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BRIEF REPORT

Is more always better? Effects of semantic richness on lexical decision, speeded pronunciation, and semantic classification

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Abstract Evidence from large-scale studies (Pexman, Hargreaves, Siakaluk, Bodner, & Pope, 2008) suggests that *semantic richness*, a multidimensional construct reflecting the extent of variability in the information associated with a word's meaning, facilitates visual word recognition. Specifically, recognition is better for words that (1) have more semantic neighbors, (2) possess referents with more features, and (3) are associated with more contexts. The present study extends Pexman et al. (2008) by examining how two additional measures of semantic richness, number of senses and number of associates (Pexman, Hargreaves, Edwards, Henry, & Goodyear, 2007), influence lexical decision, speeded pronunciation, and semantic classification performance, after controlling for an array of lexical and semantic variables. We found that number of features and contexts consistently facilitated word recognition but that the effects of semantic neighborhood density and number of associates were less robust. Words with more senses also elicited faster lexical decisions but less accurate semantic classifications. These findings point to how the effects of different semantic dimensions are selectively and adaptively modulated by task-specific demands.

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The majority of visual word recognition research has examined how lexical-level properties such as word frequency and number of letters influence performance,using tasks such as lexical decision (word/nonword discrimination), speeded pronunciation (naming words aloud), and semantic classification (e.g., classifying a word as animate or inanimate). However, there is substantial evidence that meaning-level characteristics such as imageability also affect word recognition, even after correlated lexical variables are controlled for (see Balota, Ferraro, & Connor, 1991, for a review). In the present study, we focus on the effects of *semantic richness*, the extent to which there is variability in the information associated with a word's meaning (Pexman, Hargreaves, Siakaluk, Bodner, & Pope, 2008).

Measures of semantic richness

Pexman et al. (2008) defined semantic richness as a multidimensional construct that encompasses a word's *number of semantic neighbors* (NSN), the *number of features* (NF) associated with its referent, and its *contextual dispersion* (CD). NSN refers to the number of semantic neighbors within some specified radius in high-dimensional semantic space (Buchanan, Westbury, & Burgess, 2001) and is based on lexical co-occurrences within a large corpus of words. NF indexes the number of features listed by participants for different concepts (McRae, Cree, Seidenberg, & McNorgan, 2005). Finally, CD reflects the number of contexts in which a word has been seen (Adelman, Brown, & Quesada, 2006). Words possess richer, more highly activated semantic representations when NF, NSN, and CD are high, consistent with empirical demonstrations of faster recognition for words associated with more semantic neighbors (Buchanan et al., 2001), features (Pexman, Holyk, & Monfils, 2003), and contexts (Adelman et al., 2006).

Task-specificity of semantic richness measures

Although described as semantic richness measures, NSN, NF, and CD stem from disparate theoretical perspectives and may not reflect a common underlying dimension or mechanism. Pexman et al. (2008) explored this by simultaneously comparing the effects of the three variables on lexical decision and semantic classification performance, using hierarchical regression analyses of 514 concrete words from the McRae et al. (2005) feature norms. They found that the three semantic variables were only modestly correlated and, indeed, were able to account for unique variance in both lexical decision and semantic classification performance, suggesting that they are not simply alternative measures of the same construct. More interestingly, the *relative* proportion of word recognition variance accounted for by the three measures varied across the two tasks, consistent with the different demands of each task (Balota & Yap, 2006). Specifically, meaning-level influences in lexical decision emerge due to top-down feedback from semantic to orthographic representations (Balota, 1990) and to the task's emphasis on stimulus familiarity/meaningfulness as a useful dimension for word/nonword discrimination (Balota & Chumbley, 1984). In contrast, the semantic classification task, which requires participants to ascertain the *meaning* of a word, is a more direct measure of semantic processing and should be less affected by variables correlated with orthographic familiarity (e.g., word frequency).

