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Predicting semantic priming at the item level

Keith A. Hutchison [a]; David A. Balota [b]; Michael J. Cortese [c]; Jason M. Watson [d]
[a] Montana State University, Bozeman, MT, USA [b] Washington University in Saint Louis, Saint Louis, MO, USA [c] University of Nebraska at Omaha, Omaha, NE, USA [d] University of Utah, Salt Lake City, UT, USA

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Predicting semantic priming at the item level

Keith A. Hutchison
Montana State University, Bozeman, MT, USA

David A. Balota
Washington University in Saint Louis, Saint Louis, MO, USA

Michael J. Cortese
University of Nebraska at Omaha, Omaha, NE, USA

Jason M. Watson
University of Utah, Salt Lake City, UT, USA

The current study explores a set of variables that have the potential to predict semantic priming effects for 300 prime–target associates at the item level. Young and older adults performed either lexical decision (LDT) or naming tasks. A multiple regression procedure was used to predict priming based upon prime characteristics, target characteristics, and prime–target semantic similarity. Results indicate that semantic priming (a) can be reliably predicted at an item level; (b) is equivalent in magnitude across standardized measures of priming in LDTs and naming tasks; (c) is greater following quickly recognized primes; (d) is greater in LDTs for targets that produce slow lexical decision latencies; (e) is greater for pairs high in forward associative strength across tasks and across stimulus onset asynchronies (SOAs); (f) is greater for pairs high in backward associative strength in both tasks, but only at a long SOA; and (g) does not vary as a function of estimates from latent semantic analysis (LSA). Based upon these results, it is suggested that researchers take extreme caution in comparing priming effects across different item sets. Moreover, the current findings lend support to spreading activation and feature overlap theories of priming, but do not support priming based upon contextual similarity as captured by LSA.

The semantic priming paradigm is the most popular method used to gain insight into the organization and retrieval of semantic knowledge (see Hutchison, 2003, McNamara, 2005; McNamara & Holbrook, 2003; Neely, 1991, for reviews). In most semantic priming studies, researchers ask participants either to pronounce aloud or to make lexical (i.e., “word” or “nonword”) decisions to target items. The semantic priming effect refers to the observation that people respond faster to a target word (e.g., *pepper*) when it is preceded by a semantically related prime (e.g., *salt*) rather than by an unrelated prime (e.g., *head*).

After 30 years of investigation, researchers have identified a large set of variables that modulate

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Correspondence should be addressed to Keith Hutchison, Dept. of Psychology, 304 Traphagen Hall, College of Letters and Science, Montana State University, Bozeman, MT 59717–3440, USA. E-mail: khutch@montana.edu

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the semantic priming effect (see Neely, 1991, for a review). However, simple demonstrations of factor level influences of priming effects are no longer the only focus of research as researchers have become more interested in investigating item differences in priming. For instance, several researchers have recently investigated the influence of prime–target associative strength and/or feature overlap in semantic priming. In doing so, researchers interested in semantic priming now face challenges long encountered by other psycholinguistic researchers when "selecting" items high versus low on a particular dimension. It is to these problems that we now turn.

Limitations of standard factorial semantic priming studies

Balota, Cortese, Sergent-Marshall, Spieler, and Yap (2004) identified several problems with the traditional factorial design as it is applied to the word recognition literature. These problems include (a) "matching" of item sets across related and unrelated conditions, (b) researchers' own implicit knowledge influencing selection of items, (c) list context effects potentially modulating the size of obtained effects, and (d) categorizing continuous variables. Traditionally, semantic priming researchers have worried little about such item selection confounds because they counterbalance their targets (and sometimes primes) across related and unrelated conditions. However, as researchers test for interactions between priming and item types (such as obtaining greater priming for items sharing a large overlap in semantic features) the item-selection problems of psycholinguistic research now equally apply to semantic priming studies (see Forster, 2000, for a discussion).

Item matching

It is now well recognized that it is very difficult to select words that vary on only one categorical dimension (see Cutler, 1981). For example, if one wanted to compare reaction time (RT) to high- versus low-frequency words then one would have to ensure that the two sets were matched on all other possible factors. A few of these other factors include length, regularity, consistency, bigram frequency, onset, orthographic neighbourhood, meaningfulness, and concreteness, each of which has been shown to influence performance on word recognition tasks. Moreover, even if the sets were equated on all possible known factors, there would undoubtedly be additional variables discovered in the future that could be confounded across the high- and low-frequency sets. Indeed, researchers have found semantic priming to be influenced by such potentially confounding factors as target frequency (Becker, 1979), regularity/consistency (Cortese, Simpson, & Woolsey, 1997), and concreteness (Bleasdale, 1987). This problem is at least as great in semantic priming research where one must not only match the "related" and "unrelated" targets on all these factors, but also match the primes. This creates a problem if one of these factors covaries with the researcher's variable of interest. For instance, target frequency is often confounded with common priming variables such as type of relation (semantic vs. associative, see Hutchison, 2003). Targets that are "strong associates" of their primes (e.g., the target *cheese* for the prime *mouse*) are typically higher in frequency than are nonassociated, yet semantically related, targets (e.g., the target *gerbil* for the prime *mouse*). As such, the fact that low-frequency words show greater priming should be taken into consideration when interpreting the results from such studies. It is likely that primes and targets in such sets differ on many additional variables that also influence priming.

Implicit knowledge

A second problem concerns researchers' implicit knowledge of variables that influence lexical processing. Forster (2000) asked expert word recognition researchers to repeatedly guess which of two words (controlled for frequency and length) would produce faster RTs in a LDT. The expert researchers were able to make accurate predictions among word pairs already matched on word frequency and length. It is therefore possible that researchers designing experiments could have some implicit knowledge of which words will "work" in each set to produce the desired effects. In semantic priming experiments, some pairs of items might be judged a priori as "good" or "bad" for producing priming (even if equated on a common factor such as association strength). Indeed, McKoon and Ratcliff (1992) provided an empirical demonstration using their own intuition to predict nonassociated items that show priming.

List context effects

A third problem is that list contexts often vary across experiments. Balota et al. (2004) noted that this problem is probably due to researchers selecting items that have extreme values on the variable of interest for use in a factorial design. Selecting extreme items on a certain characteristic could make that characteristic more salient to participants. Glanzer and Ehrenreich (1979) and Gordon (1983) have found that even simple word frequency effects in LDTs are modulated by the relative proportion of high- versus low-frequency words in the list.

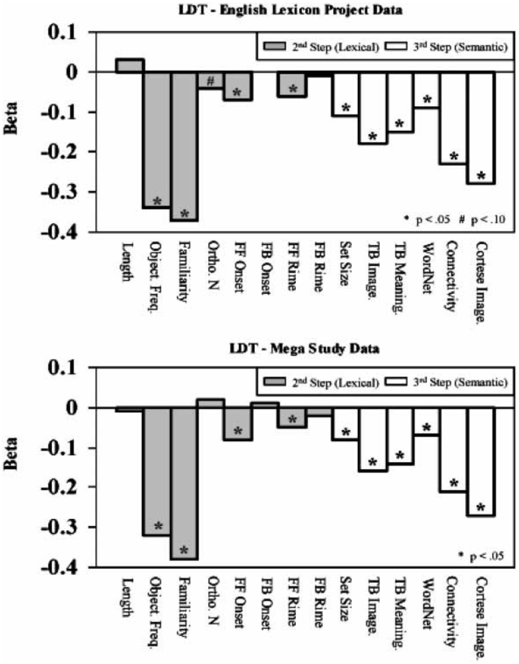
In semantic priming studies, it is generally understood that list context influences the amount of priming observed (see Neely, 1991, for a review). In these studies, list context has usually been defined as the proportion of related items in the experiment, with a higher relatedness proportion (RP) increasing the contribution of conscious strategic processes to priming (Hutchison, Neely, & Johnson, 2001; Stolz & Neely, 1995; see Hutchison, in press, for a review). However, more specific context effects also exist, such as the proportion of a particular type of relation. For instance, McKoon and Ratcliff (1995) showed that priming for synonym and antonym pairs was influenced by the proportion of synonym and antonym filler pairs in the list, even when overall RP was equated. In addition, McNamara and Altarriba (1988) showed that priming for mediated associates (e.g., *lion–stripes*) in LDTs disappeared when mixed in a list with direct associates (e.g., *salt–pepper*). Also, priming for perceptually similar pairs (e.g., *carrot–paintbrush*) appears to require a sufficiently high proportion of such items for participants to consciously direct their attention to such features (Hutchison, 2003). Finally, it is possible to influence semantic priming by adding items with certain lexical characteristics. In one example, Joordens and Becker (1997) found that adding pseudohomophones (e.g., *brane*) to the list of nonwords increased the size of priming effects in lexical decision, presumably by explicitly requiring semantic, as opposed to lexical, activation in order to verify that each item is in fact a real English word. A similar effect of context may occur in the pronunciation task by adding words with irregular pronunciations (e.g., *pint*) to a list (Zevin & Balota, 2000).

Categorizing continuous variables

A fourth problem is a reduction in statistical power and reliability that occurs when categorizing continuous predictor variables (Cohen, 1983; Humphreys, 1978; Maxwell & Delaney, 1993; see MacCallum, Zhang, Preacher, & Rucker, 2002, for simulations of how such categorization can decrease reliability). Specifically, although association norms (the most common measure of semantic relation) provide a continuous rating of how likely people are to provide a certain response to a cue word, most of this potentially valuable information is lost when grouping items in "related" and "unrelated" conditions. Moreover, if a measure of relatedness such as association strength is truly meaningful, it should capture the magnitude of priming, not just its presence or absence (McRae, De Sa, & Seidenberg, 1997).

Utility of large-scale databases

In the psycholinguistic literature, there have been recent attempts to minimize the limitations with standard factorial designs by examining speeded RTs across large datasets (Balota et al., 2004; Balota & Spieler, 1998; Besner & Bourassa, 1995; Kessler, Treiman, & Mullennix, 2002; Spieler & Balota, 1997; Treiman, Mullennix, Bijeljac-Babic, & Richmond-Welty, 1995). For example, Balota et al. (2004) analysed RTs and errors derived from 60 participants in lexical decision (30 young and 30 old) and 60 participants in naming (30 young and 30 old) who responded to 5,812 and 2,870 stimuli each, respectively. From these items, Balota et al. were able to identify surface, lexical, and semantic variables that influenced performance. In addition, Balota et al. were able to replicate patterns from previous studies (e.g., the Frequency × Orthographic Neighbourhood size interaction in word recognition) and also provide some insight into the reason for past inconsistencies and debates (e.g., the facilitatory vs. inhibitory effects of orthographic neighbourhood). Moreover, Balota et al. showed that semantic variables such as imageability and connectivity predicted variance in RTs even after surface and lexical factors were partialled out. In an even more comprehensive study, Balota et al. (in press) have compiled RT and error rates from 1,258 participants (816 in LDT and 444 in naming) on a total of 40,481 words and 40,481 nonwords. These data are available online at http://elexicon.wustl.edu/. Researchers are able to use this large database to select materials for experiments, identify variables of interest, and test theoretical models. Interestingly, Balota et al. (2004) demonstrated that selecting the same single-syllable items from the English Lexicon Project (ELP) provided a clear replication of their original study of 30 young and 30 older adults. In fact, as shown in Figure 1, the lexical decision and naming results from the ELP provide an almost perfect replication of the reliability and size of the 14 regression coefficients used in the first study. Hence, these large databases are quite stable with respect to relatively large sets of predictor variables.


