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Individual Differences in Semantic Processing: Insights From the Calgary Semantic Decision Project

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Most previous studies of semantic processing have examined group-level data. We investigated the possibility that there might be individual differences in semantic decision performance even among the standard undergraduate population and that such differences might provide insights into semantic processing. We analyzed the Calgary Semantic Decision Project dataset, which includes concrete/abstract semantic decision responses to thousands of words and also a vocabulary measure for each of 312 participants. Results of our analyses showed that semantic decision responses had good reliability, and that the speed of those responses was related to individual differences as assessed by vocabulary scores and also by diffusion model parameters. That is, semantic decisions were faster for participants with higher vocabulary scores and for participants with steeper drift rates. Further, in their semantic decision responses high vocabulary participants showed more sensitivity to some lexical/semantic predictors and less sensitivity to others. For responses to both concrete and abstract words, high vocabulary participants were more sensitive to word concreteness and less sensitive to word frequency and age of acquisition. For concrete words, high vocabulary participants were also more sensitive to semantic neighborhood similarity. The results suggest that high vocabulary participants are able to more readily access semantic information and are better able to emphasize task-relevant dimensions. In sum, the results are consistent with a dynamic, multidimensional account of semantic processing.

Keywords: abstract words, concrete words, individual differences, semantic decision, visual word recognition

The process of deriving meaning from print is central to reading but it remains a challenge to explain for theories of visual word recognition. The goal of the present research was to examine how semantic processing might vary as a function of individual differences even among undergraduate students, the standard population of word recognition studies, so as to gain new insight about the process.

One of the tools that researchers have used to study the process of deriving meaning from print is the semantic decision task, sometimes also called the semantic categorization task. In the semantic decision task, participants are asked to decide whether each word is a member of a semantic category (e.g., living/nonliving, concrete/abstract). Research with this type of task has produced a number of interesting findings about lexical semantic processing. For instance, semantic decisions tend to be influenced by the extent to which words (a) are used in many contexts (Moffat, Siakaluk, Sidhu, & Pexman, 2015), (b) evoke many semantic features (e.g., Grondin, Lupker, & McRae, 2009; Pexman, Holyk, & Monfils, 2003), or (c) reference objects associated with survival (Taikh, Hargreaves, Yap, & Pexman, 2015), emotion (Moffat et al., 2015), and extensive sensory (Zdrazilova & Pexman, 2013) and motor (Siakaluk et al., 2008) experience. Findings like these have been broadly labeled *semantic richness effects*, and they suggest that each of these types of information (contextual history, semantic features, sensorimotor experience, etc.) are important dimensions of lexical meaning. Thus, the findings can help constrain theories of semantic representation.

Although the results of semantic decision tasks have been used to make inferences about the nature of semantic representation, it is also clear that findings based on the semantic decision task reflect a combination of bottom-up and top-down processes (Amsel, Urbach, & Kutas, 2013; Hargreaves & Pexman, 2014). That is, the decision category chosen for the semantic decision task can influence the effects observed, as participants shift their attention to dimensions of meaning that are task-relevant. Narrower, more specific categories tend to encourage a focus on particular features that are diagnostic of the decision, leading to different results in terms of the semantic effects observed in behavioral responses (Hino, Pexman, & Lupker, 2006; Jared & Seidenberg, 1991; Pexman et al., 2003; Taikh et al., 2015), in the associated cortical regions implicated by fMRI (Hargreaves, White, Pexman, Pittman, & Goodyear, 2012), and in the timing of brain activity detected by event-related potentials (Amsel et al., 2013). For example, Jared and Seidenberg reported that the semantic effects observed in the classic Van Orden (1987) study involving narrow decision categories (e.g., flower/nonflower) did not extend to tasks involving broad decision categories (e.g., living/nonliving). Jared and Se-

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idenberg thus recommended that researchers avoid specific categories in semantic decision tasks. As a result, the broad concrete/abstract decision category is often used in semantic decision tasks (e.g., Yap, Pexman, Wellsby, Hargreaves, & Huff, 2012; Yap, Tan, Pexman, & Hargreaves, 2011; Zdrazilova & Pexman, 2013). Of course, even this relatively broad decision likely encourages participants to focus to some degree on particular aspects of meaning that are diagnostic of the categories "concrete thing" and "abstract thing" (Newcombe, Campbell, Siakaluk, & Pexman, 2012).

Thus, recent research with the semantic decision task has identified item-level and task-level factors that influence performance, and the consequences of these findings for theories of semantic processing have been considered. To explain conceptual processing, many theories now offer a pluralist account, whereby cognition is grounded in multimodal systems, often with some integrative processing of information across modalities (Barsalou, Santos, Simmons, & Wilson, 2008; Dove, 2011; Louwerse & Jeuniaux, 2010; Patterson, Nestor, & Rogers, 2007; Reilly, Peelle, Garcia, & Crutch, 2016; Simmons, Hamann, Harenski, Hu, & Barsalou, 2008; Vigliocco, Meteyard, Andrews, & Kousta, 2009; Zwaan, 2014). Pluralist accounts assume that there are many different dimensions of semantic information. These include dimensions that capture aspects of sensory, motor, and linguistic experience. This kind of account can accommodate findings that multiple semantic dimensions influence semantic decision performance, even simultaneously (Pexman, Hargreaves, Siakaluk, Bodner, & Pope, 2008; Yap et al., 2011, 2012), while being also consistent with the possibility that different types of information are relatively more important for representation of concrete versus abstract concepts. A pluralist account is also able to explain why effects of different semantic dimensions vary with the semantic decision category (e.g., Tousignant & Pexman, 2012), as different types of information are emphasized as a function of context and task demands (Yee & Thompson-Schill, in press). By this view, meaning is constructed dynamically to meet the demands of a particular task, and context dictates the meanings derived from print. This stands in contrast to traditional accounts of semantic memory, which assume that semantic representation is relatively fixed (e.g., Collins & Loftus, 1975; Quillian, 1967; Smith, Shoben, & Rips, 1974).

Although recent studies have explored item-level and task-level influences on semantic processing, results have sometimes been mixed. For instance, there have been a number of conflicting findings reported for semantic ambiguity in semantic tasks, with some studies reporting facilitatory effects (faster responses for ambiguous words than for unambiguous words, Hargreaves & Pexman, 2014), some reporting null effects (no difference between responses for ambiguous and unambiguous words; Hargreaves, Pexman, Pittman, & Goodyear, 2011; Pexman, Hino, & Lupker, 2004; Siakaluk, Pexman, Sears, & Owen, 2007; Yap & Pexman, 2016), and some reporting inhibitory effects (slower responses for ambiguous words than for unambiguous words; Hino et al., 2006; Hoffman & Woollams, 2015; Piercey & Joordens, 2000; Yap et al., 2011). In a further twist, Pexman, Heard, Lloyd, and Yap (2017) reported strong facilitatory effects of ambiguity for semantic decisions to abstract words but modest inhibitory effects of ambiguity for semantic decisions to concrete words. Certainly, some of this variability can be attributed to the different metrics of ambiguity that have been adopted across different studies but, so far, little attention has been given to the possibility that the influence of ambiguity also varies at the individual level, even among skilled readers. Individual differences are an unexplored source of potential variability in semantic processing. Our tendency has been to focus on group-level data, on the assumption that all skilled readers have essentially the same word recognition systems, yet semantic knowledge, in particular, is so much a function of individual experience that individual differences in semantic processing seem not just plausible, but likely.

The potential for individual differences has been explored more extensively in lexical decision and speeded pronunciation tasks, and the results show that variability in participants' reading skills and lexical experience is associated with differences in task performance (Chateau & Jared, 2000; Hargreaves, Pexman, Zdrazilova, & Sargious, 2012; Protzner et al., 2016; Unsworth & Pexman, 2003; van Hees, Seyffarth, Pexman, Cortese, & Protzner, 2017; Woollams, Lambon Ralph, Madrid, & Patterson, 2016; Yap, Tse, & Balota, 2009). Yap et al. argued that participant vocabulary knowledge could be taken as an index of *lexical integrity*; high integrity representations are rich, well specified, and more easily retrieved, whereas low integrity representations are less precise, less stable, and less fluently retrieved. In the largest of the studies on individual differences and word recognition performance, Yap et al. (2012) examined relationships between participant vocabulary size and performance in speeded pronunciation and lexical decision tasks, using archival data from the English Lexicon Project (Balota et al., 2007). Results showed that participants with higher vocabulary scores were less sensitive to effects of frequency/semantics (the frequency/semantics variable was a principal component that was strongly associated with word frequency, semantic neighborhood density, and number of senses) in speeded pronunciation and, marginally, in lexical decision. Yap et al. concluded that greater vocabulary knowledge was associated with more efficient accumulation of information and thus faster responses and reduced sensitivity to word characteristics.

In sum, there is evidence for individual differences in lexical decision and speeded pronunciation tasks, but these tasks tend not to involve extensive semantic processing. Semantic effects in speeded pronunciation tasks are usually small (for a review, see Balota, Cortese, Sergent-Marshall, Spieler, & Yap, 2004). Although semantic effects are typically larger in lexical decision than in speeded pronunciation (e.g., Cortese & Khanna, 2007), they are often attributed to indirect effects of semantic processing (Pexman, 2012). That is, it is assumed that lexical decision responses are primarily based on orthographic familiarity (Balota, Ferraro, & Connor, 1991), and the influence of semantic variables in lexical decision is attributed to feedback from semantic units to orthographic units (Hino & Lupker, 1996). Participants with strong orthographic knowledge may be able to respond in lexical decision without extensive semantic processing (Hargreaves et al., 2012; Protzner et al., 2016). In general, results of studies that have presented the same items in a lexical-decision task and a semantic decision task show that more variance in response latencies is explained by semantic variables in semantic decision than in lexical decision (Pexman et al., 2017; Yap et al., 2012; Yap et al., 2011; Zdrazilova & Pexman, 2013).

To our knowledge, only three previous studies have examined individual differences in semantic decision-making. The first was a study reported by Hogaboam and Pellegrino (1978), involving a semantic decision task with 10 different decision categories. Hogaboam and Pellegrino examined relationships between semantic decision task performance and Scholastic Aptitude Test (SAT) verbal aptitude scores for 34 undergraduate participants. They found no relationships between SAT verbal scores and speed of semantic decision responses, or between SAT verbal scores and frequency effects in semantic decision. Hogaboam and Pellegrino concluded that verbal ability did not seem to be related to "speed of accessing long-term memory codes" (p. 193). Notably, the small sample tested in this early study may have limited its potential to detect relationships between verbal ability and semantic decision-making.