Consistent with these task-specific demands, Pexman et al. (2008) reported an interesting dissociation whereby measures related to orthographic familiarity had less predictive power in semantic classification (R^2 = .10) than in lexical decision (R^2 = .44), while semantic richness measures had more predictive power in semantic classification (ΔR^2 = .10) than in lexical decision (ΔR^2 = .04). Furthermore, NF and CD facilitated both lexical decision and semantic classification, whereas NSN effects were limited to lexical decision. According to Pexman et al. (2008), high-NF and high-CD words possess more highly activated semantic representations, which produce stronger semantics→orthography feedback (yielding better lexical decision performance) and less time needed to settle on a semantic code (yielding better semantic classification performance). The NSN effect in lexical decision can be explained by greater semantics→orthography feedback when there are more semantic neighbors, while the null NSN effect in semantic classification is consistent with the opposing effects of close (facilitatory) and distant (inhibitory) neighbors trading off against each other in semantic processing (Mirman & Magnuson, 2006).

The present research

The analyses in Pexman et al. (2008) have provided compelling evidence for the multidimensionality of semantic richness and the interplay between these distinct influences and the specific demands of different lexical-processing tasks. Our aim was to replicate and extend that work in the following ways.

One, semantic richness is not circumscribed by the measures (i.e., NSN, NF, CD) described so far. It could also be reflected by a word's *number of associates* (NoA; Duñabeitia, Avilés, & Carreiras, 2008; Pexman, Hargreaves, Edwards, Henry, & Goodyear, 2007), the number of distinct first associates produced in a free-association task (Nelson, McEvoy, & Schreiber, 1998). NoA has been shown to facilitate performance across different lexical-processing tasks (see Duñabeitia et al., 2008, for a review). Another theoretically intriguing variable is *lexical ambiguity*, the extent to which a word (e.g., *bank*) possesses multiple unrelated meanings. Ambiguous words elicit shorter lexical decision (Borowsky & Masson, 1996) but longer semantic classification (Hino, Pexman, & Lupker, 2006) latencies. In lexical decision, words with more meanings receive more semantic feedback. However, semantic classification relies on semantic processing, which can be slowed down either by the one-to-many mappings between orthography and semantics for ambiguous words (Borowsky & Masson, 1996) or by the greater competition between the multiple meanings activated for ambiguous words (Grainger, Van Kang, & Segui, 2001). Thus far, previous studies have examined NoA and ambiguity effects separately from other richness effects. Our first goal was to identify the unique effects of these variables and of other measures of semantic richness across different tasks, using regression analyses of behavioral responses to the McRae et al. (2005) words. Importantly, word ambiguity has usually been defined by subjective ratings (e.g., Hargreaves, Pexman, Pittman, & Goodyear, 2011). While such ratings work well for clearly ambiguous items (e.g., *bank*), they are not so viable for less ambiguous words (e.g., *blouse*); the McRae et al. words mostly fall into the latter category. Hence, in the present study, we defined the ambiguity of a word by its number of senses in the WordNet database (Miller, 1990).

Two, the effects of semantic richness measures on speeded pronunciation performance were not studied. Generally, semantic effects, although reliable, are relatively modest in speeded pronunciation (Balota, Cortese, Sergent-Marshall, Spieler, & Yap, 2004), since the task does not place a premium on familiarity-based information or require participants to identify the meaning of the word. However, semantic effects on speeded pronunciation can still arise through early activation of meaning by way of cascaded processing (Balota et al., 2004), leading to stronger feedback activation from semantics to phonology (Siakaluk, Pexman, Aguilera, Owen, & Sears, 2008). In the present study, we explored the effects of semantic richness on lexical decision, semantic classification, *and* speeded pronunciation, after controlling for an extensive array of correlated lexical variables.

Three, Pexman et al. (2008) explored semantic richness effects after controlling for word frequency, orthographic neighborhood density, and number of letters. However, many other variables influence visual word recognition (see Yap & Balota, 2009), and spurious effects may emerge when these extraneous variables are not controlled for (Gernsbacher, 1984). In addition, since Pexman et al. (2008), updated and potentially superior semantic richness measures have become available (see Shaoul & Westbury, 2010). We used a neighborhood measure called *mean semantic similarity–5000* (MSS–5000) (C. Westbury, personal communication, October 21, 2010), which is based on co-occurrence information from a billion-word Wikipedia corpus. MSS–5000 reflects the mean cosine similarity between a target word and its closest 5,000 neighbors in high-dimensional semantic space; words with higher MSS–5000 values are associated with neighbors that are more similar to them, and should therefore enjoy a processing advantage. Moreover, the raw and CD frequency counts in Pexman et al. (2008) were based on different norms, and the predictive power of CD may have been inflated due to its being estimated with a different corpus (see Brysbaert & New, 2009). In line with Adelman et al. (2006), we used raw and CD counts from Brysbaert and New's SUBTL corpus, a 51-million-word database comprising film and television subtitles. These new norms outperform existing norms and include both raw frequency (SUBTL-WF; frequency of occurrence) and CD frequency (SUBTL-CD; number of films a word appears in).

