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There are many ways to be rich: Effects of three measures of semantic richness on visual word recognition

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Previous studies have reported that semantic richness facilitates visual word recognition (see, e.g., Buchanan, Westbury, & Burgess, 2001; Pexman, Holyk, & Monfils, 2003). We compared three semantic richness measures—*number of semantic neighbors* (NSN), the number of words appearing in similar lexical contexts; *number of features* (NF), the number of features listed for a word's referent; and *contextual dispersion* (CD), the distribution of a word's occurrences across content areas—to determine their abilities to account for response time and error variance in lexical decision and semantic categorization tasks. NF and CD accounted for unique variance in both tasks, whereas NSN accounted for unique variance only in the lexical decision task. Moreover, each measure showed a different pattern of relative contribution across the tasks. Our results provide new clues about how words are represented and suggest that word recognition models need to accommodate each of these influences.

Numerous theories describe how word meanings are represented in the mind (see, e.g., Burgess & Lund, 2000; McRae, de Sa, & Seidenberg, 1997). Concepts differ in the amounts of information they evoke, and a complete theory must capture the effects of semantic richness. There is considerable evidence that responding in visual word recognition tasks is facilitated for words with relatively richer semantic representations, even when other lexical and semantic variables are controlled (for a review, see Pexman, Hargreaves, Edwards, Henry, & Goodyear, 2007). In the present study, we compared three measures of semantic richness—number of semantic neighbors (NSN), number of features (NF), and contextual dispersion (CD)—extracted from language corpora or norms. We consider each of these to be measures of semantic richness because they each capture variability in information associated with words' meanings. Our goal was to determine whether these three measures of semantic richness predicted shared or unique response times (RTs) and error variances in responses to concrete words in a lexical decision task (LDT) and to categorization of words as concrete or abstract in a semantic categorization task (SCT).

Number of Semantic Neighbors

Buchanan, Westbury, and Burgess (2001) proposed that semantic richness can be quantified according to how words are used in language. In a high-dimensional model of semantic space (Burgess & Lund, 2000), words that co-occur or are used in similar lexical contexts cluster together as semantic neighbors. In the database constructed by Durda, Buchanan, and Caron (2006), words' semantic neighborhoods were extracted from a corpus of English text. A word's global neighbors are most likely to occur in similar lexical contexts (e.g., *book* and *movie*) and thus have similar histories of usage in the language corpus. NSN measures the number of global neighbors detected for each word within a specified radius of semantic space. High-NSN words share lexical contexts with many other words (e.g., 28 semantic neighbors for *bed*, 24 for *celery*), whereas low-NSN words share lexical contexts with few other words (e.g., 3 semantic neighbors for *door*, 2 for *carrot*). Buchanan et al. found that high-NSN words generated faster responses than low-NSN words in LDTs, and they attributed this advantage to stronger semantic activation.

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Number of Features

A second approach to measuring semantic richness relies on the feature-listing task, in which participants list attributes for different concepts. These attributes are considered to be "verbal proxies for packets of knowledge" (McRae, 2004, p. 42) rather than veridical descriptions of semantic memory. When participants list features, they are said to access representations derived from their experience with the target concepts. As such, feature norms may provide a window onto memory for meaning. In McRae, Cree, Seidenberg, and McNorgan's (2005) feature norms, participants listed more features for some words (e.g., 20 for *couch*, 23 for *cougar*) than for others (e.g., 11 for *table*, 9 for *leopard*). High-NF words have elicited faster LDT and SCT responses than low-NF words have (Grondin, Lupker, & McRae, 2006; Pexman, Holyk, & Monfils, 2003; Pexman, Lupker, & Hino, 2002), and this advantage has been attributed to greater semantic activation. Simulations using connectionist models of semantic memory suggest that the visual word recognition system settles more quickly into a stable pattern of activation for concepts with richer representations (Plaut & Shallice, 1993).