In the second relevant study, Andrews, Lo, and Xia (2017) tested a larger sample of 89 undergraduate participants and investigated individual differences in sensitivity to masked semantic priming in a task using the animal/nonanimal decision category. Andrews et al. examined sensitivity to category congruence priming; for instance, faster responses were observed when prime and target were both animals, particularly when the animal names shared semantic features. Results showed that participants with strong overall proficiency (measured by vocabulary, comprehension, and spelling skills) produced the strongest masked semantic priming effects. Since these were briefly presented masked primes that minimized conscious processing, this finding suggested that participants with greater lexical integrity enjoyed faster automatic access to semantic features. Although not the focus of their analysis, their results also showed that these more proficient participants had faster overall response latencies in the semantic decision task.

A similar finding of individual differences in speed of overall latencies was reported in the third relevant study; Pexman et al. (2017) examined relationships between participant vocabulary scores and semantic decision responses in their analysis of the Calgary Semantic Decision dataset. In the Calgary Semantic Decision Project, semantic decision responses were collected for a total of 10,000 words from a sample of more than 300 participants. Each participant made concrete/abstract decisions to 1,000 words. Vocabulary knowledge was measured for each participant. Results showed a strong relationship between vocabulary knowledge and semantic decision latencies; participants with higher vocabulary scores tended to make faster semantic decisions to both concrete and abstract words. Although this finding is consistent with the inference that high vocabulary participants enjoy faster evidence accumulation in lexical processing (Yap et al., 2012), it is also possible that individual differences in semantic decision-making might be more complicated. That is, individual differences might involve emphasizing some dimensions at the expense of others. These possibilities were investigated in the present study.

In sum, although the semantic decision task has been widely used, there is much we do not yet know about the nature of semantic decision-making. For instance, how reliable are semantic decision responses? As Yap et al. (2012) noted, the psychometric reliability of response time (RT) measures is rarely evaluated; yet it is fundamental to our question of individual differences in semantic decision-making (see also Tan & Yap, 2016, for more discussion). That is, a reliable measure is likely to be more sensitive to meaningful individual differences. In the present study, we examined the within-session reliability of semantic decision performance in both mean RTs and in the characteristics of the underlying RT distribution. Further, what is the nature of individual differences in semantic decision-making? Do high vocabulary participants simply respond faster, and with less sensitivity to all word characteristics? Such a finding would suggest a relatively fixed or invariant meaning retrieval process that can simply be made more or less efficient. Alternatively, do high vocabulary participants show less sensitivity to some word characteristics and more sensitivity to others? Such a finding would suggest a more dynamic and flexible meaning retrieval process.

In the present study, we addressed these unanswered questions through analysis of the Calgary Semantic Decision dataset (Pexman et al., 2017). We examined the reliability of performance and also tested whether participants' vocabulary skills and efficiency in accumulating information were related to their recruitment of different lexical and semantic richness dimensions in the semantic decision task. We selected lexical and semantic richness dimensions that have been shown to be relevant in this task and for which we had values on a large number of the items in the Calgary Semantic Decision dataset, allowing us to examine the influences of these variables simultaneously. Responses to concrete and abstract words were separately analyzed. In the following sections, we describe each of the semantic richness dimensions examined.

Concreteness

In much of the research on semantic processing, there has been a tendency to emphasize concrete words and less attention has been given to processing of abstract words (cf. Recchia & Jones, 2012; Troche, Crutch, & Reilly, 2014; Zdrazilova & Pexman, 2013). Half of the items presented in the Calgary Semantic Decision project were abstract words (5,000 abstract items), and so analyses of that dataset represent an opportunity to better understand abstract meaning. Although abstract stimuli have not received a great deal of attention in past studies, there is widespread recognition that the topic of abstract meaning is important, for at least a couple of reasons. First, abstract words represent a large portion of the average lexicon (Recchia & Jones, 2012) and any comprehensive theory of lexical semantic processing must be able to explain how abstract meanings are processed. Second, abstract words represent a particular challenge for some semantic theories; in particular, for embodied theories. These are theories that propose that sensorimotor modalities are integral to the processing and representation of conceptual knowledge (e.g., Barsalou, 1999, 2008; Glenberg, 2015). That is, although it is clear how embodied cognition might explain grounding of meanings for concepts that are rich in sensorimotor information (e.g., concrete objects and observable actions), it is more challenging for embodied cognition to explain grounding of meanings for abstract concepts (e.g., *truth*), because these cannot be directly experienced through the senses (Borghi et al., 2017; Mahon & Caramazza, 2008).

To address this challenge, there are now several proposals about how abstract meaning might be learned and represented (for recent reviews, see Dove, 2016; Pexman, in press). One proposal is that abstract concepts are understood through language (Andrews & Vigliocco, 2010; Antonucci & Alt, 2011) and linguistic context (Andrews, Vigliocco, & Vinson, 2009). That is, abstract meaning is represented by words' associations with other words (Andrews, Frank, & Vigliocco, 2014). It has also been argued that contextual and situational information is particularly important to abstract meaning (Wilson-Mendenhall, Simmons, Martin, & Barsalou, 2013). Another proposal is that abstract meaning is grounded through emotion (Barsalou & Wiemer-Hastings, 2005; Kousta, Vigliocco, Vinson, Andrews, & Del Campo, 2011; Newcombe et al., 2012). Abstract words tend to be more valenced than concrete words (Altarriba, Bauer, & Benvenuto, 1999), making emotion a potential strategy for learning and grounding abstract meanings. In this way, abstract meanings could be grounded in embodied experience, via introspective emotion states. Certainly, emotion cannot explain representation of all abstract meanings. Instead, some have suggested that all concepts are represented by a combination of experiential and linguistic information (Vigliocco et al., 2009), with different aspects of experience relatively more important for different types of words (Reilly et al., 2016). For instance, sensorimotor experience might dominate representations for concrete words, whereas linguistic and emotional experience might dominate representations for abstract words (Kousta et al., 2011). In the present study, we tested proposals like these by examining responses to concrete and abstract words separately, so as to gain insight about the dimensions that are important to the meanings of each. For example, to what extent do measures derived from linguistic context and emotion information influence the processing of abstract words?

In addition, we included concreteness in the present analyses to capture some of the variance that might be attributed to typicality. The stimuli for the Calgary Semantic Decision project were selected from the large set of concreteness ratings collected by Brysbaert, Warriner, and Kuperman (2014). Brysbaert et al. characterized concreteness as a continuous dimension, and we expected that in general concrete/abstract decisions would be slower for words with concreteness ratings closer to the midpoint of the scale. At the same time, Brysbaert et al. reported that the distribution of concreteness ratings tended to be somewhat bimodal, and asymmetrically so, with peaks in the distribution for moderately abstract words (ratings around 2 on the 5 point scale) and highly concrete words (ratings above 4.5 on the 5 point scale). The bimodal nature of the distribution is consistent with the notion that concreteness is not simply a continuum and may reflect somewhat different decision criteria at the concrete and abstract ends of the scale (Connell & Lynott, 2012). Thus, we expected that concreteness effects might be different for abstract and concrete words. By including concreteness as a dimension in the analysis, we were able to estimate the extent to which response latencies are explained by decision category typicality, and we could also explore individual differences in emphasis on typicality in semantic decision-making. We could also explore how those individual differences might vary for abstract and concrete words. It seemed possible that skilled readers might be better able to capitalize on typicality in their decisions, using their more extensive word knowledge to emphasize the features that are most decision-relevant. That is, high vocabulary participants might be able to increase the gain for dimensions that help them to most effectively discriminate between concrete and abstract words. If so, they would show more sensitivity to the concreteness variable. Alternatively, this kind of flexibility might not be possible in semantic processing, and high vocabulary participants might simply be more efficient evidence accumulators. If so, high vocabulary participants should be less sensitive than low vocabulary participants to the concreteness dimension, and to all other semantic factors examined.

Emotion

We also examined the possibility that emotional information may be central to the representation of abstract words (e.g., Vigliocco et al., 2009). We measured emotion information following the tradition in emotion research, wherein valence (positive-negative dimension) and arousal (intensity of the corresponding feeling) are included as separate dimensions (Russell, 1980). The effects of these variables have not often been examined in semantic decision tasks. In one of the few studies to do so, Zdrazilova and Pexman (2013) analyzed semantic decision responses to 200 abstract nouns and found facilitatory effects of valence (faster responses for positive words than for negative words) and null effects of arousal. Using other tasks, some studies have reported a similar advantage for positive over negative words (e.g., Kuperman, Estes, Brysbaert, & Warriner, 2014; Larsen, Mercer, Balota, & Strube, 2008), but some studies have found a different pattern, whereby emotion effects are best captured by extremity of valence, with an advantage for positive and negative words over neutral words (e.g., Adelman & Estes, 2013; Kousta, Vinson, & Vigliocco, 2009; Yap & Seow, 2014). Further, Kuperman et al. reported interactions of valence and frequency, with stronger effects of emotion for low frequency words. Thus, in the present study, we tested for effects of valence, extremity of valence, and arousal, as well as interactions with word frequency, and did so for concrete and abstract words separately. In terms of predictions for individual differences, we speculated that because high vocabulary participants have more extensive word knowledge, they might depend less on emotion information for semantic decisions. Low vocabulary participants, in contrast, might depend more heavily on emotion information, particularly for abstract words, to ground the meanings of those items.

Ambiguity

As mentioned, the previous findings for ambiguity effects in semantic tasks are mixed. In the initial analyses of the Calgary Semantic Decision dataset, Pexman et al. (2017) examined ambiguity effects using the semantic diversity variable (SemD) first described by Hoffman, Lambon Ralph, and Rogers (2013). SemD measures the extent to which words appear in more diverse contexts, and it is assumed that words that appear in more diverse contexts have more varied meanings. Pexman et al. reported a facilitatory effect of SemD for responses to abstract words (faster responses for high SemD words) and a modest inhibitory effect of SemD for responses to concrete words (slower responses for high SemD words). This pattern was interpreted as evidence for differences in representation for concrete and abstract words, and for the proposal that contextual and situational information is particularly important to abstract meaning (Wilson-Mendenhall et al., 2013). In the present analyses, we expected that high vocabulary participants might be more sensitive to ambiguity, because they would have more extensive knowledge of words' meanings. Thus, high vocabulary participants should show larger facilitatory SemD effects for abstract words and larger inhibitory effects for concrete words than should low vocabulary participants. Alternatively, if high vocabulary participants are simply more efficient at semantic decision-making and thus make less use of words' lexical and semantic characteristics, they should show less sensitivity to SemD than should low vocabulary participants, for decisions to both concrete and abstract words.