Method

Dependent measures

Lexical decision and speeded pronunciation data for the regression analyses were obtained from the English Lexicon Project (ELP; http://elexicon.wustl.edu), an online repository of lexical characteristics and behavioral data for 40,481 words (Balota et al., 2007). Standardized lexical decision and pronunciation latencies were used in the present analyses (cf. Pexman et al., 2008), since these minimize the influence of a participant's processing speed and variability (Faust, Balota, Spieler, & Ferraro, 1999). Semantic classification data were obtained from Pexman et al. (2008).

Predictors

The variables in the analyses were divided into three clusters: surface, lexical, and semantic variables (see Table 1 for descriptive statistics of predictors and measures). Tables 2 and 3 present the intercorrelations between the predictors and dependent variables.

Surface variables Dichotomous variables were used to code the initial phoneme of each word (1 = presence of feature; 0 = absence of feature) on 13 features: affricative, alveolar, bilabial, dental, fricative, glottal, labiodental, liquid, nasal, palatal, stop, velar, and voiced (Balota et al., 2004). These control for the variance associated with voice key biases in speeded pronunciation.

Lexical variables These included word frequency, number of morphemes, number of syllables, number of letters, number of orthographic neighbors, number of phonological neighbors, orthographic Levenshtein distance, and phonological Levenshtein distance (Yarkoni, Balota, & Yap, 2008). The Levenshtein measures are particularly useful for quantifying the orthographic and phonological distinctiveness of longer, multisyllabic words.

Semantic richness variables Semantic richness measures included NF (McRae et al., 2005), MSS–5000 (Shaoul & Westbury, 2010), log-transformed CD (Brysbaert & New, 2009), log-transformed number of senses (Miller, 1990), and NoA (Pexman et al., 2007).

Results

From the original set of 514 words, analyses were conducted on the 505[1] words that possessed values for the relevant predictors and dependent measures. Hierarchical regression analyses were then conducted on the lexical decision, speeded pronunciation, and semantic classification response time (RT) and accuracy data (Table 4). Surface variables[2] were entered in step 1, control lexical variables in step 2, and semantic richness variables (NF, MSS–5000, SUBTL-CD, number of senses) in step 3. Because NoA values were available for only 389 items, we assessed NoA effects by conducting additional regression analyses for this subset of

[1] Four truly ambiguous words (*bin*, *stool*, *plug*, and *card*) were dropped.

[2] Although surface variables mainly capture variance associated with voice key effects on speeded pronunciation times, we included them in all three tasks to maintain parity.

Table 1 Descriptive statistics for stimulus characteristics and behavioral data

Variable (*n* = 505)	*M*	*SD*
Log frequency (Brysbaert & New, 2009)	2.42	0.64
No. of morphemes	1.24	0.48
No. of syllables	1.80	0.79
No. of letters (length)	5.94	1.93
No. of orthographic neighbors	3.55	4.90
No. of phonological neighbors (Yates, 2005)	7.66	9.62
Orthographic Levenshtein distance (Yarkoni et al., 2008)	2.23	0.91
Phonological Levenshtein distance (Yarkoni et al., 2008)	2.08	1.01
No. of features (McRae et al., 2005)	12.12	3.23
Mean semantic similarity-5000 (Shaoul & Westbury, 2010)	0.43	0.14
Log contextual dispersion (Brysbaert & New, 2009)	2.19	0.60
Log number of senses (Miller, 1990)	0.60	0.26
Number of associates (Nelson et al., 1998)	13.48	5.05
Lexical decision task RTs (Z-score)	-0.40	0.30
Lexical decision task accuracy	0.94	0.09
Semantic classification task RTs	627.94	74.39
Semantic classification task accuracy	0.94	0.07
Speeded pronunciation RTs (Z-score)	-0.37	0.28
Speeded pronunciation accuracy	0.98	0.04

words. For ease of exposition, only step 3 effects are reported on Table 5.

