 negative words closely matched for other lexical variables), plus 40 additional words which were randomly selected from the valence intervals not used in that study (i.e., 20 words from the gap between "negative" and "neutral" categories defined by Kousta et al, and 20 words from the gap between "positive" and "neutral"). Finally 329 words were chosen randomly from the remaining set. Concreteness ratings of the 480 words ranged from 219 to 634 (mean = 459 ± 115); valence from 1.56 to 8.44 (mean = 5.21 ± 1.46); arousal from 2.67 to 7.67 (mean = 4.86 ± 0.93); imageability from 213 to 637 (mean = 488 ± 95); familiarity from 351 to 645 (mean = 506 ± 66); age of acquisition from 152 to 692 (mean = 389 ± 112); length from 3 to 14 letters (mean = 6.29 ± 2.31); and log frequency (HAL) from 2.77 to 12.47 (mean = 8.84 ± 1.61). 480 pseudowords were created by selecting an unused word from the set, matched in valence and length to the actual words, and changing one letter (or two letters for source words longer than 8 letters). The data were analyzed as in Experiment 2.

Procedure. The procedure was the same as in Experiments 1 and 2.

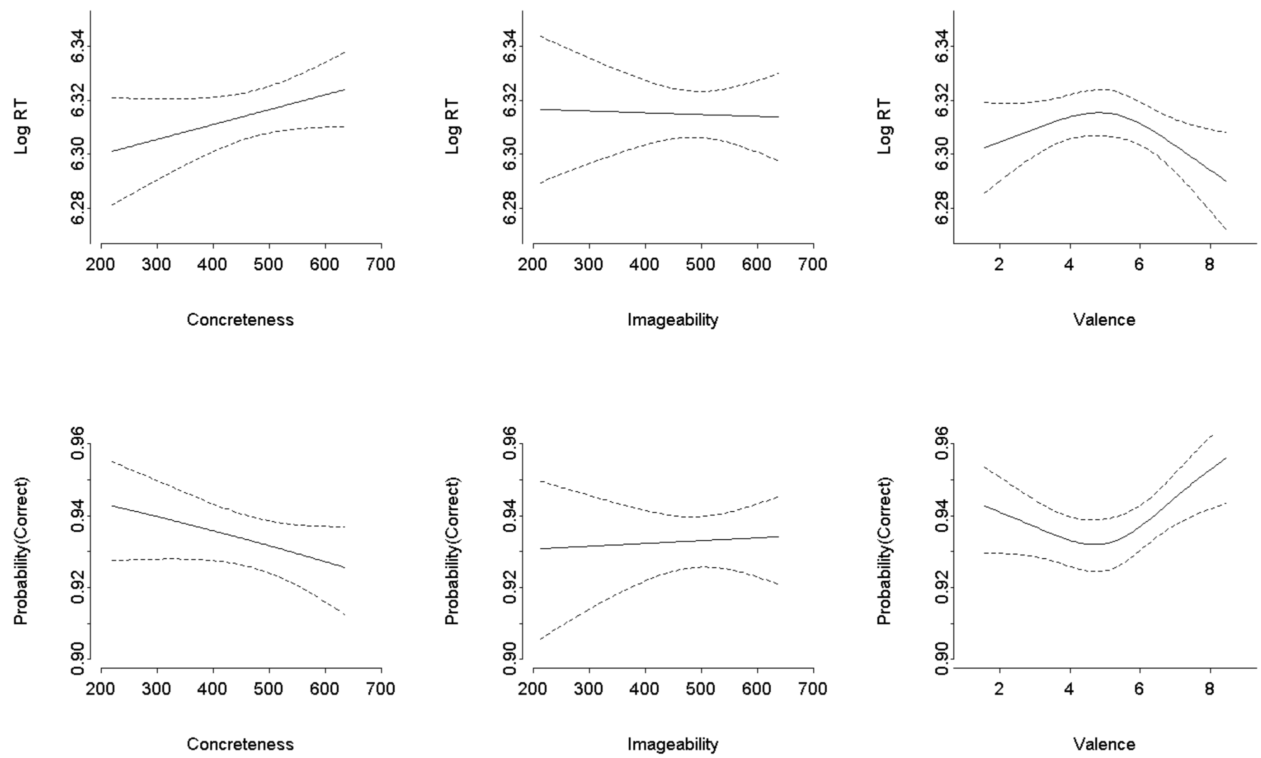
Results.

We first excluded the data from one subject who did not complete the task, and one who was less than 65% correct. All other subjects were above 75% correct. We then excluded nine words for which average accuracy was less than 60% correct in this study (prairie, herdsman, theologian, giver, nozzle, havoc, impediment, adherence, furnace), leaving us with data from 45 subjects and 471 words.