Contextual Dispersion

Evidence suggests that visual word recognition is also influenced by the particular circumstances in which a word has previously occurred (see, e.g., Goldinger & Azuma, 2004; Kolers, 1976). Words vary in the number of different content areas in which they appear, and this variability can be captured using language corpora. In the present study, we defined CD as the extent to which occurrences of a word are evenly distributed across the nine academic content areas sampled from educational materials in the Zeno, Ivens, Millard, and Duvvuri (1995) corpus (e.g., language arts and literature, social science, science and math). CD is a measure of relative entropy; it equals zero when all occurrences of a word are found in a single content area, and it equals 1 when all occurrences are distributed equally across all content areas. The occurrences of some words cluster in particular content areas (e.g., *clamp* scores .18; *parsley* scores .25), whereas occurrences of other words are more evenly distributed across content areas (e.g., .93 for *belt*, .85 for *cherry*). A similar construct was explored by Adelman, Brown, and Quesada (2006), who reported faster lexical decisions for words occurring in relatively more samples within a language corpus, even when word frequency was controlled. CD could also be described as a measure of semantic richness: Words associated with more content areas have richer representations. Adelman et al. suggested that this effect of textual context demonstrates an influence of episodic memory on word recognition.

Indeed, a model has recently been proposed that may be able to account for episodic effects in visual word recognition tasks. Wagenmakers et al. (2004) developed REM-LD to model LDT performance. REM-LD is based on the REM (retrieving effectively from memory) theory of Shiffrin and Steyvers (1997). According to REM, memory comprises instances, each of which contains a vector of features. Retrieval in REM-LD is modeled as a matching process between the presented word and these instances, guided by a Bayesian decision mechanism. Instances of a given word are composed of lexical–semantic features (orthographic, phonologic, and semantic) and episodic features, such as the contexts and circumstances in which the word has been experienced.

Like Wagenmakers et al. (2004), we do not draw a sharp distinction between lexical–semantic and episodic factors. Wagenmakers et al. asserted that lexical decision performance is based primarily on lexical–semantic traces because of the demands of the task, but this assumption does not preclude a role for episodic memory in word recognition. Lexical decisions are unlikely to be based on a single episodic experience, but commonalities across episodes can be captured within lexical–semantic traces. The underlying variability of episodic traces thus influences what is retained in the lexical–semantic trace. Wagenmakers et al. argued that these episodic influences provide a basis for explaining effects of word frequency (the response advantage for higher frequency words) and, we would argue, a potential mechanism for effects of CD. That is, decisions in REM-LD are based on the probability of matching a stored lexical–semantic trace with a presented instance. Since "high-frequency words (e.g., *chair*) generally occur in many different contexts, whereas low-frequency words (e.g., *pyramid*, *pharaoh*) are often tied to relatively few contexts" (Wagenmakers et al., 2004, p. 343), the lexical–semantic traces for high-frequency words are more likely to match the presented word than are low-frequency traces, which are more context dependent. In a similar way, the matching process for high-CD words could be facilitated relative to that for low-CD words.

Comparing Measures of Richness

Although NSN, NF, and CD have each been shown to facilitate word recognition, their correspondence has not been examined. One possibility is that all three measures tap into the same underlying dimension. If so, they should be strongly correlated and should account for the same variance in visual word recognition performance. However, differences in how these measures are derived mitigate this possibility: NSN is derived from a word's co-occurrence history—in particular, the extent to which it occurs in similar contexts as compared with other words; CD is derived from a word's history of usage in different content areas; and NF is derived from feature lists and thus is more object based. These measures might, therefore, contribute differentially both within a task and across tasks.

The present study examined whether these three measures of semantic richness each explained unique variance in visual word recognition in two tasks: LDT and SCT. Although effects of semantic richness have been observed in both LDT and SCT, each task is assumed to tap somewhat different aspects of visual word recognition (Balota, Paul, & Spieler, 1999). LDT is assumed to require assessment of the word's orthographic familiarity, and semantic effects in LDT are thought to be produced by feedback activation from semantic representations to orthographic representations (Hino & Lupker, 1996). In contrast, SCT performance is assumed to more directly involve semantic processing (Hino, Pexman, & Lupker, 2006), with less emphasis on orthographic familiarity (since the decision requires assessment of the word's meaning).