Semantic Neighborhood

Lexical processing is also influenced by characteristics of words' semantic neighborhoods (Buchanan, Westbury, & Burgess, 2001; Recchia & Jones, 2012). Semantic neighborhoods are derived from lexical co-occurrence information for a large corpus of text by high-dimensional models of semantic space (e.g., Burgess & Lund, 2000; Shaoul & Westbury, 2006, 2010). A word's semantic neighbors are the words that fall within a set radius in semantic space. In particular, the average neighbor similarity (ANS; Shaoul, 2017; Shaoul & Westbury, 2010) variable captures the average similarity of a target word to its neighbors. Words with higher ANS values are more similar to their neighbors. Several studies have reported significant facilitatory effects of this type of variable in lexical decision tasks and null effects in semantic decision tasks (Yap et al., 2011, 2012). Hargreaves and Pexman (2014) examined responses for concrete words in a concrete/abstract semantic decision task with a signal-to-respond procedure. This procedure tracks the time course of semantic decisions. Hargreaves and Pexman found facilitatory semantic neighborhood effects, but only when participants were signaled to respond relatively quickly. Because high vocabulary participants are likely to be fast responders, it seemed possible that they might be particularly sensitive to ANS effects, at least for concrete words. Again, however, it was also possible that high vocabulary participants might show diminished sensitivity to ANS, and to the other semantic variables.

Age of Acquisition

We also considered the possibility that there might be individual differences in age of acquisition (AoA) effects in the semantic decision task. Words that are acquired earlier in life tend to be recognized more efficiently than words acquired later in life, even after controlling for related dimensions like imageability and word frequency (e.g., Cortese & Schock, 2013; Morrison & Ellis, 1995; see Juhasz, 2005, for a review). One explanation for this AoA advantage is that words acquired earlier enjoy richer semantic representations, with more connections to concepts learned later (Steyvers & Tenenbaum, 2005). A different explanation is that early acquired words are represented in a more plastic system, and thus have a stronger influence on network structure (Ellis & Lambon Ralph, 2000). As the system matures, some plasticity is lost and thus later-acquired words have less influence on network structure. By this view, AoA influences multiple components of the lexical-semantic system and also the connections between those components (Lambon Ralph & Ehsan, 2006). It seemed possible that participants with lower quality lexical representations might derive more benefit from AoA, and thus be more sensitive to AoA effects, for responses to both concrete and abstract words.

The Present Study

In the present study, we considered the effects of each of these semantic variables on semantic decisions to concrete and abstract words, and also tested for interactions of each of these variables with participant vocabulary scores. To quantify individual differences in a more granular manner, we also estimated diffusion model parameters for each participant. In the context of our study, the diffusion model (Ratcliff, Gomez, & McKoon, 2004) assumes that making a binary semantic decision reflects the accumulation of noisy information over time from a starting point (*zr*) toward one of two decision boundaries, concrete words (*a*) versus abstract words (*0*). Although the diffusion model contains a large number of parameters that map onto different aspects of the decision-making mechanism (see Voss, Voss, & Lerche, 2015, for more discussion), the most relevant parameters, for our purposes, are drift rate (*v*), boundary separation (*a*), and the nondecision component (*t0*). Drift rate reflects the mean rate of information uptake, boundary separation reflects how conservative or liberal the response criterion is, and the nondecision component collectively indexes the time taken for encoding the stimulus and executing the response.

Prior research has demonstrated that theoretically important psycholinguistic variables (e.g., frequency, repetition, foil type) affect *only* drift rate in lexical decision (Ratcliff et al., 2004). Furthermore, there is a robust relationship between IQ and drift rate, wherein participants with higher IQ tend to show steeper drift rates, indicating that they are able to accumulate evidence more efficiently (Ratcliff, Thapar, & McKoon, 2010); in contrast, IQ had minimal effects on boundary separation and the nondecision component. In light of that, in addition to vocabulary scores, we also tested for interactions between variables of interest and participant-level drift rates. In this way, we approached a number of previously unanswered questions about the nature of lexical-semantic processing.

Method

Dataset

The Calgary Semantic Decision Project dataset (Pexman et al., 2017, approved by the University of Calgary Conjoint Faculties Research Ethics Board) was used for all analyses reported here. The full method for the Calgary dataset is provided in the paper describing it, so we simply summarize some key points here. The dataset includes semantic decision (concrete/abstract) responses for 312 participants to 1,000 words each. Across participants, the total stimulus list included 10,000 words (5,000 concrete, 5,000 abstract). The instructions for the semantic decision task were derived from those used in the Brysbaert, Warriner, and Kuperman (2014) concreteness ratings study; they emphasized that concrete words refer to things that exist in reality and can be experienced through senses and actions, whereas abstract words refer to things that depend on language for their meanings and cannot be directly experienced through senses and action. Descriptive statistics for the participants and words are provided in Pexman et al. in Tables 1 and 2, respectively. Before completing the semantic decision task, participants were administered the short version of the North American Adult Reading Test (NAART35; Uttl, 2002) to assess

Table 1
Descriptive Statistics for Concrete and Abstract Words

Measure	Abstract (n = 2243) Mean	SD	Concrete (n = 2073) Mean	SD
1. Word frequency	1.96	.53	1.97	.56
2. Length	7.74	1.97	7.53	1.99
3. Syllables	2.64	.94	2.33	.88
4. Orthographic N	.90	2.25	1.29	2.72
5. Age of acquisition	10.44	2.09	8.57	2.55
6. Concreteness	2.04	.28	4.33	.43
7. Valence	5.06	1.43	5.23	1.16
8. Valence extremity	1.20	.78	.94	.72
9. Arousal	4.35	.87	4.06	.91
10. Semantic diversity	1.72	.26	1.40	.28
11. Semantic neighbor similarity	.49	.12	.49	.11

vocabulary skill. The NAART35 involves a list of 35 irregular rare words (e.g., *gaoled*, *ennui*) which participants are asked to read aloud on the assumption that correct pronunciations will only be produced by participants who have prior knowledge of the words. The NAART35 correlates well with other vocabulary measures (e.g., .76 with WAIS–R Vocabulary scores, Uttl, 2002). Uttl also showed that although the NAART35 requires only pronunciation, NAAART35 scores were significantly related to performance in more meaning-based tasks (e.g., paired associate learning).

Lexical and Semantic Variables

Our goal was to have as many items as possible in the individual differences analyses. Although we did not have a complete set of lexical and semantic predictors for all of the 10,000 items in the Calgary Semantic Decision Project dataset, we had values for the following lexical and semantic predictors for 2,073 concrete words and 2,243 abstract words (see Table 1 and Figure 1 for descriptive statistics; the dataset used in the present study is available at *https://osf.io/f7mzc/*); Figure 1 presents the distributions of concreteness ratings for concrete and abstract words, and shows a similar distribution to that reported by Brysbaert et al. (2014) for their larger item set. That is, the distribution is slightly bimodal, and the most frequent rating for abstract items is in the moderately abstract range while the most frequent rating for concrete items is in the high concrete range. The lexical variables were word frequency (log of the SUBTLEXus contextual diversity values; Brysbaert & New, 2009), length, syllables, and orthographic neighborhood size (N; Coltheart, Davelaar, Jonasson, & Besner, 1977). Semantic richness variables were age of acquisition (Kuperman, Stadthagen-Gonzalez, & Brysbaert, 2012), concreteness (Brysbaert, Warriner, & Kuperman, 2014), valence (Warriner, Kuperman, & Brysbaert, 2013), valence extremity (i.e., absolute distance from the midpoint of the scale, Adelman & Estes, 2013), arousal (Warriner et al., 2013), semantic diversity (Hoffman et al., 2013), and semantic neighbor similarity (Shaoul, 2017). Table 2 presents the correlations between these variables, separately for concrete and abstract words.

Results

We first excluded incorrect trials and trials with response latencies faster than 250 ms or slower than 3,000 ms. For the remaining

Table 2
Correlations Between Lexical and Semantic Variables (Concrete Words Above the Diagonal and Abstract Words Below the Diagonal)

Variable	1	2	3	4	5	6	7	8	9	10	11
1. Word frequency	—	$-.254^{***}$	$-.220^{***}$	$.250^{***}$	$-.511^{***}$	$.113^{***}$	$.143^{***}$	$.175^{***}$	$.092^{***}$	$.418^{***}$	$.560^{***}$
2. Length	$-.283^{***}$	—	$.759^{***}$	$-.567^{***}$	$.253^{***}$	$-.088^{***}$	.015	−.007	.031	$-.130^{***}$	−.013
3. Syllables	$-.269^{***}$	$.784^{***}$	—	$-.469^{***}$	$.301^{***}$	$-.140^{***}$	−.015	.019	.026	$-.152^{***}$	$.080^{***}$
4. Orthographic N	$.185^{***}$	$-.507^{***}$	$-.438^{***}$	—	$-.229^{***}$	.019	−.024	.008	−.028	$.162^{***}$	$.052^{*}$
5. Age of acquisition	$-.624^{***}$	$.200^{***}$	$.252^{***}$	$-.142^{***}$	—	$-.369^{***}$	$-.308^{***}$	$-.129^{***}$	.026	$-.271^{***}$	$-.135^{***}$
6. Concreteness	−.019	$-.120^{***}$	$-.151^{***}$	$.078^{***}$	$-.085^{***}$	—	$.202^{***}$	−.019	$-.135^{***}$	$-.076^{***}$	$-.055^{*}$
7. Valence	$.163^{***}$	.002	.033	−.009	$-.130^{***}$	$-.065^{**}$	—	$-.049^{*}$	$-.219^{***}$	.022	$.142^{***}$
8. Valence extremity	$.202^{***}$	.028	−.032	$-.042^{*}$	$-.308^{***}$	−.022	$-.060^{**}$	—	$.336^{***}$	.000	.034
9. Arousal	$.085^{***}$	.024	.023	−.032	$-.102^{***}$	.020	$-.133^{***}$	$.343^{***}$	—	.013	.023
10. Semantic diversity	$.316^{***}$	$-.040^{\dagger}$	$-.090^{***}$	$.050^{*}$	$-.232^{***}$	$-.118^{***}$	$.065^{**}$	−.027	$-.107^{***}$	—	$.212^{***}$
11. Semantic neighbor similarity	$.540^{***}$	−.033	.034	$.048^{*}$	$-.252^{***}$	$.055^{**}$	$.240^{***}$	$-.046^{*}$	$-.039^{\dagger}$	$.205^{***}$	—

$^{*} p < .05$. $^{**} p < .01$. $^{***} p < .001$.