Latencies. We excluded from analyses responses faster than 200ms and slower than 2000ms, and reaction times 2.5 standard deviations from the mean for each participant (1.44% of the data). 3.00% of data points were further excluded as outliers following the same procedure used in previous analyses. In the analysis of reaction times, concreteness and imageability were not significant predictors (concreteness: $F(1,20790) = 2.40$, $p = .12$; imageability: $F(1,20790) = 0.02$, $p = .89$)—final model $R^2 = 4.69\%$. Valence was significant, however: ($F(2,20790) = 3.60$, $p < .05$; nonlinear $F(1,20790) = 4.79$, $p < .05$) (Figure 5, upper panels). Arousal also approached significance ($F(2,20790) = 3.35$, $p = .067$)

Accuracy. Concreteness was not a significant predictor ($\chi^2 = 2.27$ df=1, $p = .13$), nor was imageability ($\chi^2 = 0.05$ df=1, $p = .82$), while valence was significant ($\chi^2 = 9.11$ df=2, $p < 05$; nonlinear $\chi^2 = 6.97$ df=1, $p < 01$). (Figure 5, lower panels).. Again arousal approached significance ($\chi^2 = 3.17$ df=1, $p = 075$).

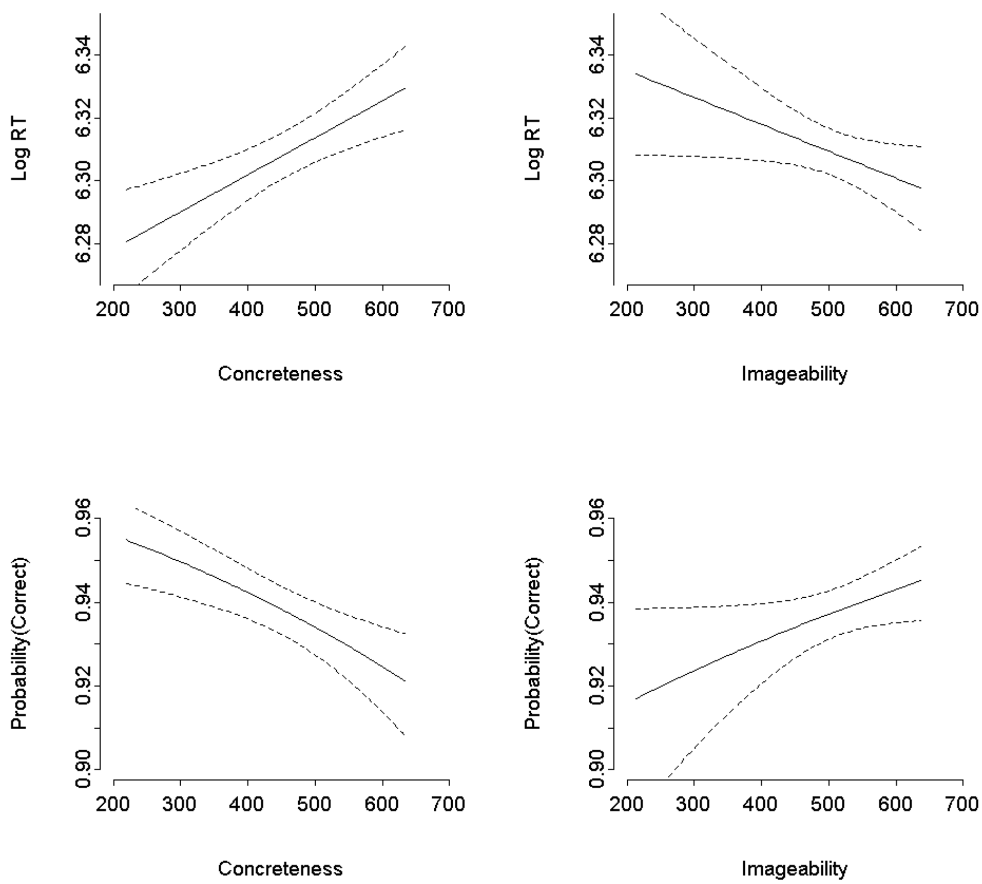
Figure 5. Plots of the partial effects of Concreteness, Imageability and Valence in Experiment 2. Above: reaction times; below: accuracy. Dashed lines indicate 95% confidence intervals.



Although the results of these analyses clearly show that emotional variables are significant predictors of reaction times and accuracy in Experiment 3, while concreteness and imageability are not, this is not yet sufficient evidence to claim that the 'abstractness effects' we observed in Experiment 1 and Regressions I and II are actually the product of these emotional variables. Data from Experiment 3 offer the possibility to test this question directly. If the emotional variables account for the abstractnesss effect, once we remove emotional variables (valence and arousal) from the regression models of Experiment 3, we should see a significant advantage for abstract words. We reanalyzed exactly the same data, with the same models, excluding valence and arousal. In this analysis, concreteness was a significant predictor of both reaction times and accuracy (RTs:

$\underline{F}(1,20793)=13.76$, $\underline{p}<.01$; accuracy $\chi^2 = 12.38$ df=1, $\underline{p} < 01$): more abstract words are faster and more accurate when emotional variables are not taken into account (see Figure 6).