Buchanan et al. (2001) observed NSN effects in LDTs and suggested that LDTs tapped a level of semantic representation that is well described by lexical co-occurrence, whereas another level of semantic representation captured more object-based information. It is possible that the SCT requires greater emphasis on this kind of object-based information than does the LDT. This multilevel framework for semantics supports the prediction that the relative influence of the three semantic richness measures will vary across the two tasks. In particular, we expected that greater NSN would facilitate LDT but not SCT responses. Indeed, NSN effects have been observed in SCT only when the response required complex decision making (i.e., go/no-go SCT; see Siakaluk, Buchanan, & Westbury, 2003). Further, Mirman and Magnuson (2006) proposed that whereas distant semantic neighbors facilitate semantic processing, close semantic neighbors interfere with semantic processing. According to this claim, all semantic neighbors would provide feedback to orthography (thus producing a benefit of higher NSN in LDT), but close versus distant neighbors would have opposite effects on semantic processing (thus producing a null effect of NSN in SCT). Essentially, activation of semantic neighbors may provide evidence that a target is a real word, but it does not resolve that word's specific meaning.

In contrast, NF was expected to have especially strong facilitatory effects in SCT since NF is derived from object-based semantics. Smaller NF effects might also be observed in LDT due to semantic feedback to orthography. Finally, greater CD was expected to have facilitatory effects in LDT, in line with Adelman et al.'s (2006) findings. CD effects have not previously been examined in SCT, but if words experienced in a greater variety of content areas have richer semantic representations, then facilitatory CD effects should be observed in SCT.

The unique contribution of this study, therefore, is the direct comparison of three measures of semantic richness, each derived from diverse theoretical backgrounds, in order to determine and compare each measure's contributions to visual word recognition performance. We examined the effects of these measures using LDT data extracted from the English Lexicon Project database (Elexicon; Balota et al., 2002) and with SCT data collected in our lab.

METHOD

Participants

Participants in the SCT were 54 undergraduate students at the University of Calgary who received course credit for participating. Participants reported that English was their first language and that they had normal or corrected-to-normal vision.

Materials

The critical stimuli for this study were 514 concrete words from McRae et al.'s (2005) norms. NF values were the "Num_Feats_No_Tax" (the total number of features listed for a concept, exclusive of taxonomic features) counts from these norms. NSN values were taken from the global semantic neighborhood variable in the Durda et al. (2006) norms. CD values were taken from the variable listed as *D* in the Zeno et al. (1995) norms. In addition, 514 abstract words were fillers in the SCT. Table 1 lists the stimulus characteristics.

Procedure

On each trial in the SCT, a word was presented in the center of a 17-in. monitor controlled by a Macintosh G3 computer using PsyScope (Cohen, MacWhinney, Flatt, & Provost, 1993). Participants classified each word as concrete or abstract by pressing the right or left button, respectively, on a PsyScope response box. Testing began with 10 practice trials with verbal feedback for incorrect responses. During the experiment, 1,028 words were presented in random order with an intertrial interval of 2,000 msec.

RESULTS

From the original set of 514 concrete words, we excluded data for words for which LDT or SCT accuracy was less than 70% (20 items), or for words not included in one set of norms (15 items). As a result, responses to 479 words were analyzed. Further, SCT responses that were incorrect (5.7% of trials) or that were faster than 250 msec or slower than 2,500 msec (less than 1% of trials) were excluded from the RT analysis. Mean RTs and errors for both tasks are presented in Table 1. Correlation coefficients (Table 2) show that higher values on each of the three semantic richness measures were associated with faster responses in both tasks and, importantly, were only modestly correlated with each other.