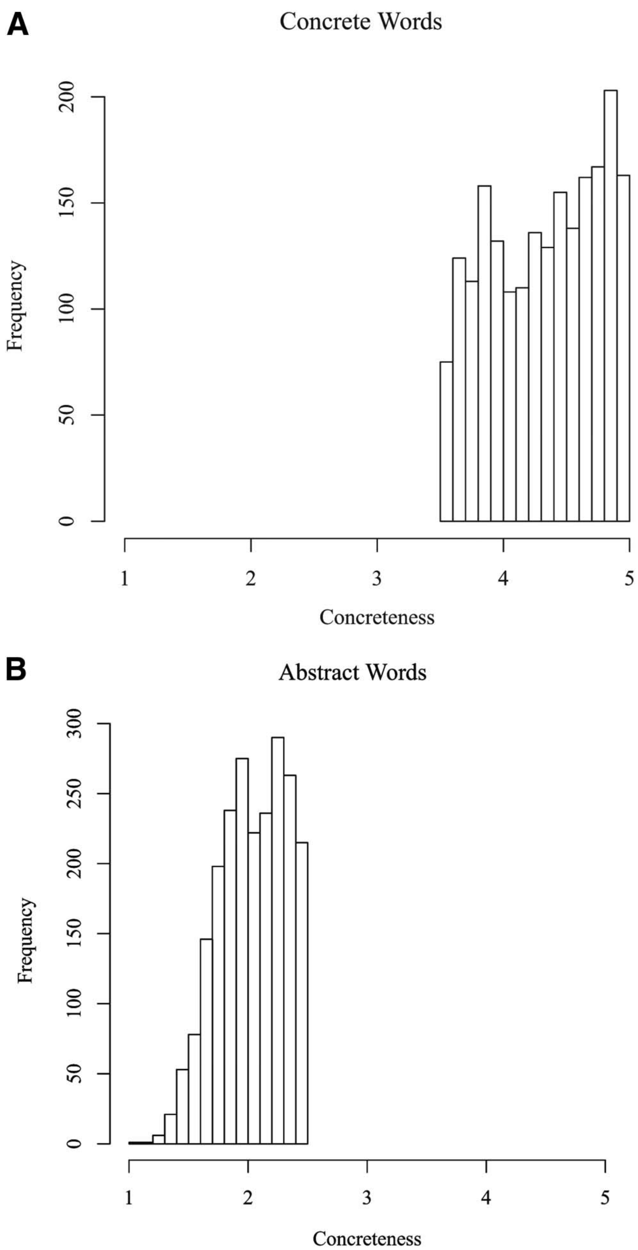

Figure 1. Frequency distributions for concreteness ratings for words included in individual differences analyses, presented separately for concrete and abstract words.

correct trials, RTs more than 2.5 standard deviations from each participant's mean were also identified as outliers. These trimming procedures resulted in the removal of 15.4% of the trials (13.7% errors; 1.7% RT outliers). We first describe the reliability analyses, before considering relationships among participants' vocabulary knowledge, drift rates, semantic decision performance, and sensitivity to different lexical and semantic dimensions. In all cases, we focus on latency data; the interpretation of accuracy data is made more complex by the multiple potential sources of semantic decision error.

Analysis 1: Reliability Analyses

Reliability was examined in two ways. First, we partitioned the trials for each participant into odd-numbered and even-numbered trials, which is a function of the order in which trials were presented. Comparing odd- versus even-numbered trials using correlations allows the within-session reliability of different measures to be evaluated. For each participant, we computed mean response time and standard deviation. The underlying RT distributional profile of each participant was also obtained by fitting his or her empirical RT distribution to both the ex-Gaussian distribution (Balota & Yap, 2011) and the diffusion model (Ratcliff et al., 2004). The ex-Gaussian model is the convolution of a Gaussian and exponential distribution and approximates the positively skewed distribution seen in empirical data, yielding three parameters: μ and σ reflect the mean and standard deviation of the Gaussian distribution, whereas τ reflects the mean and standard deviation of the exponential distribution. Turning to the diffusion model, we estimated a number of parameters, including *zr* (decision making bias), *a* (boundary separation), v_{concrete} (drift rate for concrete words), v_{abstract} (drift rate for abstract words), *t0* (nondecision time required for stimulus encoding and response execution), and *st0* (intertrial variability in nondecision time). Ex-Gaussian parameters were estimated in R (R Core Team, 2004), using Nelder and Mead's (1965) simplex algorithm; all fits could successfully converge within 500 iterations. Diffusion model parameters were estimated using the fast-dm-30 program (Voss et al., 2015); the Kolmogorov–Smirnov optimization criterion was used to quantify the goodness-of-fit between the predicted and observed RT distributions.

Table 3 presents the mean RT, standard deviation, ex-Gaussian parameters, and diffusion model parameters for semantic decision responses to concrete and abstract words, as a function of trial type (odd vs. even). The table reveals that semantic decision responses were slower for abstract (M = 1035 ms), compared with concrete (M = 958 ms), words. Furthermore, the ex-Gaussian analyses indicated that the slower mean RT for abstract words is primarily reflected by μ (distributional shifting) rather than by τ (an increase in the slow tail of the distribution). Specifically, the 77-ms difference between concrete and abstract words is mediated by a 66 ms difference in μ and an 11 ms difference in τ. This pattern also seems consistent with our finding that abstract words, despite taking longer to respond to, are associated with a *steeper* drift rate than concrete words. Collectively, these results suggest that the slowdown for abstract words mainly reflects *non*-decisional processes, such as the mechanisms underlying encoding or response execution.

Table 4 presents the split-half Pearson correlations for these parameters. The generally high to very high within-session correlations (*r*s from .590 to .987) reinforce the idea that participants tend to have stable RT distributional signatures that generalize across different sets of stimuli (Yap et al., 2012). It is also worth noting that reliability estimates appear to be slightly higher for concrete, compared with abstract, words; this trend is evident in μ, τ, and drift rate. In a complementary reliability analysis, we examined between-participants correlations in item response latencies. Specifically, we randomly divided the participants into two groups and computed, for each group, item means for the 5,000 concrete and 5,000 abstract words. The between-participants cor-

Table 3
Means, Standard Deviations, Ex-Gaussian Parameters, and Diffusion Model Parameters as a Function of Word and Trial Type

	Concrete words			Abstract words		
Measure	All trials	Odd trials	Even trials	All trials	Odd trials	Even trials
M	958	959	957	1035	1034	1036
SD	295	294	295	306	304	307
μ	652	650	650	717	711	715
σ	79	77	77	96	93	93
τ	306	311	307	317	321	321
zr	.583	.580	.586			
a	1.489	1.495	1.504			
v_{concrete}	1.213	1.236	1.227			
v_{abstract}	−1.537	−1.535	−1.556			
t0	.588	.587	.585			
st0	.273	.274	.275			

relation for concrete words, $r = .721$, $p < .001$ was higher than for abstract words, $r = .552$, $p < .001$, consistent with the earlier analyses.

Analysis 2: Individual Differences Analyses

Having established the reliability of semantic decision data, we next considered the relationships between vocabulary knowledge (as reflected by NAART35 performance) and different aspects of semantic decision performance. Figure 2 presents the scatterplots between NAART35 scores and participant mean RTs to concrete and abstract words. Vocabulary knowledge was negatively correlated with semantic decision times for both concrete ($r = -.267$) and abstract ($r = -.220$) words. To explore the relationships between vocabulary knowledge and semantic decision RT performance in a more fine-grained manner, we also examined the correlations between vocabulary knowledge with ex-Gaussian and diffusion model parameters (see Table 5).

For both concrete and abstract words, vocabulary knowledge was weakly to moderately correlated with μ, σ, τ in a negative direction. Participants with more vocabulary knowledge tended to have RT distributions characterized by a faster leading edge, less variability, and fewer slow responses in the tail of the distribution. Interestingly, higher NAART35 scores strongly predicted steeper drift rates for concrete ($r = .496$) and abstract ($r = -.375$) words; high vocabulary-knowledge participants could accumulate information more rapidly about stimuli. These participants also yielded higher values on *a* (i.e., setting more conservative decision thresholds) and lower values on *t0* (i.e., shorter nondecision times).

Table 4
Correlations Between Odd- and Even-Numbered Trial Parameters

Measure	Concrete Words	Abstract Words
M	.987***	.987***
SD	.969***	.967***
μ	.868***	.744***
σ	.590***	.596***
τ	.843***	.718***
	All words	
zr	.661***	
a	.902***	
v_{concrete}	.814***	
v_{abstract}	.764***	
t0	.945***	
st0	.806***	

*** $p < .001$.

Next, we analyzed the data with linear mixed effects (LME) models to determine the extent to which the influence of semantic richness variables was moderated by individual differences in vocabulary knowledge and drift rate, which respectively tap the integrity of underlying lexicosemantic representations and the efficiency of the evidence-accumulation process. In addition to the main effects of the lexical and semantic variables described earlier, we also controlled for the theoretically important interaction between valence and frequency (Kuperman et al., 2014).

Using R (R Core Team, 2004), we fitted z-score transformed RTs (Faust, Balota, Spieler, & Ferraro, 1999) using the lme4 package (Bates, Mächler, Bolker, & Walker, 2015); *p* values for fixed effects were obtained using the lmerTest package (Kuznetsova, Brockhoff, & Christensen, 2016). For all analyses, random intercepts for participants and items were included. To determine whether the by-participant random slope for a variable (e.g., word frequency) should be included in the model, we used likelihood ratio tests to compare models with and without the random slope, and retained the slope only when the difference between the likelihood of the two models was statistically significant.