The analyses yielded a number of noteworthy observations. First, as was expected, surface variables accounted for a substantial proportion of variance only in speeded pronunciation RTs. Second, as compared with Pexman et al. (2008), the lexical variables accounted for substantially more variance in all three tasks, due to the inclusion of more control variables. Third, as can be seen in Table 4, two semantic richness variables, NF and CD, accounted for additional unique variance across all tasks. In contrast, MSS–5000 influenced only lexical decision RTs, and latencies were shorter for words with neighbors that are more similar to them. In addition, number of senses had no effect on speeded pronunciation performance. However, there was a suggestive dissociation whereby words with more senses elicited shorter lexical decision times but less accurate semantic classification responses, although both effects were only marginally significant. Intriguingly, turning to NoA effects (Table 5), it is very clear that NoA did *not* reliably predict word recognition performance on any task. This cannot have been entirely due to attenuated statistical power as a function of fewer observations. Specifically, if one compares Tables 4 and 5, it is clear that the effects of the other semantic richness variables were broadly similar across both sets of analyses.

Although lexical-level variables collectively accounted for a substantial proportion of variance, it was surprising that some variables—notably, those capturing structural properties such as number of letters and orthographic distinctiveness (i.e., neighborhood and Levenshtein measures)—did not produce reliable effects in lexical decision and speeded pronunciation, which is inconsistent with other reports (e.g., Yap & Balota, 2009) based on large-scale datasets. The intercorrelations between the predictors in our dataset could be driving these discrepancies. For example, correlations were very high (rs $\geq .80$) between letter and syllable length, orthographic and phonological neighborhood size, and orthographic and phonological Levenshtein distance (see Tables 2 and 3). To address this multicollinearity, principal component analysis was used to combine these variable pairs to create length, neighborhood, and Levenshtein distance components, respectively. Although principal components are less straightforward to interpret, this is not a major issue for control variables (Baayen, Feldman, & Schreuder, 2006). Notably, the significant lexical effects observed in these principal component regression analyses (see Table 6) are more consistent with the extant literature, and critically, semantic richness effects were virtually identical across the different sets of control variables (compare Tables 4 and 6). NoA effects were also examined with principal component control variables, and, as before, they were not reliable on any measure (all ps $> .38$).

Discussion

The present study is the first to simultaneously examine the effects of a large array of objectively defined semantic richness measures on lexical decision, speeded pronunciation, and semantic classification. Replicating

Table 2 Correlations between predictor variables and dependent measures

Variable	1	2	3	4	5	6	7	8	9	10
1. Log frequency (Brysbaert & New, 2009)	-									
2. No. of morphemes	-.20***	-								
3. No. of syllables	-.43***	.31***	-							
4. No. of letters (length)	-.46***	.53***	.80***	-						
5. No. of orthographic neighbors	.43***	-.26***	-.62***	-.67***	-					
6. No. of phonological neighbors	.43***	-.29***	-.66***	-.67***	.80***	-				
7. Orthographic Levenshtein distance (Yarkoni et al., 2008)	-.51***	.43***	.78***	.91***	-.69***	-.67***	-			
8. Phonological Levenshtein distance (Yarkoni et al., 2008)	-.47***	.47***	.80***	.87***	-.61***	-.68***	.92***	-		
9. No. of features (McRae et al., 2005)	.29***	.05	-.06	-.03	.06	.07	-.04	-.05	-	
10. Mean semantic similarity-5000 (Shaoul & Westbury, 2010)	.83***	-.30***	-.34***	-.44***	.40***	.42***	-.47***	-.43***	.17***	-
11. Log contextual dispersion (Brysbaert & New, 2009)	.98***	-.18***	-.42***	-.44***	.42***	.43***	-.49***	-.46***	.30***	.79***
12. Log number of senses (Miller, 1990)	.53***	-.27***	-.42***	-.45***	.50***	.49***	-.49***	-.44***	.07	.56***
13. No. of associates (Nelson et al., 1998)	.28***	.02	-.07	-.01	.10†	.09†	-.05	-.04	.10*	.22***
14. Lexical decision task RTs (Z-score)	-.74***	.18***	.53***	.54***	-.45***	-.46***	.57***	.55***	-.27***	-.64***
15. Lexical decision task accuracy	.50***	.10*	-.17***	-.08†	.14**	.15**	-.14**	-.13**	.30***	.38***
16. Semantic classification task RTs	-.43***	.06	.20***	.19***	-.17***	-.13**	.14**	.12**	-.36***	-.31***
17. Semantic classification task accuracy	.23***	.05	-.11*	-.07	.09*	.06	-.02	-.01	.26***	.14**
18. Speeded pronunciation RTs (Z-score)	-.59***	.14**	.46***	.50***	-.45***	-.39***	.52***	.47***	-.22***	-.48***
19. Speeded pronunciation accuracy	.29***	.03	-.09*	-.06	.05	.06	-.08†	-.07	.15***	.23***