Table 1
Stimulus Characteristics and Mean Lexical Decision and Semantic Categorization Response Times (in Milliseconds) and Error Percentages

	Concrete Items (LDT and SCT)		Abstract Items (Fillers in SCT)	
Variable	*M*	*SD*	*M*	*SD*
Log frequency (HAL)	7.74	1.51	8.91	1.79
ON (Coltheart et al., 1977)	3.60	5.16	1.54	3.10
Word length (number of letters)	5.93	1.94	6.70	1.74
NSN (Durda et al., 2006)	3.54	6.06	30.26	87.59
CD (Zeno et al., 1995)	0.61	0.18	0.73	0.20
NF (McRae et al., 2005)	12.24	3.19	n/a	n/a
LDT RTs	671	84	n/a	n/a
LDT error percentages	4.97	5.93	n/a	n/a
SCT RTs	620	61	682	56
SCT error percentages	4.62	4.87	6.80	7.69

Note—LDT, lexical decision task; SCT, semantic categorization task; ON, orthographic neighborhood size; NSN, number of semantic neighbors; CD, contextual dispersion; NF, number of features.

Table 2
Correlations Between Predictor Variables and Measures of Performance

Measure	1	2	3	4	5	6	7	8	9	10
1. Log frequency	–									
2. ON	.43**	–								
3. Word length	−.52**	−.67**	–							
4. NSN	.29**	.07	−.10*	–						
5. CD	.55**	.28**	−.29**	.13**	–					
6. NF	.16**	.03	−.01	.15**	.12*	–				
7. LDT RT	−62**	−.42**	.53**	−.26**	−.46**	−.18**	–			
8. LDT error	−.34**	−.11*	.10*	−.16**	−.37**	−.20**	.51**	–		
9. SCT RT	−.31**	−.16**	.17**	−.10*	−.31**	−.33**	.44**	.37**	–	
10. SCT error	−.10*	−.08	.01	−.09*	−.11*	−.25**	.25**	.21**	.64**	–

Note—See Table 1 for an explanation of the abbreviations. *$p < .05$. **$p < .01$.

We next examined the data from both tasks using hierarchical regression analyses with RT and errors as separate criterion variables (Tables 3 and 4). Three nonsemantic control variables known to influence performance in lexical tasks (log frequency, orthographic neighborhood size, and word length) were entered as predictors on the first step, and the three semantic richness measures were entered on the second step. Stepwise entry allowed us to establish the change in R^2 afforded by the inclusion of the semantic richness variables.

The regression analyses revealed significant relationships between the control variables and responding in each task. There were significant effects of the three semantic richness variables, and critically, their contributions differed as a function of task. Specifically, CD and NF were related to both LDT and SCT performance (greater CD and NF were facilitatory for RT and for errors). In contrast, NSN was significantly related only to LDT performance (greater NSN was facilitatory for RT).[1]

The unique contribution of each semantic richness measure across the two tasks was also compared, using the unstandardized regression coefficients. As expected, NSN predicted significantly more RT variance in LDT than in SCT [$t(472) = 2.78, p < .05$]. In contrast, NF predicted more RT variance in SCT than in LDT [$t(472) = 3.69, p < .01$]. Finally, CD predicted a similar amount of variance in both tasks [$t(472) = 0.67, p > .05$]. Thus, each semantic richness variable showed a different pattern of effects across the two tasks.

DISCUSSION

The present study revealed that three measures of semantic richness—NSN, NF, and CD—predict unique variance in visual word recognition tasks. The three measures were only modestly correlated, and hence, interestingly, it appears that they do not all tap the same construct. Thus, although these measures have all been linked to the notion of semantic richness (which, in terms of seman-

Table 3
Results of Hierarchical Regression Analyses for Lexical Decision Task Performance