Separate analyses were conducted for concrete (see Table 6) and abstract (see Table 7) words. Partial effects for all predictors are presented in the Appendix. For concrete words, responses were faster when words were more frequent, had fewer syllables, and were more orthographically distinct. Responses were also faster for words that were more concrete, less ambiguous, more similar to their semantic neighbors, and acquired earlier. There was also a marginal effect of valence, $p = .06$, where positive words tended to be responded to faster than negative words. More pertinently for the present study, a number of semantic richness effects were moderated by the individual differences of interest (NAART35 and v_{concrete}). NAART35 interacted with word frequency, age of

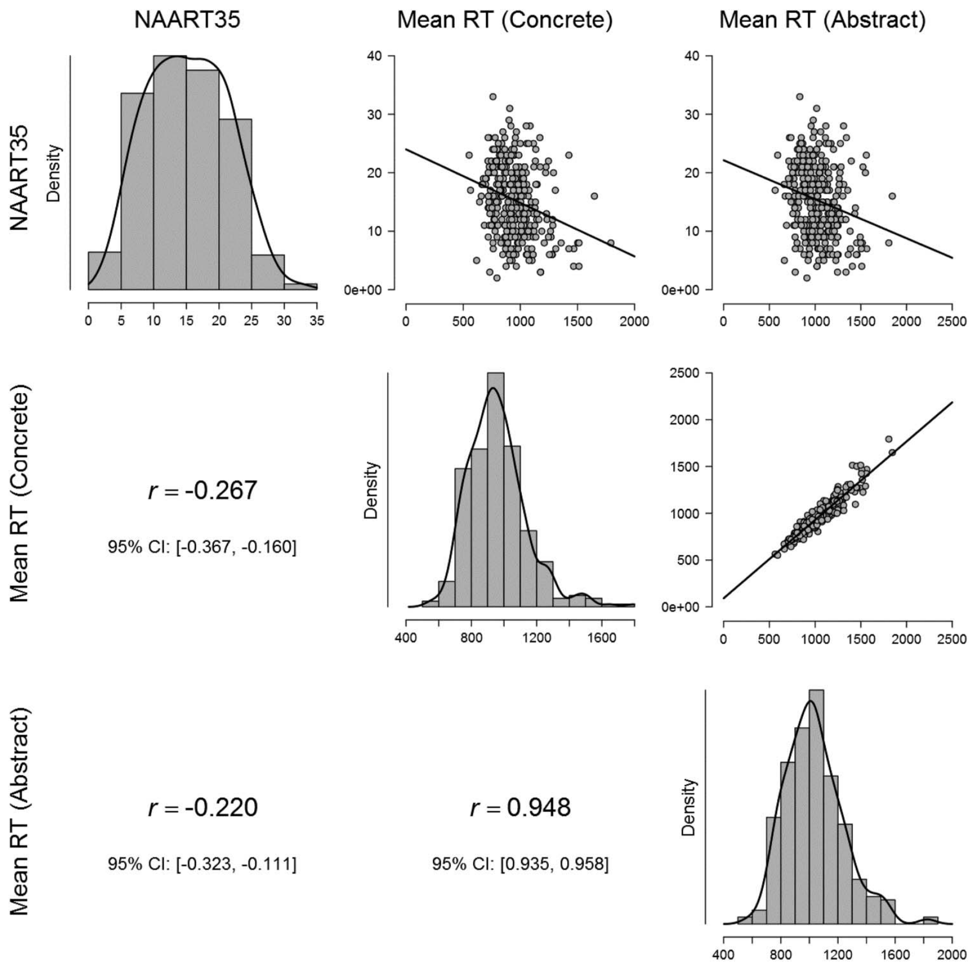

Figure 2. Frequency distributions for NAART35 vocabulary scores, concrete RT, and abstract RT, and scatterplots for relationships between these variables.

acquisition, concreteness, and semantic neighbor similarity, whereas v_{concrete} interacted with concreteness. Using the effects package (Fox et al., 2015), we plotted the statistically significant interactions (see Figure 3). The slopes indicate that as vocabulary knowledge (as reflected by NAART35 scores) increased, sensitivity to word frequency and age of acquisition decreased, whereas sensitivity to concreteness and semantic neighbor similarity *increased*. Similarly, as participant-level drift rates became steeper, sensitivity to concreteness increased (see Figure 4).

Turning to abstract words, responses were faster when words were more frequent, had fewer letters but *more* syllables, and were more orthographically distinct. Responses were also facilitated for words that were *less* concrete, more valenced, more ambiguous, and acquired earlier. Three of the interactions involving NAART35 were significant. Simple slopes revealed that as vocabulary knowledge increased, *reversed* concreteness effects (i.e., faster RTs for more abstract words) increased, alongside decreased sensitivity to word frequency and age of acquisition (see Figure 5). In addition, as participant-level drift rates became steeper, sensitivity to age of acquisition decreased (see Figure 6).

Discussion

The purpose of the present study was to examine the reliability of semantic decision performance and also to investigate individual differences in the task. Our results suggest that the semantic decision task shows good reliability, with somewhat higher reliability for responses to concrete words than for responses to abstract words. Although concrete and abstract words were on average equally frequent, responses were slower to abstract words than to concrete words. The diffusion model analyses suggested that slowing for abstract words was due to either encoding or the response and not to decision-making. As such, the slower responses for abstract words seemed to be largely mediated by slower encoding of semantic information. Further, the concreteness ratings distribution presented in Figure 1 shows some asymmetry in that the concrete words tended to be closer to the concrete end of the scale while abstract words were less close to the abstract end of the scale, in keeping with the distribution reported for the 14,000 items in the Brysbaert et al. (2014) concreteness ratings study. These findings tentatively suggest that participants may have a clearer idea of a highly concrete concept than a highly

Table 5
Correlations Between Vocabulary Knowledge and Ex-Gaussian and Diffusion Model Parameters

Measure	NAART35
μ_{concrete}	$-.241^{***}$
σ_{concrete}	$-.295^{***}$
τ_{concrete}	$-.187^{***}$
μ_{abstract}	$-.180^{**}$
σ_{abstract}	$-.187^{***}$
τ_{abstract}	$-.142^{*}$
zr	.064
a	$.131^{*}$
v_{concrete}	$.496^{***}$
v_{abstract}	$-.375^{***}$
t0	$-.285^{***}$
st0	$-.299^{***}$

Note. NAART35 = North American Adult Reading Test Scores (Uttl, 2002).
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

abstract concept. As such, they may find it easier to identify semantic features or dimensions that are characteristic of a prototypical "concrete thing" than a prototypical "abstract thing," responding more quickly and more consistently to concrete words. Abstract words may be a less coherent category for which it is harder to generate positive indicators; participants are likely to adopt the same kinds of definitions that have been offered by many researchers who have considered abstract meaning, wherein abstract words are defined by what they are *not*, as in "[r]oughly speaking, an abstract concept refers to entities that are neither purely physical nor spatially constrained" (Barsalou & Wiemer-Hastings, 2005, p. 129).

By comparing the models derived for concrete and abstract responses in the present study, however, we can offer a few clues about variables that might be positive indicators of abstractness. For responses to concrete words, concreteness and semantic neighbor similarity were the most important semantic richness predictors in our analyses, whereas for abstract words, concreteness, valence extremity, and ambiguity (SemD) were significant semantic richness predictors. These findings provide empirical evidence for some of the proposals about how abstract meanings might be represented. The significant effect of semantic diversity for abstract words provides support for the notion that contextual and situational information are important to abstract meaning (Wilson-Mendenhall et al., 2013). Extremity of valence was a significant predictor of responses to abstract words and this finding is consistent with the proposal that emotion is important to abstract meanings (e.g., Vigliocco et al., 2009).

Of course, our analysis was necessarily limited to the variables for which we had many values. It was not possible to test other proposed dimensions of abstract meaning (e.g., sociality, Borghi et al., 2017) because we do not yet have metrics for those types of information that are suited to a large-scale analysis. Further, it is possible that some predictors (e.g., emotion) are relatively more important to the meanings of some types of abstract concepts than to others (Borghi et al., 2017; Pexman, in press), but our analysis treats abstract words as one undifferentiated category. These will be important issues to tackle in future research.

We also investigated individual differences in semantic decision-making, and found that participants with more vocabulary knowledge tended to have steeper drift rates for responses to both concrete and abstract words, suggesting that high vocabulary-knowledge participants could accumulate information more rapidly about all stimuli. In addition, we tested whether participants' relative levels of vocabulary skill and efficiency in accumulating information were related to their recruitment of different lexical and semantic richness dimensions in semantic decision. We considered two general possibilities for individual differences in semantic decision-making. On the one hand, it seemed possible that participants with higher lexical quality might simply respond faster, and with less sensitivity to *all* word characteristics. On the other hand, the alternative possibility was that participants with higher lexical quality might selectively show less sensitivity to some word characteristics and more sensitivity to others. Our findings from the individual differences analyses, reviewed next, provide more support for the latter possibility, and thus are consistent with a relatively dynamic and flexible meaning retrieval process.

In the pattern of concreteness effects, we found support for the hypothesis that high vocabulary participants might be better able to capitalize on typicality in their decisions, using their more extensive word knowledge to emphasize the features that are most decision-relevant, thereby helping them to effectively discriminate between concrete and abstract words. That is, participants with higher vocabulary scores and participants with steeper drift rates showed more sensitivity to concreteness in their responses to concrete words. Similarly, participants with higher vocabulary scores showed more sensitivity to concreteness in their responses to abstract words. That is, participants with higher vocabulary scores tended to show larger *reversed* concreteness effects for abstract word responses, as they were faster to respond to very abstract words and slower to respond to moderately abstract words. In other words, high vocabulary participants were able to quickly categorize abstract words that were closer to the "abstract" end of the abstract-concrete rating scale and slower to categorize abstract words that were closer to the middle of the scale. In contrast, the abstract word responses of low vocabulary participants were less affected by the words' relative abstractness.