Figure 6. Plots of the partial effects of concreteness and imageability in Experiment 3, if emotional variables (valence and arousal) are not included in the models. Compare these plots to their counterparts in Figure 5, which illustrates these same effects when emotional variables are taken into account. Above: reaction times; below: accuracy. Dashed lines indicate 95% confidence intervals.



Discussion

Experiment 3 shows that for a relatively large set of words spanning the entire range of concreteness and, crucially, valence and arousal ratings, we find the abstractness effect in models that do not include ratings of affective associations, but the abstractness effect is eliminated in models that take affective associations into account, either by restricting the range of affective variables (as we did in Experiment 2) or by taking them into account statistically (as in Experiment 3). Thus, we can conclude that the abstractness effect we reported earlier is accounted for by affective associations, results that provide the foundations for the embodied view of the semantic representation of abstract words we spell out below.

General Discussion:

An Embodied Theoretical View of Abstract Representation

In three Experiments and two large-scale regression analyses we have shown that neither dual-coding, nor context availability can account for differences in processing of concrete and abstract words. Once imageability and context availability ratings (operationalizing dual-coding and context availability hypotheses, respectively) are taken into account, abstract words are processed faster than concrete words. As we have shown, this advantage for abstract over concrete words can be accounted for in terms of greater degree of affective associations for abstract words. Below we present an embodied theory to account for these results.

In contrast to amodal theories of semantic and conceptual representation (perhaps best exemplified in the work of Fodor, 1983 and Jackendoff, 2002), embodied theories of cognition (an early example of which is dual coding theory) propose that cognition is grounded in bodily states, modal simulations, and situated action (Barsalou, 1999; Barsalou et al., 2003; Decety & Grezes, 2006; Gibbs, 2006; Rizzolatti & Craighero, 2004). Despite the fact that embodied theories of semantic representation disagree about the directness of the link between semantic and experiential information (for instance, Gallese and Lakoff, 2005 vs. Vigliocco, Vinson, Lewis, and Garrett, 2004), they share the core assumption that the representation and processing of semantic information recruit the same neural systems that are engaged during perception and action. Recent work has provided evidence for such a link between semantic and sensorimotor information, either by showing that perception/action affects semantic computation (Kaschak, Madden, Therriault, Yaxley, Aveyard, Blanchard et al., 2005; Kaschak, Zwaan, Aveyard, & Yaxley, 2006) or that semantic computation affects perception/action (Meteyard, Bahrami, & Vigliocco, 2007; Meteyard, Zokaei, Bahrami, & Vigliocco, 2008, see Meteyard & Vigliocco, 2008 for a recent review of the evidence).

While embodied approaches can be straightforwardly applied to the representation and processing of concrete word meanings, it far less obvious how an embodied account can be valid for abstract word meanings, which have traditionally been considered to be within the purview of purely verbal systems. In one approach, which originates in work in cognitive linguistics, abstract concepts are grounded metaphorically in embodied and situated knowledge (Lakoff & Johnson 1980; 1999; Gibbs, 1994). For example communication of ideas can be understood in terms of goal-directed motion (e.g. 'throw an idea') and emotional states can be understood in terms of verticality (e.g. 'happy is up' and 'sad is down'). Although there is increasing evidence that metaphors play a role in the conceptualization of some abstract domains (Boroditsky & Ramscar, 2002; Gibbs, 2006), it is a matter of controversy to what extent they are foundational in the development (and subsequent representation) of abstract concepts and word meanings or whether they provide structure to pre-existing conceptual content (Barsalou, 1999; but see Glenberg et al., 2008).

One embodied account which offers the possibility of accounting for abstract words as well as concrete words has been put forward by Vigliocco, Meteyard, Andrews & Kousta (2009). The main assumptions of this hypothesis are as follows:

1. Two classes of information contribute to the representation of all concepts (both concrete and abstract): experiential (sensory, motor, and affective) and linguistic (verbal associations arising through patterns of co-occurrence and syntactic information).
2. Differences between concrete and abstract word meanings, as well as differences within each domain (i.e., the domain of concrete words and the domain of abstract words) arise as a result of types and relative proportions of experiential and linguistic information they bind.
3. The apparent dichotomy between concrete and abstract word meanings arises because of a statistical preponderance of sensorimotor information to underlie concrete word meanings and a statistical preponderance of affective and linguistic information to underlie abstract word meanings.