Variable	*B*	*SEB*	β	*sr*	R^2	ΔR^2
			Response Times			
Step 1 (Control Variables)					.44***	.44***
Step 2					.48***	.04***
Control Variables						
Log frequency	−18.02	2.57	−.32***	−.23		
ON	−0.61	0.74	−.04	−.03		
Word length	12.34	2.08	.28***	.20		
Semantic Richness Variables						
NSN	−1.34	0.48	−.10**	−.09		
CD	−77.57	18.58	−.17***	−.14		
NF	−2.30	0.89	−.09**	−.09		
			Errors			
Step 1 (Control Variables)					.13***	.13***
Step 2					.20***	.07***
Control Variables						
Log frequency	−0.01	0.00	−.21***	−.15		
ON	−0.00	0.00	−.01	−.01		
Word length	−0.00	0.00	−.10	−.07		
Semantic Richness Variables						
NSN	−0.00	0.00	−.06	−.06		
CD	−0.09	0.02	−.27***	−.22		
NF	−0.00	0.00	−.13**	−.13		

Note—See Table 1 for an explanation of the abbreviations. The *B*, *SEB*, β, and *sr* values are for the final step in each regression analysis, where all variables were included in the equation. **$p < .01$. ***$p < .001$.

Table 4
Results of Hierarchical Regression Analyses for Semantic Categorization Task Performance

Variable	*B*	*SEB*	*β*	*sr*	R^2	ΔR^2
			Response Times			
Step 1 (Control Variables)					.10***	.10***
Step 2					.20***	.10***
Control Variables						
Log frequency	−5.62	2.29	−.14*	−.10		
ON	−0.02	0.66	−.00	−.00		
Word length	1.61	1.86	.05	.04		
Semantic Richness Variables						
NSN	0.09	0.43	.01	.01		
CD	−63.73	16.61	−.19***	−.16		
NF	−5.25	0.80	−.28***	−.27		
			Errors			
Step 1 (Control Variables)					.02*	.02*
Step 2					.08***	.06***
Control Variables						
Log frequency	−0.01	0.00	−.04	−.03		
ON	−0.00	0.00	−.11	−.08		
Word length	−0.00	0.00	−.11	−.07		
Semantic Richness Variables						
NSN	−0.00	0.00	−.04	−.04		
CD	−0.02	0.01	−.06	−.05		
NF	−0.00	0.00	−.23***	−.23		

Note—See Table 1 for an explanation of the abbreviations. The *B*, *SEB*, *β*, and *sr* values are for the final step in each regression analysis, where all variables were included in the equation. $^*p < .05$. $^{***}p < .001$.

tic processing, translates to "more is better"), the differences between them illustrate that semantic richness can be defined in several different ways. Moreover, the three semantic richness measures had unique relationships with responding in the LDT and SCT. Each measure was a significant predictor of responses in at least one task. Lexical co-occurrence information, feature-listing responses, and the content areas in which words have been experienced, therefore, all have some purchase on the issue of how word meanings are mentally represented.

Explanations of semantic richness effects typically assume that words with relatively richer semantic representations generate stronger semantic activation. If the effect of each variable could be explained by the same mechanism, however, one would expect the same pattern of effects across tasks. Instead, we found a unique pattern of effects across tasks for each measure, as described below.

First, the particular aspect of semantic richness tapped by NSN had a significant effect on processing in LDT but not in SCT. We suggest that this dissociation reflects the different demands of the two tasks. The LDT requires judgments of lexicality and therefore encourages emphasis on a word's form, whereas the SCT requires a judgment about the referent's meaning. This task analysis is supported by the much larger contribution of the nonsemantic control variables in the LDT than in the SCT (R^2 of .44 in LDT vs. R^2 of .10 in SCT). The NSN effect in the LDT could be due to semantic neighbors' providing feedback to orthography, whereas the null NSN effect in SCT could result from close versus distant neighbors' having opposite effects on semantic processing (Mirman & Magnuson, 2006).

Second, as expected, NF affected responses in the SCT more than in the LDT. NF effects have been attributed to greater semantic activation for words with high NF (because they provide stronger feedback activation to orthographic representations and, hence, elicit faster LDT responses) and faster semantic settling for words with high NF (because they provide more rapid meaning activation and, hence, elicit faster SCT responses; see, e.g., Pexman et al., 2003). Our results suggest that activation of semantic feature information facilitates semantic settling more than it facilitates orthographic settling via semantic feedback.