LDT - English Lexicon Project Data

LDT - Mega Study Data

Figure 1. *Regression beta weights for 14 variables used to predict reaction time (RT) in the English Lexicon Project (ELP) and Spieler and Balota (1997) "Mega-Study" databases. Cortese image = the Cortese and Fugett (2004) imageability measure; TB meaning = the Toglia and Battig (1978) meaningfulness measure; TB image = the Toglia and Battig imageability measure; FB rime = feedback rime consistency; FF rime = feedforward rime consistency; FB onset = feedback onset consistency; FF onset = feedforward onset consistency; ortho N = orthographic neighbourhood; object freq. = objective frequency.*

Current experiment

The current experiment was designed as a first step in exploring variables that influence semantic priming in a large-scale database. Both young and older adults each responded to 300 targets preceded by a related, unrelated, or neutral prime word. We included two age groups because there has been some controversy regarding the size of priming effects in young and older adults (see Laver & Burke, 1993, and Myerson, Ferraro, Hale, & Lima, 1992). Although older adults often produce larger priming effects than do young adults, the slope of the young–old RT function varies greatly across studies. Explanations for the differences in priming vary as well, with some models positing a general slowing factor (Salthouse, 1985), others positing age-related slowing of sensory processes paired with spared spreading activation (Balota & Duchek, 1988), and others positing an age-related enrichment of semantic interconnectivity (Laver & Burke, 1993). Importantly, however, these previous studies have not investigated standardized priming effects, by converting each

RT to a *z*-score based on the subject's mean and standard deviation, as a function of age group (see Faust, Balota, Spieler, & Ferraro, 1999). The different procedure used in the present study should shed some light on age-related differences in priming when group differences in RT and variability are controlled.

Given recent arguments by Stolz, Besner, and Carr (2005), we were also interested in the reliability of priming effects. In particular, Stolz et al. argued that, although robust at the group level, the degree of priming for individual participants show little test–retest or split-half reliability. We believe that part of the difficulty with obtaining reliable priming effects may reflect individual variation in overall RTs. The *z*-score standardization minimizes the contribution of this individual variation. Indeed, as described below, the present results yield clear evidence for reliable priming effects.

The current study included a multiple regression analysis to estimate the degree to which different characteristics predict the degree of semantic priming. Each predictor variable fell into one of three categories: prime–target relatedness, target characteristics, and prime characteristics. The rationale for choosing each of these categories is expanded below.

Prime–target relatedness

The best way to capture "relatedness" in semantic priming is controversial. For instance, the words *cat* and *dog* not only are associated (*dog* is given as the most frequent response to the cue *cat* in word association norms), but also share a large overlap in their semantic features (they both have fur and claws and are both members of the pet category) and tend to appear in the same linguistic contexts (they co-occur with similar other words or in the same paragraphs in text). As a result, priming effects from such items could be due to lexical association, semantic feature overlap, or contextual similarity.

Whether semantic priming is due to association strength or feature overlap between concepts has been at the centre of considerable discussion, with some researchers obtaining evidence favouring feature overlap (McRae & Boisvert, 1998; Moss, Ostrin, Tyler, & Marslen-Wilson, 1995) and others for association strength (Balota & Paul, 1996; Lupker, 1984; Shelton & Martin, 1992). In her meta-analysis of the semantic priming literature, Lucas (2000) found an overall effect of semantic relatedness on priming among studies claiming a lack of association in their stimuli. In a later review, Hutchison (2003) instead argued that there was no evidence of automatic priming for categorical items lacking an association (e.g., *horse–deer*, see Lupker, 1984; Shelton & Martin, 1992, for similar conclusions) because many "pure-semantic" studies actually contained moderate-to-strong associations among their stimuli. However, Hutchison did concede, based upon a couple of reviewed studies, that some degree of feature overlap (in particular, items sharing a functional relation) may also produce priming independent of association. In contrast to the relatively sparse evidence for featural priming effects, Hutchison argued there was strong evidence for priming based purely on association. Thus, although the issue is still debated, a tentative conclusion is that priming is produced both by association and somewhat by feature overlap.

Recently, semantic priming studies have also been used to support high-dimensional semantic space models (Lund, Burgess, & Atchley, 1995; Lund, Burgess, & Audet, 1996; Landauer & Dumais, 1997). These models begin with calculations of local contiguity between words and either the paragraphs in which they occur or other words co-occurring within a prespecified window (usually between 3–10 words). A large matrix (e.g., 30,000 rows by 30,000 columns, as in the "latent semantic analysis", LSA, model) is then constructed, and data reduction techniques similar to factor analysis produce factors (around 300) to represent types of meaning (or context) in which words appear. Semantically similar words (e.g., *road* and *street*) tend to co-occur in the same contexts (co-occur with the same other words or in the same paragraphs) and hence are said to have similar representations. Preliminary evidence suggests that these models can accurately capture semantic priming effects (Landauer & Dumais, 1997; Lund et al., 1995, 1996). In fact, Chwilla and Kolk (2002) discovered that prime–target items used in mediated priming experiments (e.g., *lion–stripes*) tend to show a weak-to-moderate relation in Landauer's LSA model. Therefore, priming for these items may actually be due to direct computation of contextual similarity, rather than spreading activation across a mediated concept. This is a critical issue as mediated priming is perhaps the strongest evidence for spreading activation models of semantic memory (see Hutchison, 2003, for a review).

The variables chosen for the current investigation were forward associative strength (FAS, the proportion of participants in word association norms who gave a particular related target when given a prime as a cue), backward associative strength (BAS, the proportion of participants who gave a particular related prime when given a target as a cue), and LSA similarity (see explanation above). FAS and BAS were taken from the Nelson, McEvoy, and Schreiber (1999) word association norms and were chosen because (a) they are by far the most common measure of semantic relatedness, and (b) their effects on priming are clearly predicted in semantic priming models such as Neely and Keefe's (1990) three-process model.[1] According to the three-process model, priming is composed of spreading activation, conscious expectancy, and strategic semantic matching. In this model, it is predicted that FAS will have a larger influence at longer stimulus onset asynchronies (SOAs) for both LDT and naming. Presumably, longer SOAs allow participants time to consciously make use of the prime word to generate potential related targets. In addition, BAS is predicted to have a larger influence on priming in LDT than in naming. Neely and Keefe (1990) hypothesized that semantic matching in the LDT only occurs at longer SOAs because prime processing is still incomplete at short SOAs. For this reason, we predict that BAS will have its largest effect in predicting priming at the longer SOAs. LSA similarity was chosen because it is representative of current high-dimensional semantic space models of semantic memory and is increasingly being used to explain semantic priming effects (Arambel & Chiarello, 2006; Chwilla & Kolk, 2002). LSA similarity between primes and targets was obtained via the LSA website (http://lsa.colorado.edu/) using the suggested topic space of 300 factors, which corresponds to a general reading level (up to 1st year of college). If priming is due to the type of contextual similarity comparison captured by LSA, then we would predict LSA to predict priming across SOAs, but perhaps to a greater extent at the shorter SOAs where priming is presumably driven more strongly by automatic processing and less by the type of conscious expectancy generation, which may instead favour FAS.

Target characteristics

As noted previously, several item variables have been shown to influence word recognition performance. For example, Becker (1979) found larger semantic priming for low-frequency than high-frequency words. One simple account of this interaction is that the greater time to respond to low-frequency words allows a related prime more opportunity to affect responding. The influence of other variables such as length and orthographic neighbourhood could produce a similar effect. Perhaps any characteristic (or manipulation) that slows down target responding will boost the effect of a related prime. The current study can examine this issue, since the participant-based *z*-score transform used in the present study should not reduce the influence of "item" differences in baseline RT. The important question is, "does an item with a standardized baseline RT that is relatively slow produce more

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[1] Our choice of the Neely and Keefe three-process model to motivate the selection of the forward and backward variables was driven by the fact that this model makes clear predictions regarding the role of these variables in priming. We do not mean to imply that other priming models are not available or that this model is not without its critics (see Neely, 1991, or McNamara, 2005, for discussions of the three-process model's shortcomings).

priming than an item with a standardized baseline RT that is relatively fast?" This question is of critical importance for studies using different sets of items across conditions.

In addition to including the targets' average response latencies in the neutral prime condition, we also included predictor variables known to influence word recognition latencies (length, frequency, and orthographic neighbourhood). If indeed a target's length, frequency, and orthographic neighbourhood influence priming primarily through delaying overall RT then these variables should have minor effects relative to the effect of neutral RT. If instead these variables influence priming for other reasons, then they should predict unique variance independent of baseline response latencies.

Prime characteristics

The third category that we investigated is the item characteristics (length, frequency, orthographic neighbourhood) of the related or unrelated prime. This category of predictors may prove to be critical for future semantic priming studies. The reason is that researchers usually place more emphasis on counterbalancing targets across conditions than they do primes. If prime characteristics were found to influence priming, then the results of any study failing to counterbalance primes across related and unrelated conditions could be questioned.

As with the target characteristics, we decided to use a neutral RT for each prime word as an additional predictor. Because participants did not respond to primes in this experiment, we derived these neutral RTs from the ELP database. One possible outcome is that primes that are difficult to process will disrupt processing of the target and interfere with priming. This could occur because delayed identification of the prime (a) precludes identification and/or responding to the target, (b) prevents the generation of expected targets, or (c) disrupts attempts to semantically match the target with the prime in order to make a "word/nonword" response. In every case, delayed prime processing should have a greater effect at short SOAs, where processing of the prime item is still engaged when the target is presented.

Method

Participants

A total of 108 younger adults and 95 older adults participated in the study. The younger adults were Washington University undergraduate psychology students who participated for course credit. The older adults (>65 years of age) were recruited from the Washington University Aging and Development subject pool. Each older adult participant was paid $10.00 for his/her participation. All participants were native English speakers with normal or corrected-to-normal vision.

Stimuli

There were 300 prime words and 300 target words. Stimulus characteristics of the primes and targets are provided in Table 1. Related targets were the primary associates of the primes based on the Nelson et al. (1999) norms. The related primes and targets were recombined to create the unrelated pairs such that the new pairs were not associated according to the Nelson et al. norms (i.e., forward and backward associate strength = .00). For the lexical decision task, pronounceable nonwords were constructed by changing one or two letters of the target words, and care was taken to ensure that none of the nonwords were pseudohomophones (i.e., *brane*). For each task, three lists were constructed, with each list consisting of 100 target words preceded by a related prime, 100 target words preceded by an unrelated prime, and 100 target words preceded by a neutral prime (i.e., the word BLANK). The assignment of the targets to condition was originally determined randomly. Then, the lists were counterbalanced so that each target occurred equally often in the related, unrelated, and neutral conditions across participants. For each task, the lists were divided into four blocks of stimuli consisting of 25 of each type of pairing (i.e., related, unrelated, neutral). In the lexical decision task, 75 prime–nonword pairs were intermixed in each block of stimuli with 75 prime–word pairs. The order of

Table 1. *Means, standard deviations, and ranges for the predictor variables used in the regression analyses*

Predictor variables		*Mean*	*SD*	*Range (min, max)*
Prime	Unrelated prime length	5.44	1.84	(2, 11)
	Unrelated prime log frequency	8.52	2.10	(0, 15)
	Unrelated prime ortho	4.21	5.27	(0, 23)
	Unrelated prime RT_{elp}	646	58	(549, 860)
	Related prime length	5.44	1.84	(2, 11)
	Related prime log frequency	8.52	2.10	(0, 15)
	Related prime ortho	4.21	5.27	(0, 23)
	Related prime RT_{elp}	646	58	(549, 860)
Target	Target length	4.83	1.12	(3, 8)
	Target log frequency	10.10	1.57	(0, 14)
	Target ortho	5.55	5.08	(0, 21)
	*z*_neutral RT_LDT	0.00	0.30	(−0.67, +1.14)
	*z*_neutral RT_naming	0.00	0.32	(−0.80, +1.08)
	Neutral err_LDT	.02	.03	(.00, +.26)
	Neutral err_naming	.01	.05	(.00, +.34)
Associative/semantic	FAS	.66	.12	(.28, .94)
	BAS	.21	.22	(.00, .90)
	LSA	.51	.21	(.05, .96)

Note: ortho = orthographic neighbourhood; RT_{elp}= reaction time according to the English Lexicon Project (Balota et al., in press); *z* = *z*-score transformation of reaction time; neutral RT = reaction time in the neutral priming condition; LDT = lexical decision task; naming = naming task; FAS = forward associative strength; BAS = backward associative strength; LSA = latent semantic analysis similarity rating.

the blocks were also counterbalanced across participants such that each block appeared equally often as the first, second, third, or fourth block of trials in the experiment.