This approach is novel in that emotion is considered to be another type of experiential information (along with sensorimotor information) playing an important role in learning, representing and processing, especially for abstract semantics (Vigliocco et al., 2009). The experiments we have reported here provide the critical evidence in favor of such an account.

It is interesting to note here that recent work by Havas, Glenberg et al. (Havas, Glenberg & Rinck, 2007; Havas, Glenberg, Gutowski, Lucarelli & Davidson, 2010) has shown a link between being able to express facial emotion and comprehension of emotion. An even more dramatic demonstration has been reported by Pistoia and colleagues (Pistoia, Conson, Trojano, Grossi, Ponari, Colonnese et al., in press) for patients with locked-in syndrome who are tetraplegic and cannot command their facial muscles. Our results suggest an inability to express facial emotion should also have consequences for abstract knowledge; if emotion plays a fundamental role in acquiring and representing abstract concepts.

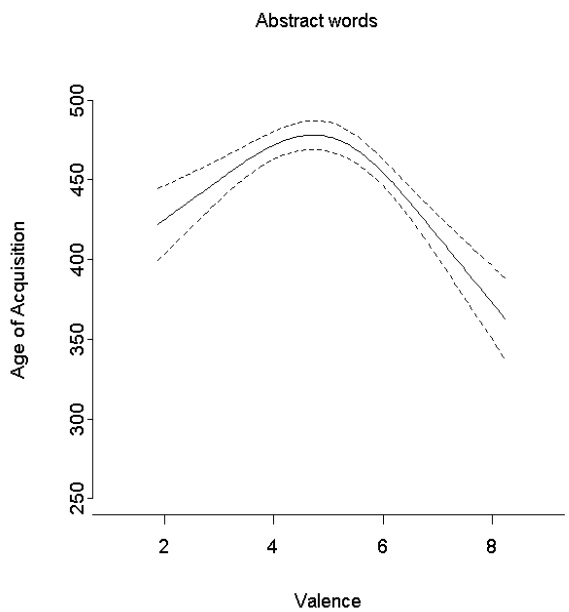
Affective Associations and Semantic Representation

The idea that internal, and especially affective, states may play a role in the representation of abstract words and concepts is not new. In addition to the work by Altarriba and colleagues (Altarriba et al., 1999; Altarriba and Bauer, 2004), already discussed, Barsalou and Wiemer-Hastings (2005) also suggest that abstract concepts and word meanings are grounded in introspective states (mental and affective). In an exploratory study, Barsalou and Wiemer-Hastings asked speakers to generate features for words varying in concreteness (three highly abstract words: truth; freedom; and invention; three highly concrete words: bird, car, and sofa; three intermediate words: cooking, farming, and carpeting). They found that abstract concepts and word meanings focus on introspective content (as well as social and event content, and less centrally content about physical settings). We take this idea further by proposing that differences between concrete and abstract words arise because of a general statistical preponderance of affective information for abstract words (and sensorimotor information for concrete words). Why would this be the case? We propose that emotion plays an important role during language acquisition, providing a bootstrapping mechanism for the acquisition of abstract lexical concepts and their labels at early stages.

Emotional development precedes the development of language in children (Bloom, 1998). Words that denote emotional states, moods or feelings may provide crucial examples of how a word may refer to an entity that is not observable but resides within the organism. In this manner, the acquisition of words denoting emotions, moods or feelings may actually be a crucial stepping stone in the development of abstract semantic representations. According to Gleitman and colleagues (Gleitman et al, 2005), early word learning is effected by means of word-to-world mappings (i.e., by observing the situational contingencies of word usage), which is the case for a limited set of words that refer to concrete, basic level concepts. Here we propose that abstract words denoting emotional states, moods or feelings also fall in the same category of words for which a mapping from the word to the world (albeit the internal world) is possible. Consistent with this hypothesis, words denoting emotional states emerge early in language development, at around 20 months of age, and their rate of acquisition increases rapidly in the third year of life (Bretherton & Beeghly, 1982; Wellman, Harris, Banerjee, & Sinclair, 1995). For instance, Ridgeway, Waters, & Kuczaj (1985) report that 76.7% of children aged 18-23 months have acquired the meaning of the words *good,* and *happy*.

Thus, according to our hypothesis, abstract words with affective associations should be acquired earlier than neutral abstract words. To address this prediction, we took 2,120 words for which we have concreteness, age of acquisition and valence ratings, partitioned the concreteness scale at the mean, and regressed age of acquisition ratings on valence ratings for abstract words using polynomial models. For abstract words, valence and AoA are related by a U-shaped function (combined linear and quadratic components: $\underline{F}(2,1026) = 28.34$; $\underline{p} < .001$; quadratic alone: $\underline{F}(1,1026) = 47.46$, $\underline{p} < .001$. Higher-order polynomial terms were not significant predictors of AoA); emotionally significant abstract words regardless of valence are acquired earlier than neutral abstract words. Although valence explains just under 8% of the variance in adult age of acquisition ratings for abstract words, this data is indicative of the possibility that emotion may provide a bootstrapping mechanism for the acquisition of abstract words.