Third, greater CD facilitated responding in the LDT and the SCT to similar degrees; thus, an influence of CD can be detected in tasks that emphasize either orthographic familiarity or semantic processing. A model like REM-LD (Wagenmakers et al., 2004), in which word recognition relies on both lexical–semantic and episodic traces, may prove useful for simultaneously modeling the effects of CD, NF, and NSN.

Although greater semantic richness defined in terms of CD facilitates word recognition in LDTs, SCTs, and naming tasks (Adelman et al., 2006), Steyvers and Malmberg (2003) reported that recognition memory was better for words that occurred in fewer contexts. High CD provides an advantage in cooperative retrieval tasks, in which multiple experiences with a word do not have to be distinguished, but is a disadvantage in competitive retrieval tasks like recognition memory, in which a single experience in a study list must be identified. As Logan (1988) put it, cooperative retrieval tasks like LDT are "like finding a forest; the more trees there are, the easier it is to find," whereas competitive retrieval tasks like recognition are "like finding a particular tree in a forest; the more dense the forest, the harder it is to find" (p. 514). Thus, greater CD appears to facilitate performance in tasks that do not require isolating a particular encoding experience in memory. Our speculation is that the same may also hold true for words with greater NF or NSN: Although these variables facilitate performance in cooperative retrieval tasks, they may interfere with performance in competitive retrieval tasks.

In the present work, we contrasted only semantic measures that reflected the sheer number of neighbors, features, or content areas connected to a concept. These measures explained only a modest portion of the variance in the LDT and the SCT. Other measures, such as semantic density (McRae et al., 1997), that tap into the strength of connections among concepts may explain additional variance in single-word processing. In addition, our findings speak only to the processing of concrete concepts; whether semantic richness effects extend to abstract concepts, for example, is unknown.

The present study shows that semantic richness has many dimensions: Visual word recognition for concrete words is influenced by knowledge of the words' meanings and also by memory for the lexical and textual contexts in which those words have appeared. Complete theories of semantic representation must attempt to capture these types of influence.

REFERENCES

Adelman, J. S., Brown, G. D. A., & Quesada, J. F. (2006). Contextual diversity, not word frequency, determines word-naming and lexical decision times. *Psychological Science*, **17**, 814-823.

Balota, D. A., Cortese, M. J., Hutchison, K. A., Neely, J. H., Nelson, D., Simpson, G. B., & Treiman, R. (2002). *The English Lexicon Project: A web-based repository of descriptive and behavioral measures for 40,481 English words and nonwords*. Retrieved July 16, 2006 from www.elexicon.wustl.edu/.

Balota, D. A., Cortese, M. J., Sergent-Marshall, S. D., Spieler, D. H., & Yap, M. J. (2004). Visual word recognition of single-syllable words. *Journal of Experimental Psychology: General*, **133**, 283-316.

Balota, D. A., Paul, S. T., & Spieler, D. H. (1999). Attentional control of lexical processing pathways during word recognition and reading. In S. C. Garrod & M. J. Pickering (Eds.), *Language processing* (pp. 15-57). Hove, U.K.: Psychology Press.

Buchanan, L., Westbury, C., & Burgess, C. (2001). Characterizing semantic space: Neighborhood effects in word recognition. *Psychonomic Bulletin & Review*, **8**, 531-544.

Burgess, C., & Lund, K. (2000). The dynamics of meaning in memory. In E. Dietrich & A. B. Markman (Eds.), *Cognitive dynamics: Conceptual and representational change in humans and machines* (pp. 117-156). Mahwah, NJ: Erlbaum.

Cohen, J. D., MacWhinney, B., Flatt, M., & Provost, J. (1993). PsyScope: An interactive graphic system for designing and controlling experiments in the psychology laboratory using Macintosh computers. *Behavior Research Methods, Instruments, & Computers*, **25**, 257-271.

Coltheart, M., Davelaar, E., Jonasson, J. T., & Besner, D. (1977). Access to the internal lexicon. In S. Dornic (Ed.), *Attention and performance VI* (pp. 535-555). Hillsdale, NJ: Erlbaum.