Procedure

A PC with a 133-MHz processor running in DOS mode controlled the experiment. A 17-inch monitor was set to 40-column mode for stimulus presentation. A voice key (Gerbrands G1341T) connected to the PC's real-time clock was used to obtain response latencies to the nearest ms.

Stimuli were presented one at a time at the centre of the computer monitor in white uppercase letters against a black background. The order of presentation was random within each block. The lexical decision task consisted of four blocks of 150 trials, and the naming task consisted of four blocks of 75 trials. In each task, the experimental trials were preceded by 10 practice trials. Participants were asked to pay attention to the first stimulus (which was always a word) and respond to the second stimulus (which was either a word or a nonword in the lexical decision task and always a word in the naming task). In the naming task, the target was read aloud, and in the lexical decision task, a word/nonword decision was made on the target. In the lexical decision task, a word decision was indicated by pressing a key labelled "YES" (the "/" key on the keyboard), and a nonword decision was indicated by pressing a key labelled "NO" (the "z" key on the keyboard). The instructions for both tasks emphasized both speed and accuracy. Each trial began with a blank screen for 2,000 ms followed by a fixation mark (+) appearing at the centre of the screen for 1,000 ms. After the fixation mark, the prime appeared either for 200 ms (250-ms SOA) or 1,000 ms (1,250-ms SOA). The prime was followed by a blank screen for 50 ms or 250 ms. The blank screen was replaced by the target, which remained on the screen until the initiation of the vocal response (naming) or a key was pressed (lexical decision). In the lexical decision task, correct responses were followed by a blank screen for 1,500 ms. For incorrect responses, a 200-Hz sound occurred for 750 ms along with a message stating "incorrect response", and this statement was followed by a blank screen for 750 ms. In the naming task, the experimenter coded the trial as correct, incorrect, or noise (some extraneous noise triggered the voice key or it failed to be triggered by the reading response). The coding of the response was followed by a 2,000-ms interval between trials. A mandatory 1-minute break occurred after each block of trials.

Results

The z-score transformation of reaction times (RTs)

Faust et al. (1999) demonstrated a linear relation between a group's (e.g., older adults vs. younger adults) baseline RT and that group's numerical priming effect, when priming was measured as millisecond difference scores between a related and unrelated condition. Faust et al. argued that Group × Treatment interactions (or lack thereof) are not easily interpreted in the face of such differences in baseline RT. Hutchison (2003) identified a similar difficulty with comparing priming across tasks such as naming versus LDT that differ in complexity (and thus in baseline RT). In general, effect sizes will increase as a function of variance in the measure, rendering it difficult to compare effect sizes across tasks or subject groups when there are differences in variance. Faust et al. recommend a *z*-score transformation of RTs in such cases because it corrects for differences in processing speed and variability across groups (or individuals within a group). The resulting priming score for each group (or individual) is expressed in standard deviation units. Using Monte Carlo simulations, Faust et al. demonstrated that this transformation effectively reduced Type I errors. Analyses on our dataset confirmed the necessity for Faust et al.'s (1999) *z*-score correction procedure.

Trimming RTs (between 200–1,500 ms for naming; 200–3,000 ms for LDT) led to the elimination of 2.8% of the overall RTs. The trimmed RTs in the neutral baseline condition were slower for older adults than for younger adults, for LDT participants than for naming participants, and for those receiving a long SOA than for those receiving a short SOA.

Table 2 displays RTs for the baseline, unrelated, and related conditions as well as priming effects expressed as raw RT and *z*-score transformed differences between unrelated and related conditions. Using traditional raw difference scores (unrelated RT − related RT), priming was greater for those participants in the LDT (56 ± 6 ms) than for those in the naming task (27 ± 6 ms), $F(1, 202) = 38.44$, $MSE = 477$, and greater for those in the long-SOA condition (52 ± 6 ms) than for those in the short-SOA condition (30 ± 6 ms), $F(1, 202) = 23.13$, $MSE = 509$. There was no priming difference between the young (40 ± 6 ms) and older participants (43 ± 7 ms), $F < 1$.

Standardized RTs were then examined by transforming each reaction time into a standard score based upon the participants' overall RT. Using standardized priming scores, we again found greater priming at the long-SOA condition (.45 ± .05 *SD*) than at the short-SOA condition (.29 ± .05 *SD*), $F(1, 202) = 20.56$, $MSE = 333$. However, the difference in priming between tasks was now eliminated ($F < 1$), with an equal degree of priming in the LDT (.39 ± .05 *SD*) and naming tasks (.35 ± .06 *SD*). Hence, the typical finding of greater priming in LDT than in naming may reflect the traditional examination of priming scores based on raw (or trimmed) means as opposed to *z*-score transformed means, in which numerical increases in the priming effect (presumably due to the decision component of the task) would be counteracted by equivalent increases in variability.[2] This can be further seen in Table 2 by examining the numerical versus *z*-score priming effects for young adults at the long SOA. A numerical 60 ms of priming in the LDT translated to a +0.45 standardized difference whereas a numerical 37 ms of priming in

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[2] It is important to note that claiming equivalence in the effect size of semantic priming across tasks is not the same as claiming equivalence in the *processes* that contribute to such effects. Variables have been identified at the sublexical, lexical, and semantic level that affect performance differently in the two tasks (see Balota et al., 2004, for a review).

Table 2. *Means, standard deviations, and ranges for the dependent variables separated by task, group, and stimulus onset asynchrony*

Task	*Group*	*SOA*	*Measure*	*Mean*	*SD*	*Range (min, max)*
Lexical decision	Young	Short	Baseline RT	615	90	(468, 917)
			Unrelated RT	610	85	(465, 959)
			Related RT	568	81	(419, 888)
			Priming (ms)	+42	126	(−297, +359)
			Priming (*z*-score)	+0.37	0.55	(−1.17, +2.46)
		Long	Baseline RT	641	75	(491, 887)
			Unrelated RT	651	73	(494, 870)
			Related RT	591	76	(440, 848)
			Priming (ms)	+60	107	(−202, +347)
			Priming (*z*-score)	+0.45	0.47	(−1.0, +2.43)
	Old	Short	Baseline RT	760	76	(622, 1102)
			Unrelated RT	775	78	(636, 1049)
			Related RT	727	75	(573, 1008)
			Priming (ms)	+48	91	(−237, +446)
			Priming (*z*-score)	+0.33	0.49	(−0.86, +2.06)
		Long	Baseline RT	857	102	(668, 1239)
			Unrelated RT	870	102	(673, 1232)
			Related RT	797	91	(601, 1074)
			Priming (ms)	+73	121	(−282, +451)
			Priming (*z*-score)	+0.39	0.55	(−1.18, +2.30)
Naming	Young	Short	Baseline RT	486	37	(415, 619)
			Unrelated RT	492	33	(404, 593)
			Related RT	474	32	(398, 569)
			Priming (ms)	+18	44	(−165, +150)
			Priming (*z*-score)	+0.28	0.58	(−2.00, +2.25)
		Long	Baseline RT	502	36	(414, 605)
			Unrelated RT	504	34	(383, 600)
			Related RT	467	35	(348, 579)
			Priming (ms)	+ 37	41	(−82, +145)
			Priming (*z*-score)	+ 0.51	0.52	(−1.00, +1.98)
	Old	Short	Baseline RT	635	58	(484, 787)
			Unrelated RT	643	58	(481, 787)
			Related RT	627	53	(493, 778)
			Priming (ms)	+16	84	(−244, +228)
			Priming (*z*-score)	+0.18	0.69	(−1.68, +2.06)
		Long	Baseline RT	657	57	(533, 798)
			Unrelated RT	659	54	(526, 818)
			Related RT	619	53	(491, 781)
			Priming (ms)	+40	76	(−183, +230)
			Priming (*z*-score)	+0.46	0.54	(−0.97, +1.99)

Note: SOA = stimulus onset asynchrony; RT = reaction time; *z*-score = *z*-score transformation of reaction time; priming = difference in reaction time between unrelated and related prime conditions.

the naming task translated to a +0.51 standardized difference. Finally, although we found equal priming for young and older adults using raw difference scores, there was a marginal interaction between age and relatedness when examining *z*-scores, $F(1, 202) = 2.85$, $MSE = 362$, with younger adults actually showing greater priming (.40 ± .05 *SD*) than older adults (.34 ± .05 *SD*). This contrasts with previous studies (Balota & Duchek, 1988; Laver & Burke, 1993; Myerson et al., 1992) and hints that older adults' priming effects may actually be smaller than younger adults' priming effects once overall RT and variability are controlled. For the present purposes, the important point is that the *z*-score transformation appears to produce a quite different picture compared to when overall differences in speed and variability are not adequately controlled.

Reliability of priming scores across participants and items

Another potential benefit to standardizing priming scores within individuals is the potential for greater power in detecting within-subject priming effects (Faust et al., 1999). this benefit is due to correcting for individual differences in both speed and variability across conditions (i.e., all participants are now on the same scale with respect to effects of the condition). This transformation therefore reduces variance in the priming measure across participants (see Bush, Hess, & Wolford, 1993, for more discussion on the benefits of *z*-score transformations on reaction time data).

As mentioned previously, Stolz et al. (2005) demonstrated that participants' individual priming effects show weak reliability. When 50% of the word trials were related (the same relatedness proportion, RP, as that used in the present study), Stolz et al. found reliable test–retest reliability effects in LDT of .30, .43, and .27 for their 200-, 350-, and 800-ms SOAs, respectively. However, when only 25% of word trials were related, these reliability estimates dropped to −.06, .18, and −.04, respectively. Stolz et al. concluded that priming effects were noisy and variable, particularly under relatively automatic conditions.

The precaution from Stolz et al. (2005) certainly warrants concern for the current study. Namely, if indeed the reliability of priming across participants is noisy and variable, then perhaps a regression analysis of priming across items is pointless because (by definition) one cannot predict random variability. However, it is possible that the *z*-score transformation will eliminate much of the variability in priming for items. As mentioned above, our procedure first transforms each RT into a *z*-score for every participant to obtain a measure of how long it took that person to respond to each item relative to his/her overall RT. Thus, what remains is a standardized distribution of item RTs for each participant. It is predicted that (a) the standardized distribution of item RTs will be similar across individuals (i.e., split-half reliability across subjects for standardized item RTs in the neutral condition), and (b) items will systematically differ in the amount of priming they receive (i.e., split-half reliability across subjects for standardized item priming effects.)

In order to test the first prediction, we averaged each item's trimmed or standardized baseline RT (using the procedures discussed above) separately for odd- and even-numbered participants. After applying the Spearman–Brown correction for split-half reliability, we obtained reliabilities of .75 for the trimmed RTs and .79 for the *z*-score transformed RTs. Both effects were highly significant ($p < .001$). When broken down by task, we obtained *r*s of .64 and .66 for our trimmed means and standardized means in the LDT, respectively, and .55 and .71 for these respective means in the naming task. Again, all effects were highly significant ($p < .001$).

To test the second prediction, we did the same odd–even split for priming effects (unrelated condition − related condition). We obtained a Pearson r of .08 for the trimmed RTs and .61 for the *z*-score transformed RTs. Only the *z*-score transformed data were significant ($p < .001$). When broken down by task, we obtained *r*s of .41 and .40 for our trimmed means and standardized means in the LDT, respectively, and *r*s of .26 and .51 for these respective means in the naming task. Thus, it appears that the naming task is particularly sensitive to the standardization procedure, and one main reason the standardization increased reliability in priming in the overall estimate is by controlling for task differences in baseline RT. These reliability estimates demonstrate that there is indeed some explainable (i.e., predictable) variability in priming across items.