Figure 6. Plot of the effect of valence on age of acquisition for abstract words. Dashed lines indicate 95% confidence intervals.



<u>The necessity of integrating experiential and linguistic information</u>

Although we have argued and provided evidence for a foundational role of experiential information in the semantic representation of abstract words, this may not be the whole story. First, it is intuitively clear that language provides vital information as well: after all, we learn a great many words from being told or reading about them. Second, many of the “nuisance variables” we have taken into account in our analyses above, are not straightforwardly linked to experiential information. After all, more linguistic factors like number of letters, orthographic neighborhood size, orthographic regularity and frequency of occurrence also consistently predict lexical decision latencies and accuracy across the analyses we report here. Although these variables on their own do not account for the abstractness effect (otherwise it would have been eliminated by taking them into account statistically), it is important not to discount linguistic factors that may relate to processing of abstract and concrete words.

A role for linguistic information in semantic representation is emphasized by most theories (see Vigliocco and Vinson, 2007 for a discussion) and is supported by the imaging studies reviewed in the introduction which report greater activation for abstract/less imageable words in a left-lateralized language network (including left inferior frontal gyrus, IFG, and left superior temporal sulcus, STS) (Perani et al., 1999; Jessen et al., 2000; Fiebach and Friederici, 2003; Noppeney and Price, 2004; Binder et al., 2005; Mellet et al., 1998; Kiehl et al., 1999; Wise et al., 2000; Binder et al, 2009). Interestingly, in the Kousta et al (submitted) fMRI study we found that, once valence and arousal ratings were entered into a regression model to predict activation data, the significant greater activations reported in rostral anterior cingulate cortex for abstract words (linked to emotion) were no longer present. However, abstract words were shown to engage left IFG to a greater extent than concrete words. Although the specific role of left IFG in language processing is still highly controversial, here these activations might simply indicate a greater reliance on linguistic information for abstract words.

Assuming greater role for linguistic information for abstract words may also provide a way to account for the electrophysiological differences between concrete and abstract words we discussed in the introduction. These studies have reported an amplified N400 in response to concrete vs. abstract words, a finding that has been accounted for in terms of amodal theories of meaning such as the context availability model: concrete words activate a larger amount of related contextual information in verbal memory, which makes integration of the appropriate featural representation into a wider contextual interpretation more difficult. However, the N400 concreteness effect has a different distribution to the classical N400 elicited in response to integration difficulties associated with texts (Kutas & Hillyard, 1980) and is more similar in distribution to the N400 elicited in single word tasks manipulating lexical variables (Bentin, Mouchetant-Rostaing, Giard, Echallier, & Pernier, 1999). Recent evidence has also suggested that the N400 is not only modulated by post-lexical controlled processes (for instance, integration processes), but also by automatic lexical processes (for instance, retrieval processes—see Barber & Kutas, 2007, for a review). It is therefore plausible that the N400 concreteness effect reflects difficulty in retrieving specifically linguistic information in response to concrete words. If this is correct, then we would expect to obtain an amplified N400 to concrete words with a similar distribution to that reported in earlier studies, even with materials such as those we used in Experiment 1, and this is precisely what Barber, Otten, Kousta and Vigliocco (submitted) found.

Finally, the importance of integrating experiential and linguistic information in learning and representing semantic and conceptual knowledge is highlighted by computational work, using Bayesian probabilistic models, in which representations that combine these two types of information (for both concrete and abstract words) provide a better fit to semantic effects in behavioral tasks (Andrews et al., 2009). Also relevant in this respect are approaches to lexical development, such as the syntactic bootstrapping account (Gleitman, 1990; Landau & Gleitman, 1985), which explore the role of syntactic information in acquiring the meaning of especially abstract words (Gleitman et al., 2005; see also Andrews & Vigliocco, 2010 for a computational demonstration of how sequential information may play an important role in learning semantic representations). In such accounts, at early stages, word acquisition relies on word-to-world mappings, where situational contingencies of use enable learning of new words. As knowledge of linguistic structure becomes more sophisticated, learners develop the ability to perform structure-to-world mappings that enable further learning of, especially abstract, words.