Durda, K., Buchanan, L., & Caron, R. (2006). WordMine2 [Online]. Available at www.wordmine2.org.

Goldinger, S. D., & Azuma, T. (2004). Episodic memory reflected in printed word naming. *Psychonomic Bulletin & Review*, **11**, 716-722.

Grondin, R., Lupker, S. J., & McRae, K. (2006). Shared features dominate the number-of-features effect. In R. Sun & N. Miyake (Eds.), *Proceedings of the 28th annual meeting of the Cognitive Science Society* (pp. 1400-1405). Mahwah, NJ: Erlbaum.

Hino, Y., & Lupker, S. J. (1996). Effects of polysemy in lexical decision and naming: An alternative to lexical access accounts. *Journal of Experimental Psychology: Human Perception & Performance*, **22**, 1331-1356.

Hino, Y., Pexman, P. M., & Lupker, S. J. (2006). Ambiguity and relatedness effects in semantic tasks: Are they due to semantic coding? *Journal of Memory & Language*, **55**, 247-273.

Kolers, P. A. (1976). Reading a year later. *Journal of Experimental Psychology: Human Learning & Memory*, **2**, 554-565.

Logan, G. D. (1988). Toward an instance theory of automatization. *Psychological Review*, **95**, 492-527.

McRae, K. (2004). Semantic memory: Some insights from feature-based connectionist attractor networks. In B. H. Ross (Ed.), *The psychology of learning and motivation* (Vol. 45, pp. 41-86). San Diego: Elsevier, Academic Press.

McRae, K., Cree, G. S., Seidenberg, M. S., & McNorgan, C. (2005). Semantic feature production norms for a large set of living and nonliving things. *Behavior Research Methods*, **37**, 547-559.

McRae, K., de Sa, V. R., & Seidenberg, M. S. (1997). On the nature and scope of featural representations of word meaning. *Journal of Experimental Psychology: General*, **126**, 99-130.

Mirman, D., & Magnuson, J. S. (2006). The impact of semantic neighborhood density on semantic access. In R. Sun & Miyake, (Eds.), *Proceedings of the 28th annual conference of the Cognitive Science Society* (pp. 1823-1828) Mahwah, NJ:Erlbaum.

Pexman, P. M., Hargreaves, I. S., Edwards, J. D., Henry, L. C., & Goodyear, B. G. (2007). The neural consequences of semantic richness: When more comes to mind, less activation is observed. *Psychological Science*, **18**, 401-406.

Pexman, P. M., Holyk, G. G., & Monfils, M.-H. (2003). Number-of-features effects and semantic processing. *Memory & Cognition*, **31**, 842-855.

Pexman, P. M., Lupker, S. J., & Hino, Y. (2002). The impact of feedback semantics in visual word recognition: Number-of-features effects in lexical decision and naming tasks. *Psychonomic Bulletin & Review*, **9**, 542-549.

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

Shiffrin, R. M., & Steyvers, M. (1997). A model for recognition memory: REM—retrieving effectively from memory. *Psychonomic Bulletin & Review*, **4**, 145-166.

Siakaluk, P. D., Buchanan, L., & Westbury, C. (2003). The effect of semantic distance in yes/no and go/no-go semantic categorization tasks. *Memory & Cognition*, **31**, 100-113.

Steyvers, M., & Malmberg, K. J. (2003). The effect of normative context variability on recognition memory. *Journal of Experimental Psychology: Learning, Memory, & Cognition*, **29**, 760-766.

Wagenmakers, E., Steyvers, M., Raaijmakers, J. G. W., Shiffrin, R. M., van Rijn, H., & Zeelenberg, R. (2004). A model for evidence accumulation in the lexical decision task. *Cognitive Psychology*, **48**, 332-367.

Zeno, S. M., Ivens, S. H., Millard, R. T., & Duvvuri, R. (Eds.) (1995). *The educator's word frequency guide*. Brewster, NJ: Touchstone Applied Science Associates.