*** $p < .001$; ** $p < .01$; * $p < .05$; † $p < .10$

Table 3 Correlations between predictor variables and dependent measures

Variable	11	12	13	14	15	16	17	18	19
1. Log frequency (Brysbaert & New, 2009)									
2. No. of morphemes									
3. No. of syllables									
4. No. of letters (length)									
5. No. of orthographic neighbors									
6. No. of phonological neighbors									
7. Orthographic Levenshtein distance (Yarkoni et al., 2008)									
8. Phonological Levenshtein distance (Yarkoni et al., 2008)									
9. No. of features (McRae et al., 2005)									
10. Mean semantic similarity-5000 (Shaoul & Westbury, 2010)									
11. Log contextual dispersion (Brysbaert & New, 2009)	-								
12. Log number of senses (Miller, 1990)	.54***	-							
13. No. of associates (Nelson et al., 1998)	.29***	.14**	-						
14. Lexical decision task RTs (Z-score)	-.74***	-.50***	-.18***	-					
15. Lexical decision task accuracy	.52***	.27***	.10*	-.64***	-				
16. Semantic classification task RTs	-.44***	-.17***	-.12*	.53***	-.49***	-			
17. Semantic classification task accuracy	.24***	.05	.02	-.33***	.36***	-.76***	-		
18. Speeded pronunciation RTs (Z-score)	-.60***	-.40***	-.18***	.71***	-.51***	.44***	-.30***	-	
19. Speeded pronunciation accuracy	.30***	.15***	.06	-.39***	.47***	-.39***	.33***	-.39***	-

*** $p < .001$; ** $p < .01$; * $p < .05$; † $p < .10$

and extending earlier work by Pexman et al. (2008), it generated the following findings. First, as was previously demonstrated, the control lexical variables accounted for much more variance in lexical decision (ΔR^2 = 60%) and speeded pronunciation (ΔR^2 = 40%), as compared with semantic classification (ΔR^2 = 21%), while the semantic variables accounted for more variance in semantic classification (ΔR^2 = 7%), as compared with lexical decision (ΔR^2 = 2%) and speeded pronunciation (ΔR^2 = 2%). This is consistent with semantic classification's emphasis on the word's *meaning* and the other two tasks' emphasis on the word's *form*. Second, two of the semantic richness variables, NF and CD, facilitated responses across lexical decision, speeded pronunciation, and semantic classification, suggesting that they are not simply driven by idiosyncratic task-specific demands. Third, MSS–5000 affected only lexical decision times, whereby RTs were shorter for words with neighbors that were more similar to them. Fourth, words with many senses elicited shorter lexical decision times but less accurate semantic classification responses (although these trends only approached significance). Fifth, after other semantic richness measures were controlled for, NoA did not account for any unique variance. Finally, the correlations in Tables 2 and 3 show that the different measures of richness are, for the most part, only modestly correlated with each other.

Our results indicate that despite controlling for a comprehensive array of correlated lexical variables, reliable effects of semantic richness could be detected across a variety of lexical-processing tasks[3]. Even in a task such as speeded pronunciation, which ostensibly does not emphasize orthographic familiarity or require meaning to be computed, facilitatory effects of NF and CD were evident. This is compatible with the view that feedback activation from semantics to orthography and from semantics to phonology (Siakaluk et al., 2008) is a general property of visual word recognition and that the strength of semantic representations can be more reliably tapped by NF and CD than by MSS–5000, number of senses, and NoA. Indeed,

[3] One potential limitation of the present analyses is that they were based on a relatively small set of items (n = 505). To establish the generality of some of our findings, we obtained ELP lexical decision and speeded pronunciation latencies for 26,652 words that possessed values for CD, number of senses, and number of semantic neighbors. Using similar regression analyses, we found that in both tasks, recognition was faster for words associated with more contexts, senses, and neighbors (all ps < .01), broadly mirroring the reported trends.