In closing, it is important to note that the abstractness effect we reported should be evaluated within the context of the concreteness effect: zero-order correlations between concreteness and behavioral measures reveal an advantage for concrete words, thus we are not invalidating this textbook finding. However, what may have created confusion in previous work is the attempt to specify a single process or type of information as responsible for differences between the two types of word meanings. Here instead we adopted a working hypothesis according to which concrete and abstract words differ along a number of dimensions, including differential recruitment of sensory, motoric, affective, and linguistic information. According to such an approach, the dimensions along which concrete and abstract words differ may not always point to an advantage for concrete words.

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Appendix I

Items for Experiment 1 (items excluded from analysis are marked with an asterisk).

Concrete	Abstract
office	horror
cancer	beauty
ounce	grief
relic	demon
trunk	spree
lamp	hell
estate	luxury
duke	fury
cousin	angel
rector	frenzy
leek	oath
gig	woe
*ether	*havoc
guest	crime
*prong	*wealth
creature	concert
oak	joy
date	love
stomach	romance
author	thrill
block	panic
asbestos	paradise
jersey	danger
channel	protest
column	temper
material	fashion
sound	minute
stick	ghost
plate	space
voice	dream
monsoon	slumber
belt	joke
freight	expanse
starch	burden
disease	number
weapon	dozen
manure	plunge
garment	bargain
lobby	quest
bureau	triumph

Appendix II

Suppression and enhancement in linear regression

Horst (1941; 1966) was first to note that there are cases where a predictor whose zero-order validity is 0 (i.e., a variable that is entirely uncorrelated with the criterion variable) but which correlates significantly with another predictor improves prediction when included in a regression model. As a substantive example, he described a World War II study aimed at predicting pilot success as a function of mechanical, numerical, spatial, and verbal ability—all measured in pen-and-paper tasks. The first three variables had a significant positive correlation with flying ability. Although verbal ability had a negligible correlation with pilot success, it correlated highly with the other three predictors. When verbal ability was included in the regression model, the amount of variance explained increased, despite the fact that verbal ability had a negligible zero-order correlation with flying ability. Verbal ability, however, was needed to read the instructions and items on the pen-and-paper tests. Thus, the way mechanical, numerical, and spatial ability were measured introduced measurement error variance into the scores. Including verbal ability scores as a predictor in the model improves overall prediction by removing artifactual measurement error from the other predictors. To illustrate, using for simplicity a two-predictor model with mechanical ability (X_1) and verbal ability (X_2) as predictors of flying ability (X_0), we assume the following sample correlations between the (standardized) variables: $r_{01} = .8$; $r_{02}=0$ and $r_{12}= .4$.

We use (1) to calculate the least squares estimate of the regression coefficients

$$\beta_1 = (r_{01} - r_{02}\, r_{12})/(1-r_{12}^2) \qquad (1)$$

and find that the coefficient for X_1 is higher than r_{01},

$$\beta_1 = (.8 - 0*.4) / (1 - .4^2) = .95 > .8 \qquad (2)$$

while the coefficient for X_2 receives a negative weight despite the fact that $r_{02} = 0$

$$\beta_2 = (0 - .8*.4) / (1 - .4^2) = -.38 \neq 0 \qquad (3)$$

The amount of variance explained in the criterion is given by (4) and calculated in (5)

$$R^2 = (r_{01}^2 + r_{02}^2 - 2\, r_{01} r_0\, r_{12})/(1 - r_{12}^2) \qquad (4)$$

$$R^2 = (.8^2 + 0^2 - (2*.8*0*.4)/(1-.4^2) = .76 > .8^2 + 0^2 \qquad (5)$$

In other words, the squared multiple correlation coefficient exceeds the sum of the two squared simple correlation coefficients with X_0: $R^2 > r_{01}^2 + r_{02}^2$. Including verbal ability with a negative weight in the regression equation serves to 'penalize' those participants whose mechanical ability scores were high purely because of verbal ability and to 'compensate' for those participants whose mechanical ability scores were low purely because of low verbal ability. This improves the predictive validity of mechanical ability and hence the amount of variance explained by the model. It is not necessary for X_2 to be 0 for predictive validity to be improved; enhancement/suppression is possible even when $X_2 \neq 0$

(termed net enhancement/suppression—see Freedman and Wall, 2005, for intervals of possibilities for r_{01}, r_{02} and r_{12} for net enhancement/suppression to obtain)[7].

The explanation of enhancement as suppression of irrelevant variance in another predictor implies a specific underlying model, the two-factor model (Conger, 1974). Conger (1974: 37) introduces the two-factor model thus: 'Discussions of suppressor variables […] suggest an underlying model in which there is nonerror variance in the predictor which is unrelated to the criterion (factor S) as well as an uncorrelated common factor of that which the criterion is measuring (factor T). The suppressor either has no relation to the criterion (a loading of zero for factor T) or is measuring the criterion less than it is measuring the irrelevant variance.'. So in the example above, verbal ability scores measure true verbal ability (T), while mechanical ability scores measure both true flying ability (S) and true verbal ability (T)—the latter because the mechanical ability test needed verbal ability in order to be carried out. Verbal ability and flying ability are uncorrelated.