A third test was performed to examine the odd/even split-half reliability of baseline error rates and priming effects measured in errors. For the baseline analysis, we obtained an overall Pearson r of .46 ($p < .001$). When broken down by task, we obtained rs of .35 and .41 for error rates in the LDT and naming, respectively. Both effects were highly significant ($p < .001$). For the priming analysis, we obtained an overall Pearson r of .35 ($p < .001$). When broken down by task, we obtained rs of .32 and .44 for error rates in the LDT and naming, respectively. Again, both effects were highly significant ($p < .002$).

Overall, these data suggest that one can obtain reliable priming estimates once RTs are standardized across individuals. These data are within approximately the same range as those reported by Stolz et al. (2005) with the same relatedness proportions of .5. Future studies will be needed to determine whether standardizing the RTs increases reliability of priming when the relatedness proportion is reduced.

Regression analyses: Task × SOA

We conducted two hierarchical regression analyses for both the RT z-scores and errors to examine item priming effects in the LDT and naming task. The predictor variables used in these regression analyses are shown in Table 1. By collapsing over age, we were able to obtain more stable estimates of priming per item in each SOA (18 observations in each relatedness condition per item in LDT; 16 observations in each relatedness condition per item in naming). We conducted additional analyses collapsing over SOA as well to further increase the stability of our predictors in LDT and naming (36 and 32 observations per condition, respectively). We used the z-score priming effects, rather than the raw priming effects, in order to increase the predictability of our measures by reducing the amount of error variance in the dependent variable. Indeed, regression analyses on raw priming effects rather than standardized priming effects consistently yielded much smaller R-squared estimates. For instance, our predictor variables were able to account for 16% of variance in overall priming using raw priming estimates and 25% of variance in overall priming using standardized priming estimates. The 25% of predicted variance is impressive, given that our reliability analysis indicated that only 61% of priming variance was “explainable”.

The prime variables entered into the regression model included length, number of orthographic neighbours, frequency, and average RT (collapsed across LDT and naming) of the related and unrelated primes according to the ELP database (Balota et al., in press). The ELP RT estimates were included in addition to other prime characteristics to capture whether latency to respond to a prime word would increase or decrease priming.

The target characteristics entered in the regression model included length, number of orthographic neighbours, frequency, and baseline RT (or baseline error rate) averaged across all subjects within either the LDT or naming task of the current experiment. Because previous research has shown that priming effects are positively correlated with subjects’ baseline RTs (Faust et al. 1999), it is predicted that item differences in baseline RT (and possibly error rate) will also correlate with item differences in priming. What is not known, however, is whether item differences in RT will account for additional variance in priming effects above and beyond that explained by the lexical variables of length, orthographic neighbourhood, and frequency. Of all the predictor variables entered, target length appeared to have a relatively restricted range ($M = 4.83$, $SD = 1.12$) due to the deliberate selection of target words between 3 and 8 letters long. In fact, a vast majority of these targets (85%) were between 4 and 6 letters long. Therefore, results should be interpreted with caution as the ability of target length to predict priming may be underestimated in the current analysis.

The associative/semantic predictors were forward associative strength (FAS), backward associative strength (BAS), and semantic similarity as measured by LSA. The LSA estimates were based upon 300 underlying factors—the default number of factors suggested for most studies and estimated to mimic the semantic space of people at a general reading level up to the first year of college.[3] Of particular interest was whether associative strength or semantic similarity would account for any variance in priming above and beyond that explained by prime and target lexical characteristics.

Predictor variable intercorrelations. Examination of Table 3 reveals that there were strong intercorrelations among the prime, target, and associative/semantic predictor variables used in the regression analyses. Prime length was negatively correlated with prime frequency and prime orthographic neighbourhood. Thus shorter primes had higher frequency and more orthographic neighbours than did longer primes. Replicating Balota et al. (2004), RT for primes (derived from the ELP database) and targets were longer for low-frequency primes, long primes, and primes with few orthographic neighbours. In addition, prime length was positively correlated with target length, and prime frequency was positively correlated with target frequency for related primes, suggesting that people tend to free associate to items with other items similar in length and frequency (e.g., respond *negative* to cue *positive*). An examination of all single-word cues and targets (70,707 pairs) in the Nelson et al. (1999) norms revealed a significant correlation ($r = .164$, $p < .001$) between cue and target word length, indicating that this is indeed a general phenomenon.

Consistent with the primes, target length was negatively correlated with target frequency and orthographic neighbourhood and positively correlated with target baseline RT. We also replicated Balota et al. (2004) in finding a positive correlation between each item's baseline RTs and error rates in the LDT and its RTs and error rates in the naming task.

Turning to the associative/semantic level, FAS was negatively correlated with target length, and BAS was negatively correlated with prime length, revealing that shorter words are more often given as word association responses. This pattern was also replicated in the more extensive Nelson et al. (1999) norms, with significant Pearson r correlations of −.075 and −.125 between FAS and target length and BAS and prime length, respectively. In the current data, BAS was also positively correlated with both prime frequency and prime orthographic neighbourhood, whereas FAS was positively correlated with target orthographic neighbourhood. LSA similarity values were positively correlated with prime frequency and negatively correlated with prime RT for both related and unrelated primes. Finally, although there was no correlation between FAS and BAS, both variables were positively correlated with LSA. Because of these intercorrelations between variables, it is important that all variables are entered simultaneously in the regression model to afford an estimate of each variable's unique contribution to priming.

Regression coefficients. The beta weights for the 15 variables used to predict priming in the current experiment are shown in Figure 2 separated by task. What is immediately apparent is how consistent the predictors were across tasks. In fact, only 3 of the 15 variables produced beta weights in numerically different directions across tasks. This pattern is significantly lower than one would expect by chance ($z = 2.32$, $p < .001$) indicating stable and reliable patterns of prediction. The ability of each variable to predict priming in each of the Task × SOA conditions is elaborated below.

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[3] Of the 300 prime–target pairs, 8 were eliminated from all analyses because, due to chance repairing, the "unrelated" pairs (e.g., *flesh–knife*) had higher LSA scores than the corresponding related pairs (e.g., *dagger–knife*, with LSA values of .49 and .27 for the unrelated and related pairs, respectively). Although a couple of these pairs (such as the example above) make intuitive sense and may be eliminated prior to an experiment through careful scrutiny by experimenters, the "relation" for most of these unrelated pairs is not intuitively obvious (e.g., *avenue, insane, crazy* for the unrelated prime, related prime, and target, respectively).

Table 3. *Intercorrelations among predictor variables used in the z-score and error regression analyses*

	U_len	*U_Fre*	*UOrth*	*U_RT*$_{elp}$	*R_len*	*R_Fre*	*R_Orth*	*R_RT*$_{elp}$	*T_Len*	*T_Fre*	*T_Orth*	*Neut_L*	*Neut_N*	*Neut_Lerr*	*Neut_Nerr*	*FAS*	*BAS*	*LSA*
U_len	1	−.25**	−.62**	.55**	.03	−.00	−.03	.07	.03	−.06	.02	−.01	.03	.00	.04	.06	−.04	.05
U_Fre		1	.22**	−.54**	−.08	−.02	.06	−.02	−.04	−.07	−.05	−.02	−.01	.09	.05	−.04	.06	−.07
U_Orth			1	−.41**	−.07	−.02	.05	−.05	−.04	.05	−.03	.02	−.01	.00	−.03	−.02	.05	.00
U_RT$_{elp}$				1	.02	.02	−.02	.09	.04	.00	.00	.00	.00	.03	.11	.10	−.02	.06
R_len					1	−.25**	−.62**	.54**	.18**	−.01	−.05	.01	−.01	−.02	.03	−.09	−.34**	−.05
R_Fre						1	.22**	−.53**	−.04	.50**	−.05	−.11	−.18**	.00	−.03	−.02	.47**	.17**
R_Orth							1	−.39**	−.06	.01	.01	−.01	−.04	.02	.00	.02	.28**	.08
R_RT$_{elp}$								1	.07	−.21**	−.01	.06	.06	.02	.03	.03	−.42**	−.18**
T_Len									1	−.22**	−.66**	.24**	.34**	−.02	−.01	−.20**	.05	−.01
T_Fre										1	.17**	−.33**	−.31**	−.15*	−.09	.07	.03	−.03
T_Orth											1	−.07	−.18**	.05	.08	.14*	−.15*	−.03
Neut_L												1	.47**	.39**	.10	−.11	.03	−.08
Neut_N													1	.24**	.11	−.15**	−.02	−.07
Neut_L$_{err}$														1	.19**	−.02	.14*	.06
Neut_N$_{err}$															1	−.10	.01	.03
FAS																1	−.02	.14*
BAS																	1	.29**
LSA$_{rel}$																		1

Note: U = unrelated prime; R = related prime; T = target; len = length; Fre = logarithmic transformation of printed word frequency according to the Hyperspace Analog to Language database (Lund & Burgess, 1996); Orth = orthographic neighbourhood; RT$_{elp}$= reaction time according to the English Lexicon Project (Balota et al., in press); Neut = Neutral prime condition; Neut_Lerr = errors in the neutral prime condition for lexical decision; Neut_Nerr = errors in the neutral prime condition for naming. FAS = forward associative strength; BAS = backward associative strength; LSA = latent semantic analysis similarity rating.

$^{*}p < .05$. $^{**}p < .01$.

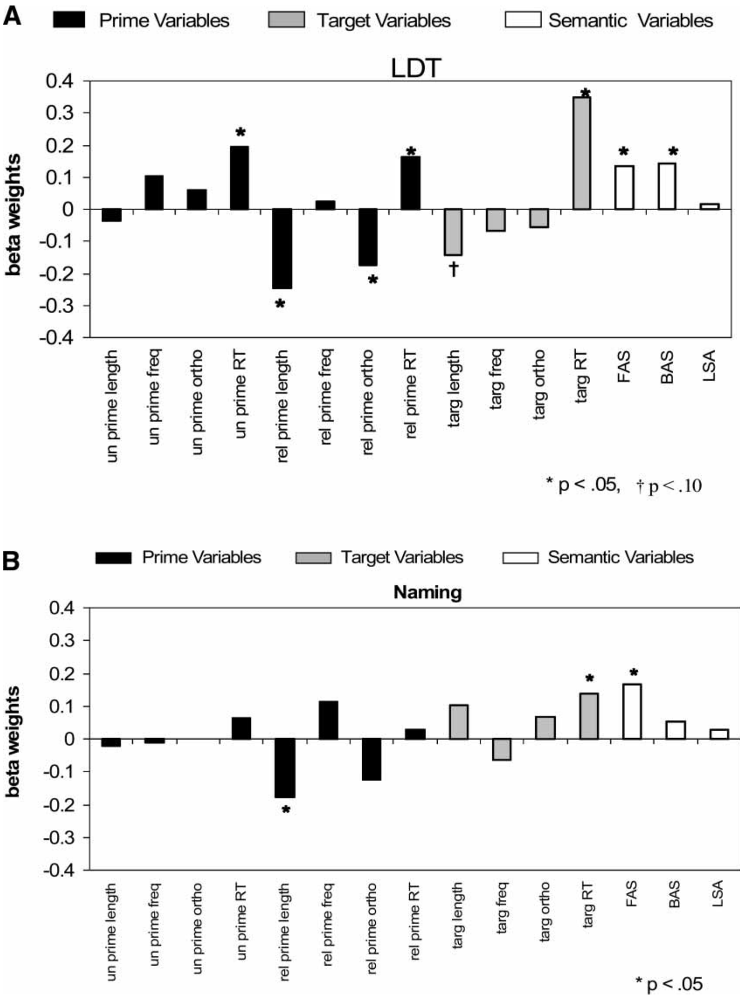

Figure 2. *Beta weights for 15 variables used to predict z-score priming effects in (A) the current lexical decision task (LDT) and (B) naming task. LSA = latent semantic analysis similarity index; FAS = Nelson et al.'s (1999) forward associative strength measure; BAS = Nelson et al.'s (1999) backward associative strength measure; ortho = orthographic neighbourhood; targ = target; rel = related prime; un = unrelated prime; RT = reaction time according to the English Lexicon Project (Balota et al., in press); freq = logarithmic transformation of printed word frequency according to the Hyperspace Analog to Language database (Lund & Burgess, 1996).*