For the emotion variables, we hypothesized that high vocabulary participants might depend less on emotion information for semantic decisions because they should have more extensive word knowledge. We predicted that low vocabulary participants, in contrast, might depend more heavily on emotion information, particularly for abstract words, in order to ground the meanings of those items. These hypotheses were not supported. Specifically, although we found a main effect of valence extremity for abstract words, we did not find interactions of any of the emotion variables with the individual difference measures, for concrete or for abstract words. One interpretation of this finding is that all participants relied on emotion information to classify abstract words, consistent with the suggestion that emotion is an effective way of grounding meanings of abstract words (e.g., Borghi et al., 2017; Vigliocco et al., 2009).

As mentioned, in the preliminary analyses of the Calgary Semantic Decision Project dataset, Pexman et al. (2017) found a small inhibitory effect of ambiguity for concrete words, and a facilitatory effect of ambiguity for abstract words. In our analysis,

Table 6
LME Model Estimates (Based on ZRT) for the Effects of Semantic Richness and Individual Differences for Concrete Words

Effect	Variance		*SD*
Random effects			
Items			
Intercept	.0547		.2338
Participants			
Intercept	.0047		.0687
Word frequency	.0020		.0452
Length	.0000		.0016
Syllables	.0005		.0216
Orthographic *N*	.0002		.0129
Age of acquisition	.0003		.0179
Concreteness	.0093		.0965
Valence	.0004		.0209
Semantic diversity	.0042		.0644
Semantic neighbor similarity	.0688		.2622
	Coefficient	Standard error	*p* value
Fixed effects			
Intercept	−.280	.008	<.001
Word frequency	−.073	.017	<.001
Length	−.003	.005	.516
Syllables	.063	.011	<.001
Orthographic *N*	.006	.003	.032
Age of acquisition	.042	.003	<.001
Concreteness	−.408	.017	<.001
Valence	−.011	.006	.061
Valence extremity	−.006	.009	.515
Arousal	−.012	.007	.116
Semantic diversity	.058	.025	.021
Semantic neighbor similarity	−.235	.070	<.001
NAART	−.001	.001	.216
v_{concrete}	−.005	.018	.791
Word frequency × Valence	.012	.009	.181
Word frequency × Valence extremity	−.025	.015	.087
NAART × Word frequency	.008	.002	<.001
NAART × Age of acquisition	−.002	.000	<.001
NAART × Concreteness	−.009	.002	<.001
NAART × Valence	.001	.001	.132
NAART × Valence extremity	−.002	.001	.065
NAART × Arousal	.001	.001	.225
NAART × Semantic diversity	.001	.003	.608
NAART × Semantic neighbor similarity	−.020	.007	.007
v_{concrete} × Word frequency	−.022	.028	.436
v_{concrete} × Age of acquisition	−.001	.006	.821
v_{concrete} × Concreteness	−.093	.031	.003
v_{concrete} × Valence	−.006	.010	.575
v_{concrete} × Valence extremity	.012	.015	.412
v_{concrete} × Arousal	−.010	.012	.410
v_{concrete} × Semantic diversity	.036	.042	.383
v_{concrete} × Semantic neighbor similarity	.106	.118	.369

which involved a slightly different (but overlapping) set of items and predictors, we also found a modest inhibitory effect of ambiguity for concrete words and a facilitatory effect of ambiguity for abstract words. Indeed, several other studies have shown null or modest effects of ambiguity for responses to concrete words in semantic decision (Hargreaves et al., 2011; Pexman et al., 2004; Siakaluk et al., 2007; Yap & Pexman, 2016). Thus, the findings further reinforce the view that ambiguity seems to exert quite different effects in semantic decisions to abstract and concrete words. Our predictions for individual differences in ambiguity effects were that high vocabulary participants, who have more extensive knowledge of words' meanings, might be more sensitive to ambiguity. Our results were not consistent with this hypothesis, as neither of the individual difference metrics interacted with SemD effects. Thus, in terms of potential explanations for the mixed effects of ambiguity that have been observed in previous semantic decision studies (e.g., Hino et al., 2006; Hoffman & Woollams, 2015; Yap et al., 2011), our results do not lend support to the possibility that individual differences serve as an explanatory variable. Instead, they are consistent with the possibility that concreteness may be an ex-

Table 7
LME Model Estimates (Based on ZRT) for the Effects of Semantic Richness and Individual Differences for Abstract Words

Effect	Variance		SD
Random effects			
Items			
Intercept	.0339		.1840
Participants			
Intercept	.0059		.0769
Word frequency	.0042		.0650
Syllables	.0003		.0170
Orthographic *N*	.0001		.0106
Age of acquisition	.0003		.0167
Valence extremity	.0012		.0352
Semantic diversity	.0193		.1391
Semantic neighbor similarity	.1686		.4106
	Coefficient	Standard error	*p* value
Fixed effects			
Intercept	.005	.007	.517
Word frequency	−.071	.016	<.001
Length	.024	.005	<.001
Syllables	−.041	.009	<.001
Orthographic *N*	.010	.003	<.001
Age of acquisition	.022	.004	<.001
Concreteness	.202	.019	<.001
Valence	.005	.004	.230
Valence extremity	−.042	.008	<.001
Arousal	−.009	.006	.158
Semantic diversity	−.159	.024	<.001
Semantic neighbor similarity	.020	.061	.741
NAART	.002	.001	.046
$V_{abstract}$	−.007	.015	.644
Word frequency × Valence	.003	.007	.705
Word frequency × Valence extremity	.000	.013	.993
NAART × Word frequency	.005	.002	.009
NAART × Age of acquisition	−.001	.000	<.001
NAART × Concreteness	.006	.002	.012
NAART × Valence	−.001	.000	.137
NAART × Valence extremity	.000	.001	.692
NAART × Arousal	.000	.001	.845
NAART × Semantic diversity	−.006	.003	.052
NAART × Semantic neighbor similarity	.002	.008	.809
$V_{abstract}$ × Word frequency	−.012	.026	.641
$V_{abstract}$ × Age of acquisition	−.018	.006	.002
$V_{abstract}$ × Concreteness	−.025	.030	.408
$V_{abstract}$ × Valence	.004	.006	.522
$V_{abstract}$ × Valence extremity	−.016	.013	.213
$V_{abstract}$ × Arousal	−.009	.010	.363
$v_{abstract}$ × Semantic diversity	−.021	.041	.606
$V_{abstract}$ × Semantic neighbor similarity	−.075	.104	.469

planatory variable, as different effects of semantic ambiguity were observed for concrete and abstract words.

In our hypotheses for the semantic neighborhood variable, we predicted that high-vocabulary participants might be particularly sensitive to ANS effects, particularly for concrete words. This hypothesis was supported; there was a significant interaction between vocabulary and ANS (larger ANS effects for high-vocabulary participants) for concrete words, and a null effect of ANS for abstract words. As such, the results are consistent with those of Hargreaves and Pexman (2014), whose investigation on the time course of semantic processing revealed an early influence of semantic neighborhood. It is possible that high-vocabulary participants, who are also more fluent lexical processors, are more sensitive to these early influences.

The individual differences analyses also showed that age of acquisition interacted with vocabulary scores for concrete word responses, and with both vocabulary scores and drift rates for abstract word responses. Low vocabulary participants were more sensitive to age of acquisition; this may indicate that lower quality lexical representations are more vulnerable to the network consequences of late word acquisition. The mechanisms underlying these individual differences are likely to be complicated and will need to be investigated more systematically in future research, but one possibility involves developmental differences between participants in terms of rates of vocab-

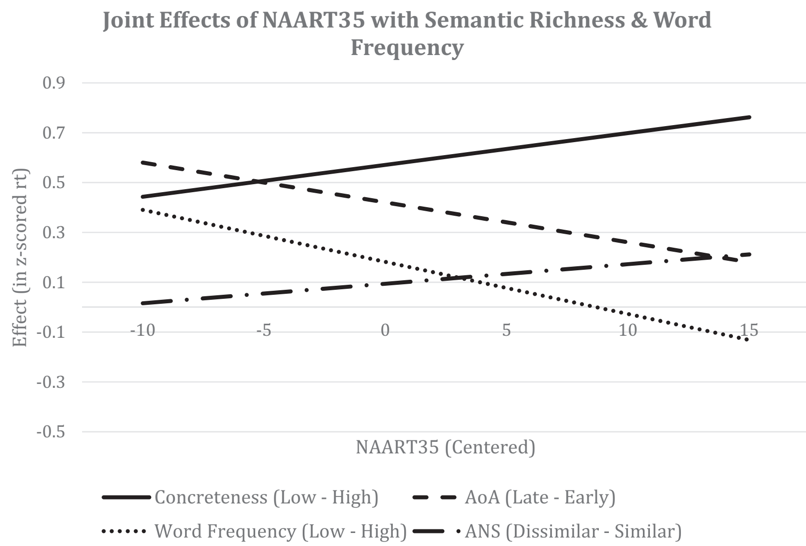

Figure 3. Statistically significant interactions of NAART35 vocabulary scores with semantic richness variables and word frequency for concrete words.

ulary acquisition (e.g., Sénéchal, Thomas, & Monker, 1995). That is, low vocabulary participants may have been slower to acquire late-acquired words, resulting in relatively weak representations for these items.

In summary, the findings of the present study showed that high-vocabulary participants were more sensitive to some semantic richness dimensions and less sensitive to others. As such, the results provide evidence for the separability of those dimensions, and thus for the multidimensional nature of semantic representation (Pexman et al., 2008; Pexman, Siakaluk, & Yap, 2014; Yap et al., 2011, 2012). Semantic processing was influenced by language-based (ANS) and also simulation or experience-based (concreteness, emotion) semantic dimensions, providing support for hybrid or pluralist models of semantic representation (Barsalou et al., 2008; Borghi & Binkofski, 2014; Dove, 2011; Louwerse & Jeuniaux, 2010; Reilly et al., 2016).