Table 4 Standardized response times (RTs) and accuracy regression coefficients from steps 1 to 3 of the item-level regression analyses (n = 505) for lexical decision, speeded pronunciation, and semantic classification. The p-value for each R^2 change is represented with asterisks. Note that the regression coefficients reported reflect the coefficients entered in that particular step

Predictor Variable	LDT		Pronunciation		SCT	
	RT	Accuracy	RT	Accuracy	RT	Accuracy
Step 1: Onsets						
Adjusted R^2	.01†	.00	.14***	.00	.03**	.03**
Step 2: Lexical variables						
Log frequency	-.61***	.57***	-.43***	.35***	-.47***	.28***
No. of morphemes	-.09*	.13**	-.15***	.05	-.04	.10†
No. of syllables	.11*	-.15*	.13*	-.09	.14†	-.16†
No. of letters (length)	.11	.22*	.13	.03	.41***	-.36**
No. of ortho. neighbors	-.01	.00	-.10†	-.06	-.08	.08
No. of phono. neighbors	.02	.00	.10†	-.03	.14†	-.11
Ortho. Levenshtein distance	.03	-.02	.13	.02	-.46***	.44**
Phono. Levenshtein distance	.09	.00	.00	.05	-.08	.09
Adjusted R^2	.61	.28	.54	.07	.24	.12
Change in R^2	.60***	.28***	.40***	.07***	.21***	.09***
Step 3: Semantic variables						
No. of features	-.09**	.14***	-.09**	.06	-.24***	.19***
Mean semantic similarity-5000	-.12*	.05	.05	.02	-.01	.01
Log contextual dispersion	-.36**	.65**	-.45**	.25	-.68**	.60**
Log number of senses	-.07†	.05	-.04	.05	.08	-.10†
Adjusted R^2	.63	.31	.56	.07	.31	.16
Change in R^2	.02***	.03***	.02***	.00	.07***	.04***

*** p < .001; ** p < .01; * p < .05; † p <.10

LDT = lexical decision task; SCT = semantic classification task

we were surprised not to find reliable NoA effects on any measure (cf. Duñabeitia et al., 2008), which suggests that NoA effects may not be robust when one controls for other lexical and semantic variables.

It is worth noting that Pexman et al. (2008) also reported that denser semantic neighborhoods facilitated lexical decision performance but had no effect on semantic classification, consistent with the present analyses (see Table 4). The null effect of MSS-5000 in semantic classification could reflect the trade-off between close and distant neighbors, which respectively facilitate and inhibit semantic processing (Mirman & Magnuson, 2006). Future work could examine this intriguing interplay between close and distant semantic neighbors by parametrically manipulating the number of closest neighbors (e.g., MSS-50 vs. MSS-500 vs. MSS-5000).

Turning to multiple meanings, we found an intriguing dissociation whereby words with more senses yielded shorter lexical decision times but less accurate semantic classification responses. These trends, which approached statistical significance, are consistent with the idea that multiple meanings lead to greater semantic activation, which is beneficial in tasks that emphasize stimulus familiarity but can hurt performance when participants

Table 5 Standardized response times (RTs) and accuracy regression coefficients from step 3 of the item-level regression analyses (n = 389) for lexical decision, speeded pronunciation, and semantic classification, when number of associates is included in step 3

Predictor Variable	LDT		Pronunciation		SCT	
	RT	Accuracy	RT	Accuracy	RT	Accuracy
Step 3: Semantic variables						
No. of features	-.06†	.07	-.09*	.02	-.19***	.16**
Mean semantic similarity-5000	-.13*	.01	.06	-.10	-.07	.06
Log contextual dispersion	-.34†	.87**	-.57**	.05	-.47†	-.11
Log number of senses	-.04	.11†	-.10*	.08	.10†	-.11
Number of associates	.01	-.05	.00	.04	-.01	-.04