Prime characteristics. The standardized priming regression coefficients are given in Table 4 for *z*-score priming and in Table 5 for error priming. For the *z*-score priming, related prime length had reliable effects in both LDT and naming with standardized beta coefficients of −.24 and −.18, respectively. For related prime orthographic neighbours, the standardized beta coefficient was −.17 in LDT but a nonsignificant −.12 in naming ($p > .10$). As with prime length, the effect of prime orthographic neighbourhood is greater at a short SOA. Finally, the RT_{elp} (reaction time according to the ELP) estimates for both unrelated and related primes predicted priming in LDT (standardized beta coefficients of .16 and .19, respectively), but not in naming. Thus, priming in the LDT is increased following primes that produce slow RTs in the ELP

Table 4. *Standardized regression coefficients predicting z-score transformed priming effects for lexical decision and naming performance as a function of SOA and overall*

		LDT			*Naming*		
Variables		*Short*	*Long*	*Overall*	*Short*	*Long*	*Overall*
Prime	Unrelated prime length	−.04	−.01	**−.03**	.00	−.03	**−.02**
	Unrelated prime log frequency	.08	.08	**.10**	−.07	.05	**−.01**
	Unrelated prime ortho	.01	.07	**.06**	−.07	.07	**.00**
	Unrelated prime RT_{elp}	.14†	.16*	**.19****	−.02	.12	**.07**
	Related prime length	−.27**	−.13	**−.24****	−.19*	−.08	**−.18***
	Related prime log frequency	.13	−.07	**.02**	.17†	.00	**.11**
	Related prime ortho	−.19*	−.10	**−.17***	−.18*	−.01	**−.12**
	Related prime RT_{elp}	.03	.21**	**.16***	.00	.06	**.03**
Target	Target length	−.02	−.19*	**−.14†**	.06	.10	**.10**
	Target log frequency	−.10	−.02	**−.07**	−.12	.03	**−.07**
	Target ortho	.11	−.17*	**−.06**	.10	.00	**.07**
	z_neutral RT	.26***	.29***	**.35*****	.13†	.08	**.14***
Associative/semantic	FAS	.12*	.09	**.13***	.06	.20**	**.17****
	BAS	.00	.21**	**.14***	−.09	.19*	**.05**
	LSA	−.02	.04	**.02**	.09	−.05	**.03**
	R−squared	*.17****	*.21****	*.25****	*.09**	*.10**	*.10**

Note: SOA = stimulus onset asynchrony; LDT = lexical decision task; ortho = orthographic neighbourhood; log frequency = logarithmic transformation of printed word frequency according to the Hyperspace Analog to Language database (Lund & Burgess, 1996); RT_{elp}= reaction time according to the English Lexicon Project (Balota et al., in press); neutral = performance in the neutral prime condition; FAS = forward associative strength; BAS = backward associative strength; LSA = latent semantic analysis similarity rating.

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

database, and this pattern appears greater at the long SOA. When collapsed across task, priming at the short SOA was significantly greater for short primes, frequent primes, and primes with few orthographic neighbours. In contrast, priming at the long SOA was affected only by the prime's baseline RT, with longer RT_{elp}estimates predicting greater priming effects.

For the error analysis, no variables significantly predicted priming across both tasks. The only beta coefficient to reach significance was greater priming in the LDT following low-frequency related primes at the long SOA.

Target characteristics. The target variables were length, frequency, orthographic neighbourhood, and standardized RTs and error rates for items in the neutral condition. The baseline was chosen from either the LDT or the naming task depending upon the dependent variable used in the regression analysis. As predicted, target variables had an influence on priming effects. Overall, priming was greater for targets that had long baseline RTs, especially in the LDT (standardized beta coefficients of .35 and .14 for the LDT and naming task, respectively). At the long SOA, priming in the LDT was greater for short targets and targets with few orthographic neighbours (standardized beta coefficients of −.19 and −.17, respectively).

The error analysis resembled the RT analysis in that priming was influenced by the variables of target length (standardized beta coefficients of −.21 and −.15 in LDT and naming) and baseline RT (standardized beta coefficients of .27 and .19 in LDT and naming). In addition, marginally greater priming was found for targets that produced fewer errors in the baseline condition, but only in the short-SOA LDT condition.

Semantic characteristics. An examination of the beta coefficients revealed that only FAS and BAS

Table 5. *Standardized regression coefficients predicting error priming effects for lexical decision and naming performance as a function of SOA and overall*

		LDT			*Naming*		
Variables		*Short*	*Long*	*Overall*	*Short*	*Long*	*Overall*
Prime	Unrelated prime length	.03	−.12	**−.06**	−.07	−.01	**−.06**
	Unrelated prime log frequency	.09	.11	**.13†**	.01	−.08	**−.04**
	Unrelated prime ortho	.08	−.06	**.01**	−.11	−.04	**−.10**
	Unrelated prime RT_{elp}	.05	.08	**.09**	−.07	−.11	**−.11**
	Related prime length	−.02	.03	**.01**	−.02	.07	**.04**
	Related prime log frequency	.07	−.27**	**−.14**	−.08	.13	**.02**
	Related prime ortho	−.04	.03	**.00**	−.05	−.09	**−.09**
	Related prime RT_{elp}	.02	−.03	**−.01**	−.07	−.01	**−.06**
Target	Target length	−.19*	−.13	**−.21***	.03	−.27**	**−.15†**
	Target log frequency	−.08	−.03	**−.08**	.08	−.07	**.02**
	Target ortho	−.03	−.05	**−.06**	.01	−.14†	**−.08**
	z_neutral RT	.23**	.19**	**.27*****	.14*	.15*	**.19****
	Target neutral errors	−.12†	−.07	**−.12†**	−.02	−.01	**−.03**
Associative/Semantic	FAS	−.10	.07	**−.01**	.18**	.04	**.15***
	BAS	−.05	.22**	**.13†**	.00	.07	**.05**
	LSA	.01	−.03	**−.02**	−.04	−.07	**−.08**
	R−squared	*.08*	*.13***	*.13***	*.06*	*.08*	***.08***

Note: SOA = stimulus onset asynchrony; LDT = lexical decision task; ortho = orthographic neighbourhood; log frequency = logarithmic transformation of printed word frequency according to the Hyperspace Analog to Language database (Lund & Burgess, 1996); RT_{elp}= reaction time according to the English Lexicon Project (Balota et al., in press); z_neutral = standardized performance in the neutral prime condition; FAS = forward associative strength; BAS = backward associative strength; LSA = latent semantic analysis similarity rating.

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

accounted for significant amounts of variance in priming. For the LDT, FAS significantly predicted priming at a short SOA, and BAS significantly predicted priming at a long SOA. For naming, both FAS and BAS predicted priming at a long SOA, but neither measure predicted priming at the short SOA. When collapsed across task, priming at the short SOA was significantly predicted by FAS only (standardized beta coefficient of .12), whereas priming at the long SOA was significantly predicted by both FAS and BAS (standardized beta coefficients of .19 and .24, respectively). LSA similarity did not predict priming in any of the four Task × SOA conditions.

In the error analysis, FAS had a significant predictive effect in the naming task at a short SOA whereas BAS had a significant effect in the LDT at a long SOA. Consistent with the RT analyses, the LSA measures did not predict priming in any condition.

Discussion

Several important findings emerged from the current analyses, perhaps the most important of which is that priming effects in both the LDT and naming task are reliable and can be predicted based upon item characteristics. The finding of predictable priming in the LDT and naming tasks opens up the possibility for research investigating the critical predictors of semantic priming. In addition, even though priming effects were numerically larger in the LDT (as they often are), the standardized priming effects were equivalent in naming and LDT tasks. Both tasks showed the same increase in RT following a related than following an unrelated prime, relative to the overall RT and variability produced by the task. In addition, young adults were found to have marginally larger standardized priming effects than older adults. This pattern is opposite to the typical pattern found for unstandardized RTs. Finally, the regression analyses produced significant predictors of semantic priming. Some of these predictors exerted dissociable effects either across tasks or across SOAs. The main findings for each of the three types of variables entered into the regression equation are discussed below.

Prime characteristics

Priming was greater when related primes were short and had few orthographic neighbours. These effects were especially pronounced at the short SOA, where priming was also greater following high-frequency related primes. This pattern makes intuitive sense in that related primes that are quickly identified can exert a greater influence on recognition of the target, especially at short SOAs where quick identification of the prime is critical. Interestingly, there was a general effect of prime RT (computed through ELP) in which priming in the LDT is increased following primes that produce slow RTs in the ELP database. This mainly occurred at the long SOA. It is unclear why this would have occurred, especially given the zero correlation between prime RT and target RT (see Table 3). Clearly, further research is needed to investigate the generalizability of this effect.

The obtained effect of prime characteristics on semantic priming has implications for any experiment that (a) uses different primes for the related and unrelated conditions or (b) examines priming from different sets of prime–target pairs. In either case, there is a possibility that the primes either across conditions or across item sets differ in baseline RT, length, frequency, or orthographic neighbourhood. As shown above, all of these confounds have the potential for exerting an influence on the size of the observed priming effect.

Target characteristics

A strong predictor of priming in both z-score and error analyses was the target items' baseline RT in the neutral condition. This positive relation was greater in the LDT than in naming, indicating that items that are difficult to classify show a greater benefit from related primes than do items that are easily classified. This may be another example of the well-established finding that slower target processing leads to larger priming effects (Becker & Killion, 1977; Stanovich & West, 1979). At the long SOA, z-score priming in the LDT was greater for short targets with few orthographic neighbours. Error priming was also greater for short targets, though this effect occurred at the short SOA for LDT and long SOA for naming. One possible explanation is the $-.20$ correlation between target length and FAS. Shorter target words tend to have higher associative strength to their primes than do longer words. As evidence for this explanation, the partial correlation between z-score priming in LDT and target length (controlling for FAS) was .00; however, the partial correlation between z-score priming in LDT and FAS (controlling for target length) was .15 ($p < .01$). Thus, target length is unrelated to priming once its shared variance with FAS is partialled out.

As with the prime characteristics, researchers examining priming using different sets of prime–target pairs run the risk of confounding target item characteristics with priming effects. In addition to the continued need to counterbalance targets across related and unrelated conditions, it is recommended that researchers examining differences in priming across different sets of items first demonstrate that their target items are matched in baseline RT as well as length, frequency, and other potential confounds. This can be done either by pretesting or through the ELP online database (Balota et al., in press).