Recall that in their examination of individual differences in the English Lexicon Project dataset, Yap et al. (2012) found only modest evidence that high vocabulary participants were less sensitive to frequency effects, and ultimately concluded that there was little evidence to suggest that word frequency effects in lexical decision were negatively related to vocabulary knowledge. In contrast, the present results showed that more skilled participants tended to produce smaller effects of frequency for concrete words and also for abstract words. This is illustrated in Figures 3 and 5, with the plots showing that the

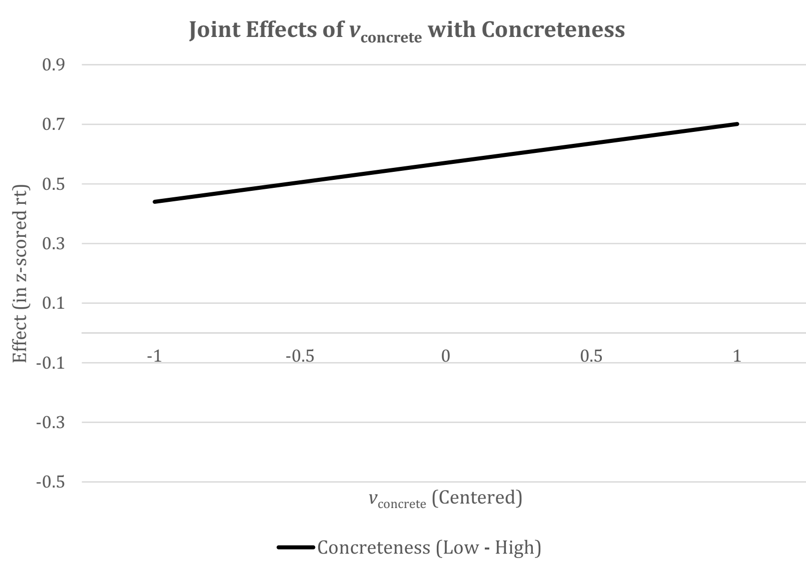

Figure 4. Statistically significant interaction of drift rate with concreteness for concrete words.

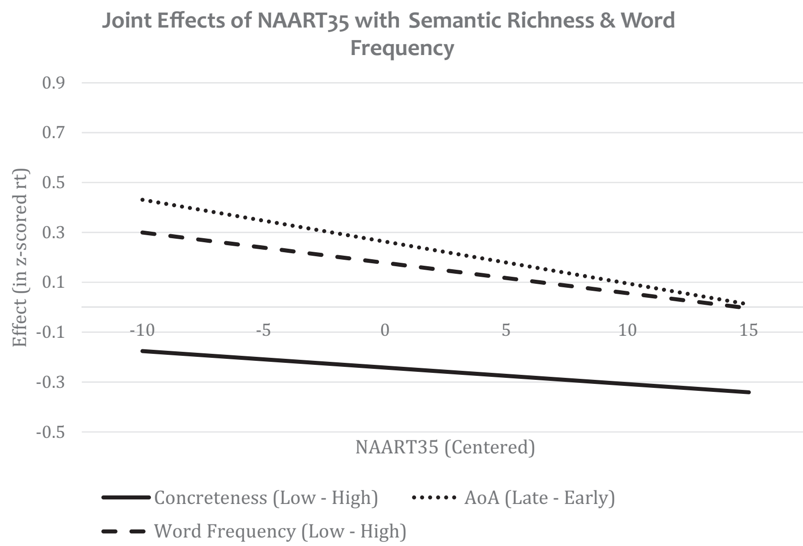

Figure 5. Statistically significant interactions of NAART35 Vocabulary scores with semantic richness variables and word frequency for abstract words.

highest vocabulary participants tended to show essentially null effects of frequency. In explaining the different findings for word frequency in the Yap et al. lexical decision results and the present semantic decision results, one possibility comes from the potential strategies that are available to participants in each task.

Lexical decisions are thought to be performed on the basis of a familiarity/meaningfulness assessment and decision/verification stage (Balota & Chumbley, 1984). Both stages involve lexical/orthographic processing and can be affected by word frequency. Semantic decisions require some initial orthographic/lexical processing but the decision is primarily based on semantic processing. Indeed, several studies have shown that frequency effects tend to be somewhat larger in the lexical-decision task than in the semantic decision task (Taikh et al., 2015; Yap et al., 2011, 2012). If cascaded processing is assumed, then orthographic processing need not be completed before semantic processing begins (e.g., Balota et al., 1991). Given these characterizations of the two tasks and the assumption that frequency effects are localized to lexical/orthographic processes, the effects of frequency may be inevitable for all participants in lexical decision, whereas in semantic decision high vocabulary participants may be able to more rapidly engage semantic processing, minimizing frequency effects in that task. The notion that highly skilled participants may be able to

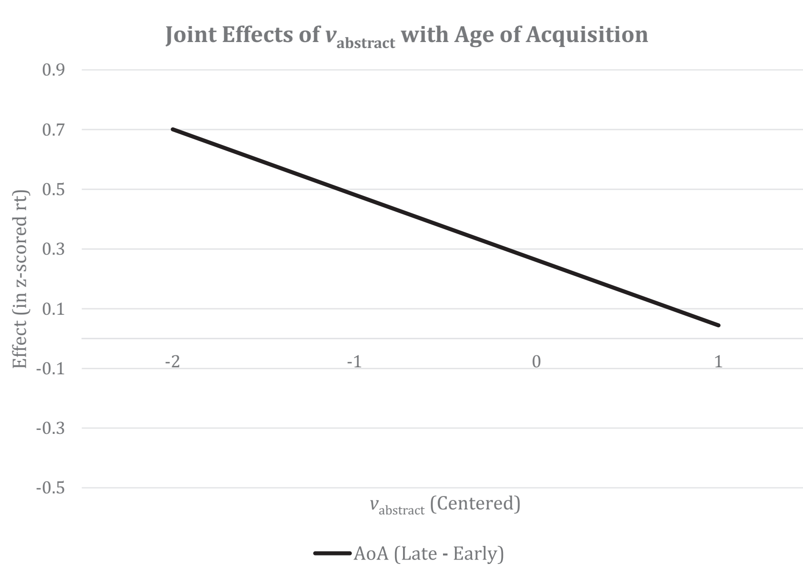

Figure 6. Statistically significant interaction of drift rate with age of acquisition for abstract words.

rapidly activate semantic information would be consistent with the findings reported by Andrews et al. (2017) in their examination of individual differences in automatic semantic priming.

Another explanation for the differences between the present results and those of Yap et al. (2012) involves the individual differences measures used. Yap et al. used the Shipley (1940) synonym judgment task to estimate participant vocabulary, whereas we used the Uttl (2002) NAART35 pronunciation task to estimate vocabulary. It is possible that the NAART35 is somehow more sensitive to individual differences in word frequency than the Shipley measure. Although possible, we think this explanation is rather unlikely because both vocabulary measures have established external validity. We should also note that although we have attributed the individual differences observed in the present study to vocabulary skills, it is not possible to rule out a more general factor like IQ as a driver of individual differences we observed in the semantic decision task. As mentioned, drift rate in lexical decision tasks tends to be strongly related to IQ (Ratcliff et al., 2010), and it seems likely that IQ also plays a role in drift rate and other individual differences in the semantic decision task.

Most research on lexical-semantic processing has examined group-level data. The present findings suggest that additional insights can be gleaned from individual differences analyses. Participants with higher levels of vocabulary skill were able to derive word meanings more efficiently, and to modulate their sensitivity to semantic richness dimensions, seeming to emphasize those that were task-relevant. It is worth noting that these results were based on a sample of undergraduate students, who in their admission to University are partly selected for their vocabulary knowledge and, as such, will show less variability in vocabulary scores than readers in general. In light of that, it is possible, even likely, that our results underestimate the magnitude of the relationships between individual differences and semantic processing performance. Our results build on those of previous studies to demonstrate that the process of deriving meaning from print varies as a function of item, task, and individual differences. As such, the findings are consistent with dynamic, multidimensional accounts of word meaning.

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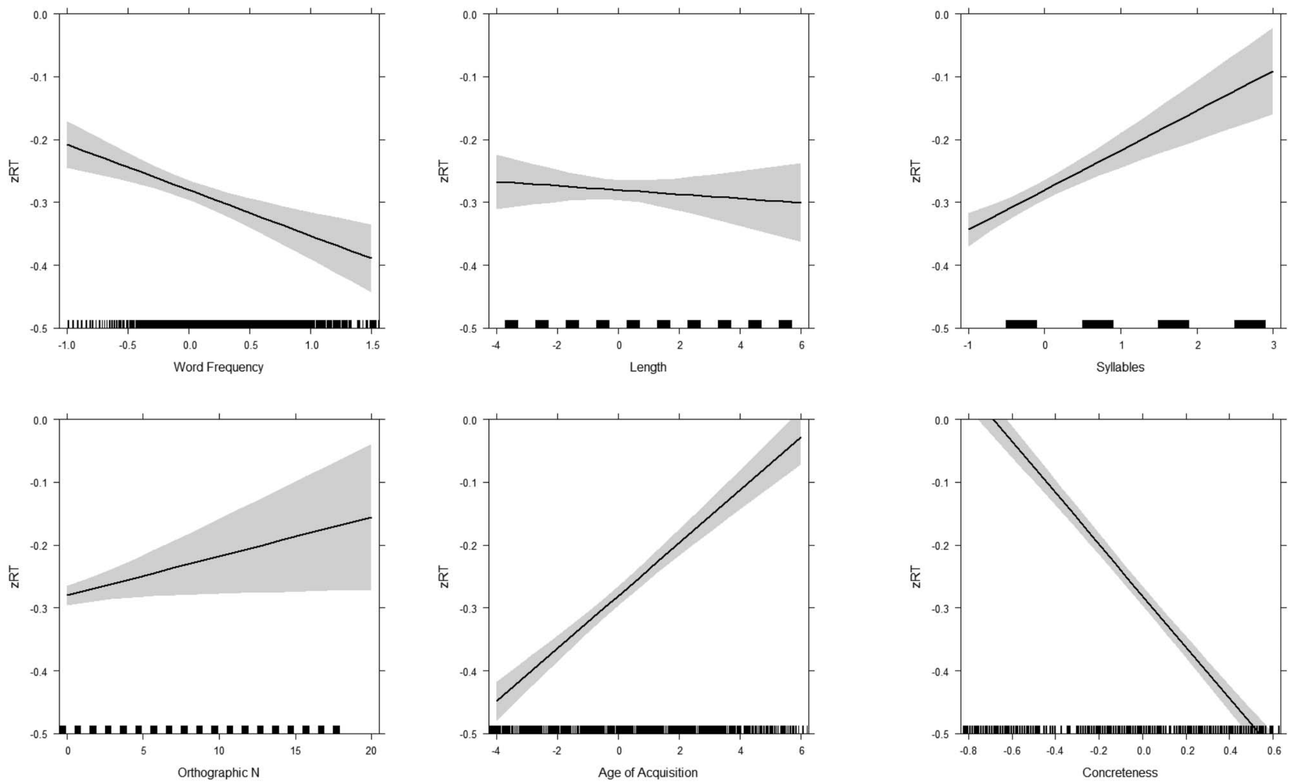
(*Appendix follows*)