Although the misconception that enhancement can only be interpreted as suppression of irrelevant variance continues in some settings until today, McFatter (1979; see also Bollen, 1989; MacKinnon, Krull, & Lockwood, 2000; Shrout & Bolger, 2002 for more recent treatments) pointed out that the two-factor model is just one type of underlying model that can give rise to enhancement and that there are several cases in which interpreting enhancement as suppression of irrelevant variance is not warranted. He provides the following substantive example of a case in which interpreting enhancement as suppression of irrelevant variance is meaningless: 'Suppose one were interested in predicting the number of errors made by assembly-line workers as a function of IQ and Intolerance of Boredom scores.

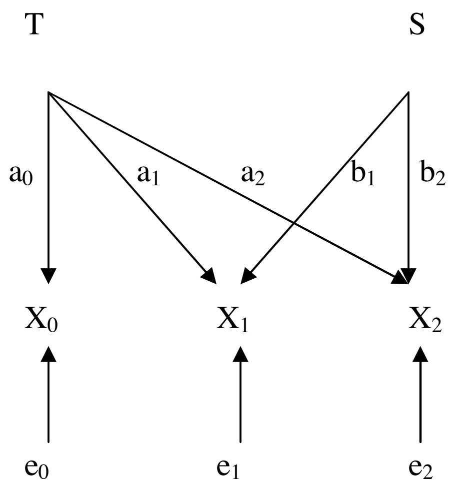
[7] There is a third type of enhancement/suppression (co-operative enhancement/suppression), first introduced by Conger (1974), but it is beyond the scope of this appendix.

Let X_0 be number of errors, X_1 be Intolerance of Boredom score, and X_2 be IQ score. If one obtained sample correlations of $r_{01} = .3535$, $r_{02} = 0$, and $r_{12} = .707$; noted that this was a case of classical enhancement; and relied on the usual discussions of suppression, one might be tempted to conclude that IQ was totally irrelevant to the number of assembly-line errors made, but did measure precisely that aspect of Intolerance of Boredom which is also irrelevant to the number of errors made. This is the interpretation one would make were the two-factor model the structure underlying these variables.' (1979: 128).

He formally demonstrates that a number of completely different underlying models can give rise to enhancement and that the only case in which enhancement can be interpreted as suppression of irrelevant variance is if the underlying model is assumed to be the two-factor model. For instance, he shows how enhancement can arise out of both the two-factor model and an alternative model where a predictor has both a direct and indirect effect on the criterion. In both cases below it is assumed that variables are standardized and that $r_{01}, r_{12} > 0$. He specifies these two alternative models in the following manner:

A. Two-factor model

McFatter (1979) specifies the following path diagram for the two-factor model:



The structural equations corresponding to the path diagram above are as follows:

$X_0 = a_0 T + e_0$

$X_1 = a_1T + b_1S + e_1$

$X_2 = a_2T + b_2S + e_2$

Given the equations above, the population correlation matrix for this model would be given as follows:

$\rho_{01} = a_0a_1$

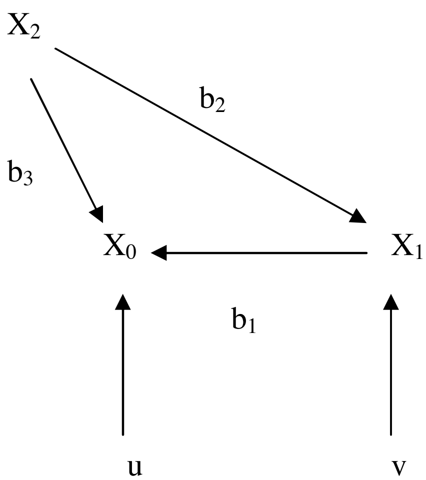
$\rho_{02} = a_0a_2$

$\rho_{12} = a_1a_2 + b_1b_2$

McFatter shows that classical enhancement obtains in this model if $a_2 = 0$ and $b_1b_2>0$; net enhancement obtains if $a_2 < a_1(a_1a_2 + b_1b_2)$.

B. Direct and indirect effects

McFatter (1979) then presents the following path diagram for a model where a predictor has both a direct and an indirect effect (through another predictor) on a dependent variable:



In this model, stochastic disturbance terms u and v are included in order to represent all sources of variation that are not included in the model (with $E(u)=E(v)=E(uv)=0$). The structural equations for this model are the following:

$X_0 = b_1X_1 + b_3X_2 + u$

$X_1 = b_2X_2 + v$

These equations generate the following correlation matrix for this model:

$\rho_{01} = b_1 + b_2b_3$

$\rho_{02} = b_1 + b_1b_2$

$\rho_{12} = b_2$

When b_1 and b_2 are positive and b_3=-b_1b_2, classical enhancement will obtain in this model; when – b_1b_2 < b_3 and b_1, b_2 < 0, net enhancement will obtain. Returning to the IQ-boredom-errors example above, if, for instance, b_1=b_2=.707 and b_3= -.50, the population correlations are the same as those in the IQ example, r_{01}=.3535, r_{02}=0 and r_{12}=.707.