Semantic relatedness measures

Priming at the short SOA was predicted by FAS only, with effects in z-scores for LDT and errors for naming. FAS also contributed to priming at the long SOA, but this effect was only significant in the naming task. Consistent with Neely and Keefe's (1990) version of semantic matching, BAS predicted priming for LDT only at the long SOA. BAS also predicted LDT priming in errors at the long SOA as would be expected if semantic matching produced a bias to respond "word" or "nonword". There was no effect of

BAS in predicting error priming in naming. Interestingly, BAS did predict *z*-score priming at the long SOA in the naming task. This finding appears to be inconsistent with Neely's (1991) three-process model in which backward semantic matching influences priming in the LDT, but not naming. This assumption stems partially from evidence from "backward priming" studies in which items sharing an asymmetrical association (e.g., stork–baby) typically show priming at long SOAs only in the LDT and not in naming (Kahan, Neely, & Forsythe, 1999; see Hutchison, 2003, for a review). It is indeed unlikely that participants strategically engage in semantic matching in naming, since checking back to see whether the prime is related would not help you pronounce the target. Therefore, the current evidence suggests that BAS may play a role in priming beyond the strategic type of semantic matching described in the three-process model. However, it should be noted that with this exception, these data are remarkably consistent with the Neely framework. Specifically, BAS had more of an overall effect in LDT than in naming, and the effect of BAS was much stronger at the long SOA in both RTs and errors in LDT than in naming. Finally, FAS predicted priming in both naming and LDT in errors and/or response latencies.

The LSA similarity measure failed to predict priming in either the LDT or naming task. This "null" predictability is not due to a restriction of range as LSA similarity values ranged from .05 to .96 with a standard deviation of .21 (compared to ranges of .28 to .94 for FAS and .0 to .90 for BAS).[4] Thus, LSA similarity did not predict priming effects at the item level in either task or at either SOA, even though the LSA estimates were much higher for the current related items (LSA = .49) than unrelated items (LSA = .08), $t(191) = 29.5$.

Perhaps the failure of LSA to predict priming at the individual-item level may have occurred in the presence of preserved ability to predict priming at more intermediate levels. To test this possibility, we conducted median splits on LSA, FAS, and BAS and then performed a between-item *t*test on priming effects for each of these measures. There was a nonsignificant 0.00 ± 0.06 difference in *z*-score priming between items high (.68) and low (.33) in LSA similarity ($t < 1$). In contrast, items high in FAS (.76) showed 0.08 ± 0.06 more *z*-score priming than did items low in FAS (.56), $t(280) = 2.92$, and items high in BAS (.38) showed marginally 0.05 ± 0.05 more *z*-score priming than did items low in BAS (.03), $t(280) = 1.75$.

We also tested the upper versus lower quartiles in each of the three measures. This analysis replicated the median split analysis. Specifically, there was a nonsignificant 0.03 ± 0.09 difference in *z*-score priming between items high (.79) and low (.24) in LSA similarity ($t < 1$). In contrast, items high in FAS (.81) showed 0.14 ± 0.08 more *z*-score priming (.46) than did items low in FAS (.52), $t(140) = 3.28$, and items high in BAS (.55) showed 0.10 ± 0.08 more *z*-score priming than did items low in BAS (.01), $t(139) = 2.49$.

For our final analysis, we subtracted the LSA similarity values for the unrelated pairs from the related pairs to derive an "LSA difference score". Both the median and quartile splits on this LSA difference variable failed to predict priming (both *t*s < 1.2). We can therefore confidently conclude that, although LSA accurately predicted that priming would occur overall in our experiment, it failed in predicting which items would produce priming and which items would not.

The failure of LSA to predict priming at the item level casts some doubt on claims that high dimensional semantic space models such as LSA

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[4] Indeed it is much more likely that FAS suffered a restricted range problem than LSA. Examination of Table 1 reveals that the variance in FAS ($M = .66$, $SD = .11$) was much less than backward associative strength ($M = .21$, $SD=.22$) and LSA ($M = .51$, $SD = .21$). As with target length, items were chosen that were high in FAS. As a result, 98% of the items had FAS of .50 or higher. In contrast, the range of items in BAS and LSA was 0.0 to .90, and .05 to .96, respectively. It is therefore likely that the ability of FAS to predict priming was underestimated in this study. Nonetheless, FAS did an adequate job of predicting priming in both tasks.

can accurately capture semantic priming effects. Similar to LSA, other high dimensional semantic space models such as the Hal model (Lund et al., 1995, 1996) and the BEAGLE model (Jones, Kintsch, & Mewhort, 2006) have been demonstrated to accurately predict semantic priming from their stimuli. However, as with LSA, these demonstrations have focused only at predicting overall priming effects, not item-level effects. A challenge therefore is for semantic space models to capture not only overall priming effects from factorial studies, but also item-by-item differences in magnitude in priming as a function of semantic similarity. Based on the current analyses, associative strength measures passed this second test, whereas LSA did not.

As mentioned previously, the results are broadly consistent with Neely's three-process model, which suggests that priming occurs through the processes of spreading activation, expectancy generation, and backward semantic matching. The finding that only FAS predicted priming at the short SOA is consistent with the model's assumption that priming at short SOAs is driven primarily by spreading activation. In addition, the model accurately predicts that BAS should play a larger role in the LDT and at longer SOAs because participants are more likely to check back to determine whether the target is related to the prime prior to responding. Finally, these results are also consistent with feature overlap theories of semantic priming because most associated pairs also share a large overlap in semantic features (see Hutchison, 2003, for a discussion). However, because feature overlap models generally make no predictions concerning *directionality* of association, the pattern of FAS versus BAS effects more strongly supports spreading activation models than feature overlap as the impetus for priming (but see Plaut, 1995; Plaut & Booth, 2000, for a model that combines priming based upon both association and feature overlap).

Is association strength an "empty variable"?

On the surface, associative strength measures have considerable face validity. What better measure is there than associative strength to capture our intuitive notion of priming: that one concept "brings to mind" another concept? However, it is important to remember that association norms are themselves dependent measures. Using one dependent measure to predict another measure is not necessarily "explaining" the target phenomenon of interest. Instead, one might more appropriately ask "what drives the association itself?" In this case, the goal for psycholinguists is to remove association norms as explanatory constructs and replace them with explanations for why words are likely to co-occur in the first place. Of course, this is precisely the goal of feature-based models and semantic similarity models, but our initial attempt to test this possibility with LSA was not successful. Here it is important to remember that word association responses reflect several distinct types of relations (e.g., contiguity in text, script relations, functional relations, category coordinates) making it unlikely that all associations are based upon one particular type of relation (see Hutchison, 2003). Moreover, it is possible that once two items are associated it no longer matters what type of relation or circumstances initially caused them to be paired together (i.e., classical conditioning). Based upon the current paper, it is clear that association strength does a good job of accounting for priming data. Therefore, before simply dismissing association norms as emptyvariables, alternative models of semantic priming must demonstrate that they can at least match predictions made by association strength alone.

Limitations and concerns

Despite the increase in understanding the characteristics of semantic priming, there are some inevitable methodological limitations and theoretical concerns that accompany such an analysis. Undoubtedly, the most obvious issue is our limited selection of predictor variables. We chose item characteristics that were theoretically motivated and relatively easily available. However, there are several other potentially important variables that also need to be included in future analyses of this type. Three categories of such variables are discussed below.

Sublexical variables including grapheme-to-phoneme regularity and word-body consistency should be included in future regression studies. Cortese et al. (1997) demonstrated that semantic priming was larger for irregular target words than for regular words. However, it is unclear whether or not the effect of target regularity is exerted through increasing overall target RT or through some other mechanism. Adding target regularity into a regression analysis similar to the current analysis may answer this question. Unfortunately, a large percentage of the current items (over 30%) involve multisyllabic words, and there are not well established norms of regularity for multisyllabic words. In addition, Zevin and Balota (2000) demonstrated greater effects of lexicality, frequency, and imageability following a string of irregular words than following nonwords. The authors suggested that participants can adjust the relative contribution of lexical and sublexical information depending upon the context (i.e., usefulness of grapheme-to-phoneme correspondence rules). A reasonable prediction is that one would obtain greater priming following irregular primes than following regular primes (but see Kinoshita & Lupker, 2003, for an alternative interpretation of such route priming results).

There are also additional semantic relatedness variables that should be included in future regression analyses. The most obvious omission from the current study is prime–target feature overlap. Feature overlap norming procedures require an extremely large amount of time and participants. A single participant may provide a list of features for about 20 words in an hour, and each word should be rated by at least 20 participants for stable estimates (see McRae et al., 1997, for an example). Because at least 600 additional participants would therefore be needed in order to compare feature overlap for the 600 words (300 targets and 300 primes) used in the current study, we decided to restrict our relatedness analysis to the readily available FAS, BAS, and LSA norms. Hopefully, future large-scale studies can incorporate feature overlap from such a large group of items. In a study using a relatively small sample of 100 prime–target items, McRae et al. (1997) had participants perform a feature listing task and found that feature overlap accounted for a significant amount of variance in priming in a category verification task. Thus, such an undertaking could indeed provide theoretically important results. It is unclear whether the McRae et al. results would hold when the other variables of the current analysis are also included in the regression model and/or when examining LDT or naming tasks that do not explicitly require access to semantic information to make a decision.

A final concern about associative strength was recently raised by Anaki and Henik (2003). These authors argued that associative *rank order* from word association norms is a more important determinant of priming than is associative *strength*. According to Anaki and Henik, perhaps all that matters is that the item is given as a response at all, and the strength of such a response is irrelevant. Indeed, Anaki and Henik (Exp. 1) found no difference in LDT priming between weak associates ($FAS = .10$) and strong associates ($FAS = .42$) as long as the item was the primary associate to the cue in word association norms. It is unclear why Anaki and Henik found no effect of FAS while the present study did. An obvious difference is that our study included a regression approach, which partialled out variables that could have masked the predictive power of associative strength on priming effects. A second possibility is that our prime–target pairs were stronger on average than those used in their study. The average FAS used in our study was .65, which was 23% higher than that of the "strong" group used by Anaki and Henik. Also, we only had three items with FAS less than .50. Thus, the different results may be partially due to a restriction of range for FAS on the part of both studies. Generalizability may be particularly difficult based upon the Anaki and Henik study because they only included 72 pairs, in comparison to the 300 pairs in the present study. To explore this issue in more detail, future studies should use the full range of FAS and also include associative rank order as another variable by including targets that are second, third, or fourth associative responses rather than only using primary responses.

CONCLUSIONS

To summarize, we obtained evidence that semantic priming is a reliable phenomenon that can be predicted on an item-by-item basis. Priming was related to both target and prime characteristics including length, orthographic neighbourhood, and baseline RT. These variables will need to be carefully controlled in any future experiment that investigates differences in priming across item sets. In addition, priming was greater for items high in FAS and BAS whereas LSA similarity had little to no ability to distinguish priming among related pairs. These results lend support to spreading activation models of priming (and perhaps feature-overlap models), but do not support the LSA model based upon contextual similarity. It is hoped that this study will encourage future regression studies using a larger set of items and additional theoretically motivated predictor variables.

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APPENDIX

The 300 items used in the current study with three measures of semantic relatedness, the raw priming effects in the lexical decision and naming tasks, and the *z*-score transformed priming effects.