Appendix

Partial Effects for Predictors

Concrete Word Responses



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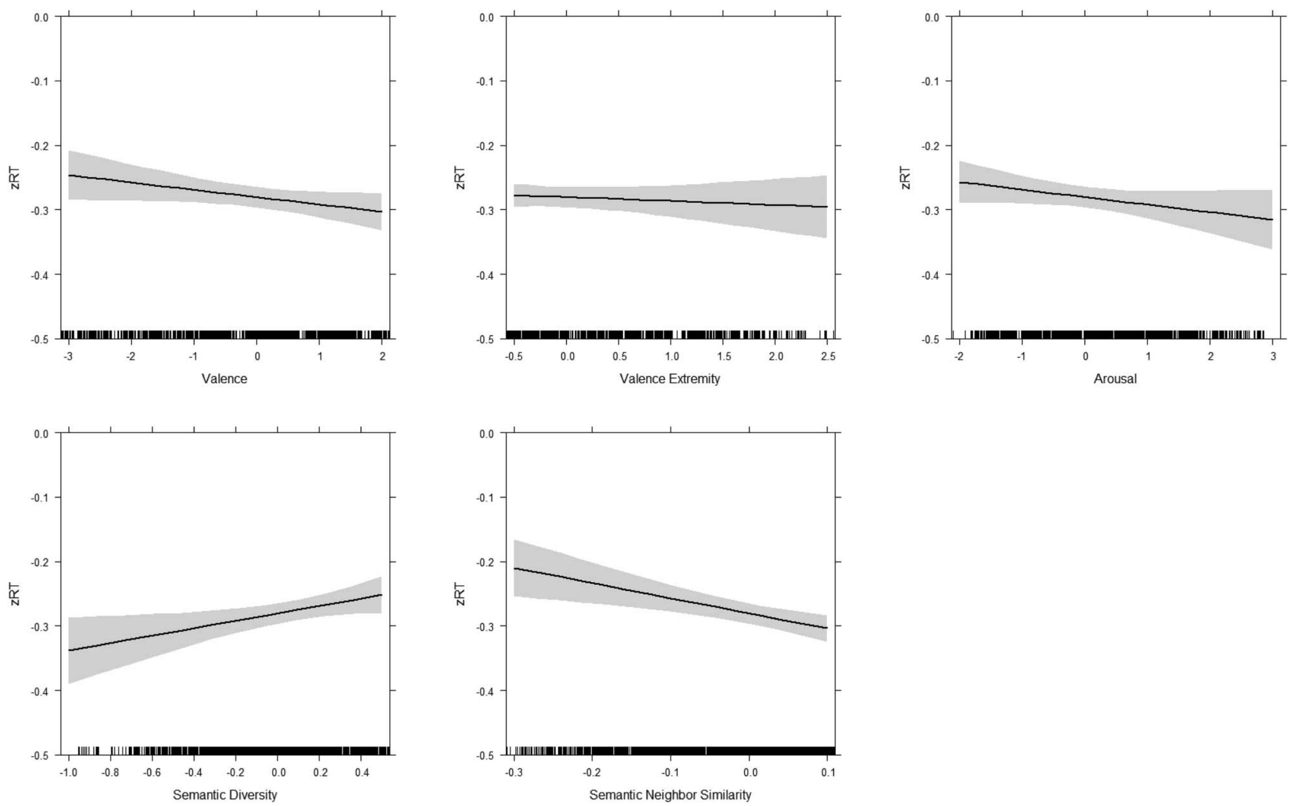

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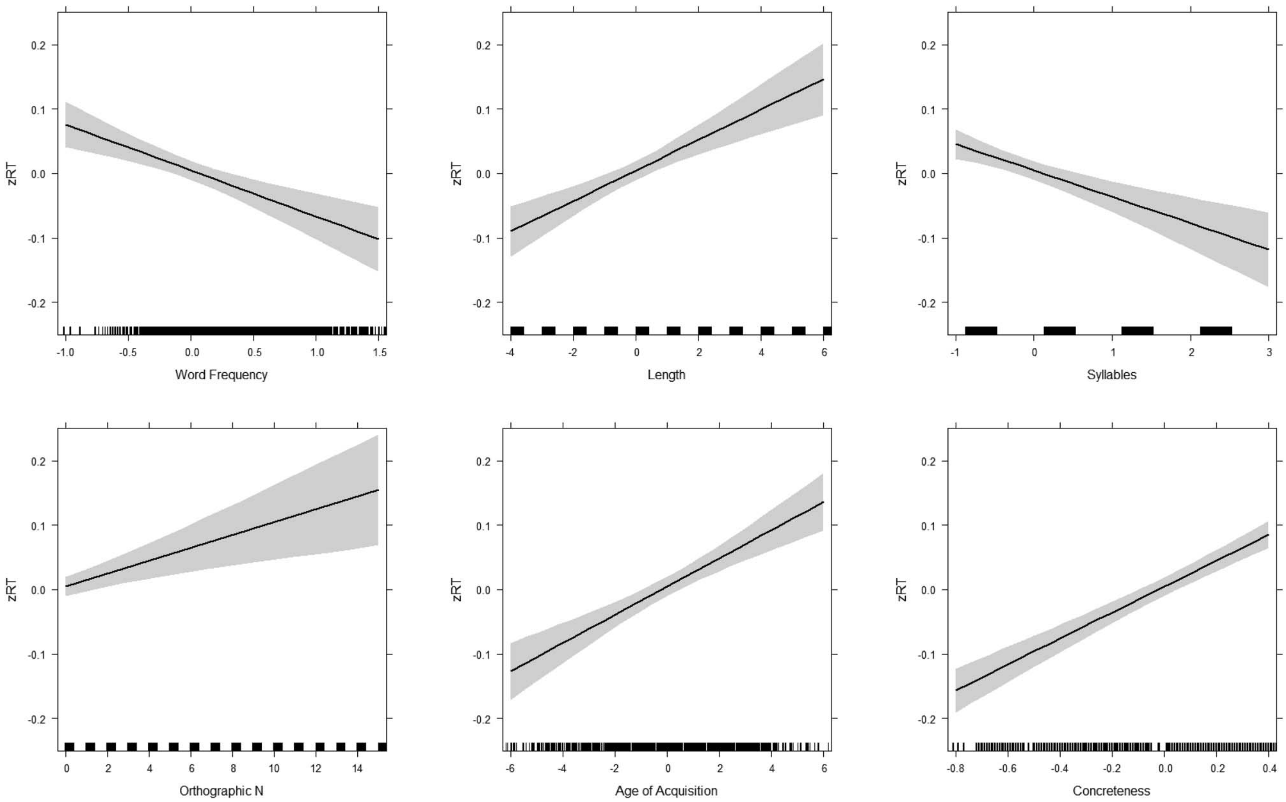
Abstract Word Responses



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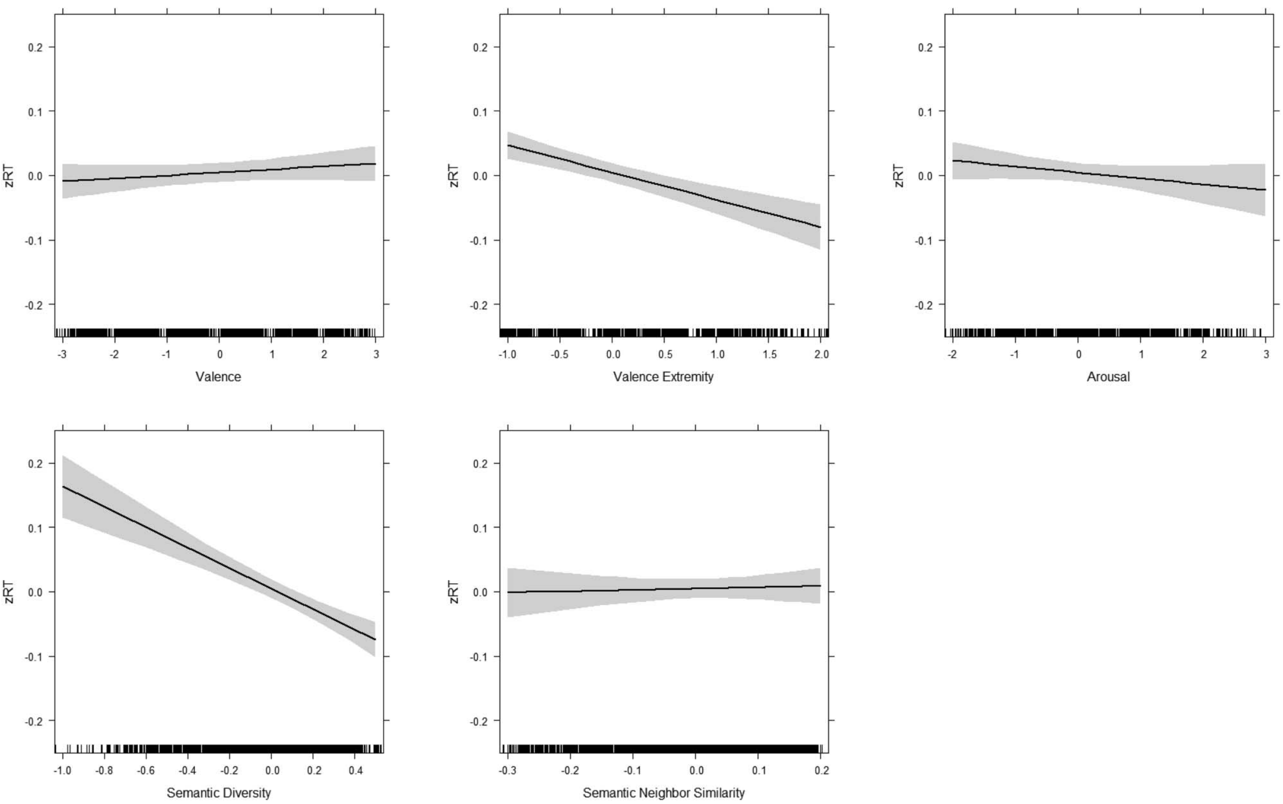

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