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NOTE

1. Imageability is also related to LDT performance (see, e.g., Balota, Cortese, Sergent-Marshall, Spieler, & Yap, 2004), and, given the concrete/abstract decision category in our SCT, it seemed possible that it would also be related to SCT performance. We therefore ran separate regression analyses with rated imageability included as a control variable (see Appendix). Imageability ratings were available for 333 of the 514 items. The range in imageability ratings for these items was quite narrow (4.94–6.59, $M = 5.88$, $SD = 0.32$) since they were all concrete terms. Nonetheless, the relationships between rated imageability and LDT and SCT performance were significant. The only change in the overall pattern of results was that NF was significantly related only to SCT performance.

APPENDIX

Table A1
Results of Hierarchical Regression Analyses for Lexical Decision Task Performance With Rated Imageability Included As a Predictor Variable

Variable	B	SEB	β	sr	R^2	ΔR^2
Response Times						
Step 1 (Control Variables)					$.51^{***}$	$.51^{***}$
Step 2					$.53^{***}$	$.02^{*}$
Control Variables						
Log frequency	−18.15	2.98	$-.34^{***}$	−.23		
ON	0.64	0.72	−.05	−.03		
Word length	14.16	2.28	$.34^{***}$	.24		
Rated imageability	−0.42	0.10	$-.17^{***}$	−.16		
Semantic Richness Variables						
NSN	−1.07	0.48	$-.09^{*}$	−.09		
CD	−49.80	22.25	$-.11^{*}$	−.09		
NF	−1.08	0.99	−.05	−.05		
Errors						
Step 1 (Control Variables)					$.17^{***}$	$.17^{***}$
Step 2					$.20^{***}$	$.03^{**}$
Control Variables						
Log frequency	−0.01	0.00	$-.21^{**}$	−.15		
ON	−0.00	0.00	−.07	−.05		
Word length	−0.00	0.00	−.11	−.08		
Rated imageability	0.00	0.00	$-.19^{***}$	−.18		
Semantic Richness Variables						
NSN	0.00	0.00	−.04	−.04		
CD	−0.07	0.02	$-.21^{**}$	−.17		
NF	−0.00	0.00	−.06	−.06		

Note—See Table 1 for an explanation of the abbreviations. The B, SEB, β, and sr values are for the final step in each regression analysis, where all variables were included in the equation. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table A2
Results of Hierarchical Regression Analyses for Semantic Categorization Task Performance With Rated Imageability Included As a Predictor Variable

Variable	B	SEB	β	sr	R^2	ΔR^2
Response Times						
Step 1 (Control Variables)					$.25^{***}$	$.25^{***}$
Step 2					$.31^{***}$	$.06^{***}$
Control Variables						
Log frequency	−3.74	2.90	−.09	−.06		
ON	−0.16	0.70	−.02	−.01		
Word length	4.31	2.22	.13	.09		
Rated imageability	−0.74	0.10	$-.37^{***}$	−.34		
Semantic Richness Variables						
NSN	0.21	0.47	.02	.02		
CD	−57.29	21.65	$-.15^{**}$	−.12		
NF	−4.01	0.96	$-.21^{***}$	−.19		
Errors						
Step 1 (Control Variables)					$.13^{***}$	$.13^{***}$
Step 2					$.18^{***}$	$.05^{***}$
Control Variables						
Log frequency	0.00	0.00	.06	.04		
ON	−0.00	0.00	−.10	−.07		
Word length	0.00	0.00	.02	.01		
Rated imageability	0.00	0.00	$-.28^{***}$	−.25		
Semantic Richness Variables						
NSN	−0.00	0.00	−.09	−.08		
CD	−0.04	0.02	$-.13^{*}$	−.10		
NF	−0.00	0.00	$-.19^{***}$	−.18		

Note—See Table 1 for an explanation of the abbreviations. The B, SEB, β, and sr values are for the final step in each regression analysis, where all variables were included in the equation. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

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