Unrelated prime	*Related prime*	*Target*	*FAS*	*BAS*	*LSA*	*LDT*	*Naming*	*LDT_z*	*Naming_z*
league	flight	airplane	.67	.05	.73	−32	68	0.03	0.77
question	halo	angel	.65	.06	.21	−9	29	0.34	0.33
aunt	rage	anger	.54	.04	.55	86	24	−0.07	0.41
precise	sprain	ankle	.60	.05	.62	158	−8	0.39	0.11
jaws	question	answer	.77	.54	.85	−26	10	0.17	0.14
chowder	knight	armor	.52	.29	.60	25	83	0.75	0.77
navy	legs	arms	.54	.55	.64	115	14	0.33	0.42
planet	navy	army	.54	.50	.55	109	−2	0.08	0.29
rob	awake	asleep	.62	.37	.90	−6	50	0.45	0.42
denim	crib	baby	.84	.03	.64	14	37	0.39	0.24
escargot	front	back	.72	.52	.61	133	101	0.93	1.28
brother	bounce	ball	.56	.06	.64	55	8	0.71	−0.02
clock	helium	balloon	.56	.12	.14	90	22	0.80	0.46
blaze	teller	bank	.81	.03	.80	26	78	0.49	0.90
dagger	league	baseball	.55	.00	.66	−11	−12	0.25	−0.17
toss	sand	beach	.72	.39	.73	2	−3	0.44	0.11
intelligent	grizzly	bear	.72	.11	.90	65	77	0.74	0.77
slipper	hive	bee	.81	.17	.92	33	74	0.66	0.34
doe	keg	beer	.89	.00	.16	125	103	0.99	0.98
rich	end	begin	.52	.49	.37	95	38	0.14	0.67
error	above	below	.56	.50	.79	−7	27	0.21	0.21
quiz	buckle	belt	.67	.21	.38	−10	37	0.14	0.40
sparrow	pedal	bike	.54	.05	.50	55	0	0.48	0.02
umbrella	sparrow	bird	.75	.00	.32	17	10	0.32	0.08
lather	white	black	.66	.56	.72	20	29	0.31	0.44
bed	clorox	bleach	.79	.07	.34	107	55	0.93	0.49
house	brunette	blonde	.57	.24	.	140	32	0.35	0.74
shopping	plasma	blood	.82	.05	.72	81	61	0.52	0.69
row	sky	blue	.52	.28	.43	68	21	0.79	0.15
cautious	chalk	board	.69	.11	.26	105	41	0.82	0.27
hammer	row	boat	.74	.02	.20	−88	16	−0.23	−0.07
cigar	anatomy	body	.61	.00	.38	−4	25	0.28	0.37
spoon	atom	bomb	.59	.00	.18	207	24	0.78	0.61
pocketbook	marrow	bone	.78	.12	.84	10	60	0.49	0.46
airport	library	book	.79	.00	.74	−30	24	−0.48	0.51
sofa	lend	borrow	.55	.41	.81	272	57	1.13	0.96
cinema	top	bottom	.70	.51	.77	11	−6	0.40	0.06
king	girls	boys	.50	.50	.89	73	82	0.68	0.77
add	comb	brush	.64	.16	.29	5	40	0.40	0.37
new	pail	bucket	.50	.22	.54	71	24	0.63	0.22
comedian	construct	build	.61	.13	.35	−10	76	0.22	0.80
yolk	margarine	butter	.86	.27	.75	−35	29	0.08	0.19
stumble	icing	cake	.81	.05	.24	107	−23	0.23	−0.06

(*Continued overleaf*)

Appendix (Continued)

Unrelated prime	*Related prime*	*Target*	*FAS*	*BAS*	*LSA*	*LDT*	*Naming*	*LDT_z*	*Naming_z*
auto[a]	opener	can	.77	.05	.21	68	0	0.00	0.47
difficult	wick	candle	.84	.05	.46	−29	3	0.33	0.06
assist	auto	car	.78	.13	.60	114	19	0.48	0.72
keg	credit	cards	.65	.00	.29	−2	60	0.14	0.49
ounce	cautious	careful	.51	.39	.34	18	−5	0.42	−0.25
cavern	meow	cat	.84	.00	.77	129	−8	0.23	0.14
instructor	cavern	cave	.53	.05	.56	130	4	0.28	0.20
discuss	table	chair	.76	.31	.61	164	15	0.52	0.32
buckle	alter	change	.63	.03	.44	−39	18	0.19	0.27
annual	inexpensive	cheap	.75	.08	.24	−68	−15	−0.09	−0.08
toes	macaroni	cheese	.60	.00	.39	123	38	0.31	0.46
breeze	gum	chew	.56	.36	.55	117	2	0.20	0.35
crescent	option	choice	.64	.03	.30	4	−12	0.31	0.02
flunk	steeple	church	.66	.05	.52	109	4	0.21	0.28
opener	town	city	.53	.31	.27	171	−5	0.56	0.24
vacate	chowder	clam	.76	.04	.34	111	104	1.24	0.84
end	spotless	clean	.63	.04	.25	131	−72	0.34	−0.43
listen	clarify	clear	.54	.00	.36	−47	24	−0.07	0.26
construct	outfit	clothes	.54	.00	.62	−35	28	0.11	0.09
north	circus	clown	.59	.24	.52	137	82	0.88	0.98
bad	miner	coal	.50	.05	.42	201	−25	0.63	0.09
man	jacket	coat	.56	.18	.60	9	60	0.32	0.50
grasp	chill	cold	.73	.00	.51	170	21	0.61	0.37
arithmetic	hue	color	.55	.02	.77	−17	66	0.17	0.59
toe	chef	cook	.62	.05	.43	56	17	0.64	−0.13
best	husk	corn	.64	.12	.29	52	9	0.47	−0.10
up	sofa	couch	.51	.19	.71	79	41	0.20	0.82
flood	saltine	cracker	.84	.11	.	115	60	1.02	0.57
avenue[a]	insane	crazy	.52	.21	.16	41	14	0.49	−0.09
front	sob	cry	.76	.07	.54	0	14	0.20	0.17
acre	scissor	cut	.88	.03	.42	95	12	0.34	0.35
enter	mom	dad	.76	.71	.94	131	11	0.39	0.34
helium	son	daughter	.59	.44	.63	6	41	0.46	0.56
far	dusk	dawn	.61	.45	.62	198	65	0.78	0.91
bounce	alive	dead	.55	.40	.52	−42	42	0.03	0.28
cash	doe	deer	.72	.13	.44	17	75	0.22	0.63
macaroni	offense	defense	.64	.30	.35	115	28	0.31	0.26
gum	rely	depend	.56	.06	.43	172	35	0.54	0.63
tile	demolish	destroy	.54	.07	.05	−19	−23	0.18	−0.39
truthful	supper	dinner	.55	.54	.76	72	8	0.09	0.43
banner	soil	dirt	.72	.06	.16	−10	33	0.28	0.23
brunette	scuba	dive	.51	.04	.36	152	86	0.44	1.41
chill	physician	doctor	.80	.04	.61	132	0	0.50	0.08
above	puppy	dog	.75	.12	.76	1	54	0.27	0.66
sob	knob	door	.67	.14	.37	16	22	0.20	0.35
jog	up	down	.85	.58	.87	189	59	0.93	0.86
oak	sketch	draw	.76	.11	.78	137	36	0.49	0.45
circus	addict	drugs	.69	.03	.89	−8	−5	0.20	−0.09
beginning	intoxicated	drunk	.70	.00	.67	196	−13	0.68	0.29
ill	washer	dryer	.76	.43	.45	158	87	1.47	1.18
venom	stupid	dumb	.59	.53	.70	77	39	0.81	0.28

(*Continued overleaf*)

Appendix (Continued)

Unrelated prime	*Related prime*	*Target*	*FAS*	*BAS*	*LSA*	*LDT*	*Naming*	*LDT_z*	*Naming_z*
legs	planet	earth	.61	.16	.49	184	−5	0.50	0.33
knight	yolk	eggs	.84	.08	.87	−7	35	0.32	0.23
sprain	beginning	end	.75	.00	.54	136	5	0.26	0.38
decrease	grammar	English	.53	.03	.60	18	33	0.43	0.33
son	odd	even	.56	.62	.54	−1	82	0.41	1.04
bunny	precise	exact	.51	.39	.60	121	−48	0.26	−0.46
mom	enter	exit	.57	.39	.32	182	8	0.43	0.24
table	flunk	fail	.62	.09	.08	182	−10	0.61	0.07
fall	stumble	fall	.71	.00	.24	280	79	1.16	1.09
meow	swift	fast	.61	.02	.32	86	−17	0.27	0.15
day	touch	feel	.67	.39	.46	25	14	0.25	0.20
lime	toes	feet	.53	.47	.62	168	0	0.61	0.11
rely	male	female	.65	.55	.96	153	50	0.55	1.08
bulb	brawl	fight	.80	.00	.14	187	24	0.61	0.53
roar	seek	find	.54	.07	.34	117	−20	0.39	0.32
grizzly	done	finish	.68	.08	.40	23	47	0.41	0.37
reflection	blaze	fire	.81	.00	.67	13	24	0.31	0.48
boulder	last	first	.58	.47	.59	32	56	0.50	0.38
forgive	trout	fish	.91	.04	.85	−15	33	0.01	0.48
clorox	banner	flag	.69	.00	.53	−29	74	0.15	0.66
chalk	tile	floor	.58	.17	.37	−14	46	0.13	0.41
intoxicated	tulip	flower	.78	.01	.69	134	31	0.33	0.75
white	swatter	fly	.75	.04	.36	−26	−24	0.04	−0.25
globe	grocery	food	.28	.00	.27	112	12	0.16	0.40
girls	toe	foot	.61	.24	.67	−13	49	0.35	0.30
labor	forgive	forget	.64	.01	.51	−124	9	−0.22	0.00
lend	spoon	fork	.61	.44	.48	124	27	0.40	0.48
thick	pal	friend	.77	.09	.39	51	67	0.58	0.59
pail	toad	frog	.83	.26	.87	42	6	0.42	−0.05
steeple	empty	full	.61	.58	.40	110	3	0.37	0.42
margarine	comedian	funny	.55	.03	.17	13	85	0.56	0.50
despise	trash	garbage	.53	.46	.86	56	50	0.59	0.32
desire[a]	ghoul	ghost	.65	.03	.07	81	23	0.59	0.16
addict	lens	glasses	.55	.02	.26	−124	53	−0.35	0.60
physician	paste	glue	.63	.07	.38	210	−5	0.63	0.21
slay	silver	gold	.64	.47	.88	16	72	0.32	0.74
scale	bad	good	.75	.76	.65	82	5	0.14	0.21
attempt	vine	grape	.61	.22	.17	36	34	0.54	0.18
outfit	bride	groom	.87	.62	.74	23	42	0.61	0.39
icing	pistol	gun	.77	.06	.62	221	−6	0.51	0.50
dusk	glove	hand	.55	.05	.35	68	−31	0.13	0.00
mustard	sad	happy	.63	.63	.78	29	0	0.39	−0.02
bubble	difficult	hard	.59	.00	.36	−19	7	0.18	0.23
guardian	cap	hat	.71	.06	.52	−48	16	0.01	−0.02
tardy	despise	hate	.80	.02	.26	3	132	0.40	1.35
lens	listen	hear	.51	.32	.72	43	53	0.33	0.58
male	assist	help	.84	.02	.29	151	28	0.55	0.59
supper	low	high	.78	.66	.79	106	22	0.21	0.47
grocery	grasp	hold	.53	.11	.43	69	−13	0.01	0.21
library	house	home	.58	.33	.43	146	−4	0.43	0.20
chimpanzee	truthful	honest	.65	.00	.32	151	48	0.32	0.83

(*Continued overleaf*)

Appendix (Continued)