*** p <.001; ** p <.01; * p <.05; † p < .10

LDT = lexical decision task; SCT = semantic classification task

Table 6 Standardized response times (RTs) and accuracy regression coefficients from steps 1 to 3 of the item-level regression analyses (n = 505) for lexical decision, speeded pronunciation, and semantic classification. The p-value for each R^2 change is represented with asterisks. Note that the regression coefficients reported reflect the coefficients entered in that particular step

Predictor Variable	LDT		Pronunciation		SCT	
	RT	Accuracy	RT	Accuracy	RT	Accuracy
Step 1: Onsets						
Adjusted R^2	.01†	.00	.14***	.00	.03**	.03**
Step 2: Lexical variables						
Log frequency	-.61***	.57***	-.43***	.35***	-.46***	.27***
No. of morphemes	-.09**	.17***	-.16***	.06	.00	.08
Length component	.21**	-.03	.24***	-.08	.44***	-.43***
Neighborhood component	.01	-.03	.00	-.09	.05	-.03
LD20 component	.13†	.08	.13†	.09	-.46***	.46***
Adjusted R^2	.61	.28	.54	.07	.23	.12
Change in R^2	.60***	.28***	.40***	.07***	.20***	.09***
Step 3: Semantic variables						
No. of features	-.09**	.14***	-.09**	.06	-.24***	.19***
Mean semantic similarity-5000	-.12*	.03	.05	.01	.00	.00
Log contextual dispersion	-.35*	.65**	-.43*	.25	-.65**	.57*
Log number of senses	-.07†	.06	-.05	.05	.08	-.11†
Adjusted R^2	.63	.31	.56	.07	.30	.16
Change in R^2	.02***	.03***	.02***	.00	.07***	.04***

*** $p < .001$; ** $p < .01$; * $p < .05$; † $p < .10$

LDT = lexical decision task; SCT = semantic classification task

need to resolve the specific meaning of a word. The absence of a number-of-senses effect on semantic classification RTs is interesting and is consistent with recent demonstrations that although ambiguity effects may not be reflected in semantic classification RTs (Pexman, Hino, & Lupker, 2004), they can be detected using neuroimaging techniques (Hargreaves et al., 2011). Of course, despite its greater objectivity, number of senses is, at best, a crude proxy for ambiguity, since it does not distinguish between related and unrelated multiple definitions. Nonetheless, the present results are intriguing and merit further investigation.

Conclusions and future directions

The present study further underscores the multidimensionality of word meaning and the task-generality and task-specificity of semantic richness effects. Intriguingly, both the strength and direction of a semantic effect can be systematically modulated by the specific demands of a task, consistent with a flexible lexical-processing system that relies on attentional mechanisms to optimize information processing for accomplishing the goals of any given lexical-processing task (Balota & Yap, 2006).

An important methodological advantage of the present work is that all semantic richness measures examined are objectively defined metrics based on corpus statistics or normative data derived from either feature listing or free association tasks. For this reason, semantic variables such as imageability and age of acquisition were excluded. Although these have been well-studied in the literature, they are defined by subjective ratings, and it is not entirely clear what dimensions participants rely on to drive their ratings. However, future work could more systematically tease apart the effects of objectively and subjectively defined semantic measures.

In addition, we have suggested that semantic richness can be captured by a number of dimensions, some of which (e.g., number of features and neighborhood density) are more unequivocally semantic. However, dimensions such as CD may reflect both lexical–semantic representations and episodic traces, indicating that the distinction between "lexical" and "semantic" is better conceptualized as continuous than as categorical. It is also noteworthy that semantic richness measures accounted for relatively little variance in the present study, particularly in lexical decision and speeded pronunciation performance. One might argue that these effects, although statistically reliable, are not substantive. In response to this, semantic variables typically explain far less variance than do lexical variables (see Balota et al., 2004), and it is worth reiterating that these effects were reliable after controlling for many lexical variables, including an optimized word frequency measure. More crucially, the theoretical importance of an effect cannot be fully gauged by its magnitude. For example, spelling-to-sound consistency typically accounts for very little variance in word recognition performance, but this variable imposes critical constraints on the mechanisms that mediate print and speech in computational models. In the same way, by highlighting the pervasiveness, adaptability, and multidimensionality of semantic richness effects, we hope to better characterize the dynamic contribution that word meaning makes to visual word recognition.

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