As McFatter notes, in this model the interpretation of the effect of X_2 subtracting or suppressing irrelevant or invalid variance in X_1 is nonsensical. The negative weight of the coefficient for X_2 represents the fact that X_2 in this model has a direct negative effect on X_0, and a compensating positive influence on X_0 through X_1.

It is important to note that there are no objective criteria for deciding between Model I and Model II as presented above—there is nothing in the statistical computations that forces the adoption of either model. Both models can generate the correlation matrix which produces enhancement and the choice between the models is a matter of theoretical consideration and *a priori* hypotheses.

In our multiple regression models we found an indication that concreteness was functioning as an enhancer variable. Although enhancement/suppression has been extended to models involving more than two-predictors (see Tzelgov and Henik, 1991), the situation becomes much more complex. In our case, we are interested in the relationship between the distinction between concrete and abstract concepts and one of its reflexes, i.e., the ability to form a mental image to the referents of words. For this reason, we decided to look at a two predictor model, where concreteness and imageability are used as predictors of lexical decision reaction times in order to confirm our intuition that in our large-scale model concreteness functions as an enhancer with respect to imageability. For these analyses, we used imageability (X_1) and concreteness (X_2) ratings for 4,075 words from the MRC Psycholinguistic Database (Coltheart, 1981) and lexical decision latencies (X_0) from the English Lexicon Project (Balota et al., 2007). The correlation between imageability and latency is $r_{01} = -.261$; the correlation between concreteness and latency is $r_{02} = -.137$ and the correlation between concreteness and imageability is $r_{12} = .849$. For simplicity, we assume that the relationship between each of the two predictors and the dependent variable is linear. The beta weight for imageability in the two-predictor model is $\beta = -.520$ ($> r_{01}$); the beta weight for concreteness is $\beta = .305$ (different in sign from r_{02}); and the squared multiple correlation coefficient is $R^2 = .094$, which is higher than the sum of the two squared simple correlation coefficients ($r_{01}^2 + r_{02}^2 = .087$). This is indeed a case of net enhancement.

As we saw above, the sample simple correlations between concreteness, imageability, and latency can be generated by both the two-factor model and a model in which concreteness has a direct effect on reaction times and an indirect effect through imageability (although there are other possibilities, we will not discuss them here as we consider them theoretically irrelevant). We argued in the main text of this article that by hypothesis the latter model fits the data better than the former. Let us, however, consider the possibility that the two-factor model underlies our data and let us try to construct latent variables for this model. For the two-factor model to work we would need to assume that concreteness is a measure of true concreteness (e.g. the ontological distinction between concrete and abstract concepts) and that true concreteness is a poor measure of word recognition speed. Imageability measures both word recognition speed and true concreteness. Including concreteness in the model suppresses variance in imageability scores that is due to concreteness, and which is irrelevant to measurement of word recognition speed. Such an interpretation goes against everything anybody has ever claimed about the relationship between concreteness and imageability. The assumption in the concreteness literature is that, theoretically, concreteness reflects the directness of connections between verbal representations and modality-specific imagery (Paivio, 2007). In other words, the assumption is that there is nothing in concreteness that is not explained by the perceived ability (or otherwise) to evoke modality-specific imagery. We are claiming instead that, although the image-evoking aspect of word meanings is one of the reflexes of concreteness, variation in concreteness is not exhausted by the extent to which visual imagery is evoked by the referents of words, but that other critical variables are involved. Our point here is that there is no theoretical account of concreteness advanced up to the present to support the proposal that the two-factor model is an appropriate underlying model for the trivariate relationship we are considering. The earlier literature would assume that the effect of concreteness is completely mediated by the effect of imageability; schematically, the model assumed is the following:

$$\text{Concreteness} \longrightarrow \text{Imageability} \longrightarrow \text{Behavior}$$

We are instead proposing that, apart from the indirect link between concreteness and imageability there is also a direct link from concreteness to word recognition (and we attempt to specify this relationship further by identifying other variables that mediate the relationship between concreteness and behaviour); schematically:

$$\begin{tikzcd}
\text{Concreteness} \arrow[rr] \arrow[dr] & & \text{Behavior} \\
& \text{Imageability} \arrow[ur] &
\end{tikzcd}$$

The two-factor model is inappropriate in either case.

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