Unrelated prime	*Related prime*	*Target*	*FAS*	*BAS*	*LSA*	*LDT*	*Naming*	*LDT_z*	*Naming_z*
crib	saddle	horse	.88	.10	.93	52	56	0.39	0.48
syrup	harm	hurt	.64	.01	.42	17	40	0.54	0.23
grammar	decrease	increase	.52	.45	.82	42	60	0.48	0.58
quiver	denim	jeans	.82	.05	.18	115	80	0.97	0.75
diamond	pun	joke	.58	.00	.16	25	30	0.35	0.33
done	leap	jump	.52	.07	.44	20	19	0.22	0.31
ghoul	mustard	ketchup	.58	.48	.41	67	20	0.63	0.14
silver	slay	kill	.69	.00	.19	34	40	0.65	0.42
town	throne	king	.76	.00	.73	59	20	0.05	0.37
flesh[a]	dagger	knife	.61	.00	.27	−19	−38	0.12	−0.50
dime	acre	land	.68	.02	.58	143	0	0.42	0.17
loose[a]	tardy	late	.90	.09	.22	26	105	0.45	1.14
gums	giggle	laugh	.78	.07	.49	3	34	0.22	0.55
spotless	mower	lawn	.66	.19	.50	81	−36	0.06	−0.09
puppy[a]	evacuate	leave	.50	.00	.05	−41	−51	−0.02	−0.59
noun	vacate	leave	.63	.00	.01	−57	11	−0.06	−0.13
shingle	lime	lemon	.57	.43	.33	99	48	0.16	0.66
dill	more	less	.63	.63	.80	186	1	0.61	0.28
pedal	fib	lie	.82	.07	.12	71	21	0.71	0.30
brawl	bulb	light	.79	.21	.49	138	−59	0.41	−0.36
blouse	roar	lion	.61	.03	.52	101	6	0.08	0.27
comb	found	lost	.81	.75	.41	27	23	0.46	0.29
itch	noisy	loud	.34	.30	.64	17	−4	0.25	0.08
marsh	affection	love	.80	.00	.74	−48	30	−0.09	0.25
credit	minor	major	.41	.54	.35	19	−4	0.35	−0.12
wick	shopping	mall	.51	.26	.43	41	30	0.48	0.36
caboose	arithmetic	math	.76	.05	.65	63	47	0.63	0.35
loser	kilometer	mile	.50	.15	.40	−14	−8	0.39	−0.07
tale	reflection	mirror	.72	.38	.82	−73	33	−0.17	0.36
anatomy	error	mistake	.68	.24	.42	20	30	0.33	0.68
husk	cash	money	.81	.21	.22	12	49	0.34	0.37
salt	chimpanzee	monkey	.68	.04	.42	187	12	0.66	0.35
noisy	crescent	moon	.52	.00	.41	42	15	0.51	0.21
stupid	father	mother	.71	.60	.55	14	67	0.26	0.59
toad	climber	mountain	.60	.03	.70	20	24	0.35	0.31
yell	cinema	movie	.79	.03	.57	127	39	0.89	0.33
web	hammer	nail	.80	.62	.50	−7	79	0.30	0.57
offense	far	near	.50	.54	.51	112	−20	0.30	−0.05
scuba	dime	nickel	.53	.47	.38	162	78	0.55	1.02
swatter	day	night	.82	.69	.54	41	37	0.33	0.61
harm	digit	number	.72	.00	.40	−20	42	0.25	0.60
agony	cashew	nut	.75	.05	.	74	70	0.65	0.77
tangerine	on	off	.88	.90	.22	100	18	0.93	0.17
on[a]	new	old	.73	.47	.34	21	68	0.47	0.77
unhappy	closed	open	.68	.00	.75	145	6	0.51	0.28
awake	tangerine	orange	.73	.05	.25	−9	35	0.23	0.47
halo	inside	outside	.59	.50	.70	14	56	0.41	0.66
trousers	agony	pain	.65	.03	.36	34	27	0.42	0.17
alter	syrup	pancake	.50	.42	.36	54	2	0.63	0.10
spoiled	trousers	pants	.85	.00	.71	1	23	0.28	0.22
hive	guardian	parent	.54	.06	.21	−70	40	−0.05	0.23

(*Continued overleaf*)

Appendix (Continued)

Unrelated prime	*Related prime*	*Target*	*FAS*	*BAS*	*LSA*	*LDT*	*Naming*	*LDT_z*	*Naming_z*
flavor	celebrate	party	.60	.00	.17	−30	26	0.06	0.21
esteem	ink	pen	.70	.15	.34	188	26	0.62	0.42
no[a]	salt	pepper	.70	.70	.21	173	103	0.41	1.34
husband	dill	pickle	.87	.14	.42	121	−15	0.35	−0.10
east	frame	picture	.81	.32	.16	−16	−9	0.14	0.01
pistol	airport	plane	.76	.00	.75	179	9	0.54	0.57
tomorrow	minus	plus	.52	.68	.49	58	41	0.64	0.47
pane	venom	poison	.51	.00	.40	−26	41	0.14	0.31
knob	cop	police	.53	.22	.61	3	9	0.20	0.13
dictionary	rich	poor	.66	.51	.55	114	18	0.38	0.62
vine	ounce	pound	.53	.12	.54	−24	21	0.18	0.08
washer	gift	present	.61	.31	.17	0	25	0.49	0.41
halt	princess	prince	.55	.41	.75	−74	−11	−0.17	0.00
cavity	dilemma	problem	.61	.00	.39	39	−2	0.49	0.12
trash	tug	pull	.58	.13	.48	−82	27	−0.18	0.12
affection	pocketbook	purse	.51	.07	.59	17	71	0.32	0.64
observe	king	queen	.77	.73	.77	138	62	1.08	0.48
over	bunny	rabbit	.74	.10	.36	146	−5	0.31	0.24
minus	umbrella	rain	.70	.04	.41	56	−3	0.68	0.10
pun	left	right	.94	.41	.72	41	70	0.51	0.67
saddle	diamond	ring	.63	.08	.25	−21	11	0.16	0.03
hue	boulder	rock	.66	.04	.47	99	69	0.81	0.57
sketch	shingle	roof	.61	.12	.44	30	−13	−0.23	0.15
demolish	spoiled	rotten	.51	.11	.24	39	39	0.59	0.44
dinner	jog	run	.78	.14	.39	139	12	0.51	0.38
tiny	unhappy	sad	.74	.05	.56	120	−41	0.43	−0.27
alive	fright	scare	.64	.46	.23	0	78	0.27	0.56
princess	itch	scratch	.85	.36	.11	17	34	0.70	0.69
broom	yell	scream	.58	.57	.49	−20	7	0.17	0.16
ink	esteem	self	.58	.03	.86	106	−47	0.18	−0.26
deputy	quiver	shake	.62	.01	.29	12	58	0.35	0.33
giggle	jaws	shark	.59	.16	.63	8	30	0.30	0.54
leap	deputy	sheriff	.68	.17	.43	−1	104	0.41	1.18
miner	blouse	shirt	.65	.14	.64	87	−3	0.17	0.20
atom	socks	shoes	.66	.31	.67	49	1	−0.01	0.24
glove	tall	short	.70	.42	.48	153	32	0.60	0.56
digit	ill	sick	.82	.36	.63	59	19	0.64	0.14
fright	brother	sister	.75	.54	.77	68	33	0.72	0.45
dilemma	flesh	skin	.58	.03	.27	84	4	0.55	0.09
lumber	bed	sleep	.64	.09	.72	4	52	0.20	0.37
swift	tiny	small	.65	.09	.54	152	18	0.47	0.22
odor	intelligent	smart	.71	.20	.25	−26	32	0.11	0.22
cobra	odor	smell	.70	.16	.66	54	48	0.75	0.69
found	cigar	smoke	.51	.00	.24	25	18	0.26	0.23
cop	escargot	snail	.63	.06	.	−53	−31	0.07	−0.25
sky	cobra	snake	.83	.00	.44	56	64	0.70	0.76
top	lather	soap	.67	.03	.66	−17	23	0.17	0.34
tall	apology	sorry	.58	.21	.29	66	−36	0.06	0.01
clarify	north	south	.77	.69	.87	59	53	0.66	0.57
minor	astronaut	space	.53	.03	.76	42	51	0.65	0.24
rectangle	web	spider	.85	.25	.77	6	85	0.38	0.90

(*Continued overleaf*)

Appendix (Continued)

Unrelated prime	*Related prime*	*Target*	*FAS*	*BAS*	*LSA*	*LDT*	*Naming*	*LDT_z*	*Naming_z*
cashew	rectangle	square	.72	.00	.52	−1	47	0.30	0.27
plasma	astronomy	star	.75	.02	.45	−5	37	0.22	0.36
paste	remain	stay	.78	.11	.25	124	−33	0.30	−0.16
odd	rob	steal	.67	.07	.40	34	13	0.46	0.14
inexpensive	halt	stop	.91	.05	.46	23	−1	0.48	0.10
sand	tale	story	.59	.11	.75	5	0	0.27	0.01
powerful	avenue	street	.68	.10	.82	7	10	0.51	0.01
quench	powerful	strong	.59	.00	.56	−41	69	0.18	0.66
empty	pupil	student	.68	.05	.37	73	−8	0.18	0.31
inside	add	subtract	.69	.69	.36	89	45	0.83	0.75
scissors	dinner	supper	.54	.55	.76	190	26	0.67	0.56
insane	marsh	swamp	.52	.09	.42	202	65	1.53	0.69
gift	broom	sweep	.50	.41	.30	−11	36	0.42	0.49
socks	discuss	talk	.69	.02	.30	153	25	0.53	0.65
false	flavor	taste	.50	.02	.51	7	5	0.35	−0.02
more	instructor	teacher	.57	.07	.53	93	−42	0.17	−0.34
fib	gums	teeth	.71	.08	.92	38	5	0.53	0.08
seek	racket	tennis	.50	.19	.56	122	1	0.22	0.33
kilometer	quiz	test	.79	.11	.10	−41	18	0.22	0.40
tug	thick	thin	.68	.08	.70	68	50	0.93	0.27
cap	quench	thirst	.82	.10	.34	111	66	1.14	0.57
astronomy	toss	throw	.62	.20	.66	108	57	1.01	0.62
soil	loose	tight	.57	.44	.58	76	72	0.78	0.58
cork	clock	time	.65	.37	.32	−42	12	−0.06	0.27
option	tomorrow	today	.53	.50	.35	−49	19	−0.07	0.11
flight	cavity	tooth	.54	.04	.56	−4	6	0.38	0.06
astronaut	caboose	train	.72	.05	.32	120	72	0.94	0.58
incorrect	oak	tree	.80	.04	.80	196	80	0.85	1.05
celebrate	false	true	.70	.53	.58	−6	33	0.21	0.37
bride	attempt	try	.75	.13	.37	−11	12	0.16	0.06
closed	aunt	uncle	.75	.71	.82	89	3	0.24	0.22
rage	over	under	.54	.48	.59	129	−19	0.32	−0.18
father	noun	verb	.69	.64	.70	57	58	1.20	0.36
chef	desire	want	.61	.28	.37	−37	78	0.03	0.54
saltine	observe	watch	.50	.06	.31	77	71	0.85	0.60
last	flood	water	.62	.00	.33	46	110	0.44	1.19
racket	scale	weight	.53	.01	.18	118	−18	0.19	0.07
frame	east	west	.89	.78	.83	63	13	0.62	0.15
left	slippery	wet	.80	.01	.31	90	−1	0.78	0.07
remain	husband	wife	.89	.68	.87	208	28	0.78	0.60
throne	breeze	wind	.61	.12	.59	118	20	0.41	0.25
sad	pane	window	.83	.18	.61	−33	53	0.07	0.25
teller	cork	wine	.52	.00	.14	−77	26	−0.16	0.33
trout	loser	winner	.51	.60	.55	−11	20	0.31	0.14
marrow	man	woman	.66	.60	.37	2	97	0.32	0.96
jacket	lumber	wood	.60	.00	.71	−5	22	0.29	0.10
tulip	dictionary	words	.52	.06	.77	57	−29	−0.08	0.03

(*Continued overleaf*)

Appendix (Continued)

Unrelated prime	*Related prime*	*Target*	*FAS*	*BAS*	*LSA*	*LDT*	*Naming*	*LDT_z*	*Naming_z*
climber	labor	work	.69	.02	.20	−14	8	0.21	0.00
apology	globe	world	.68	.18	.22	52	79	−0.02	0.97
pal	best	worst	.54	.50	.35	40	57	0.31	0.50
pupil	incorrect	wrong	.67	.05	.33	81	−4	0.01	0.16
touch	annual	yearly	.71	.00	.43	42	52	0.59	0.66
low	no	yes	.76	.83	.52	82	12	0.29	0.31

Note: FAS = forward associative strength. BAS = backward associative strength. LSA = latent semantic analysis similarity rating. LDT = lexical decision task. Raw priming effects = unrelated − related.

[a] Denotes items eliminated from analyses due to higher LSA similarity between the target and unrelated prime than target and related prime.