**The Neural Dynamics of Semantic Diversity in Spoken Word Recognition: The
Role of Alpha-Beta Power**

by

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Abstract

Word recognition performance is significantly affected by semantic diversity (SemD), a corpus-based measure that indexes the degree to which the contexts associated with a word are similar in meaning. Due to the prominence of SemD as a determinant of behaviour, it is important to understand its neural correlates, but these remain underexplored. To address this gap, this study examines whether and how SemD information is reflected in alpha-beta power dynamics during spoken word recognition. Given previous evidence linking stronger alpha-beta power decreases to semantically richer words, high-SemD words were predicted to elicit stronger alpha-beta power decreases relative to low-SemD words. Electroencephalographic data were recorded while 13 older adults performed a word-picture verification task. Average alpha-beta (10–20 Hz) power around 400–600 ms post-word onset served as the dependent variable in linear mixed models whose fixed effects included SemD and other psycholinguistic variables. Results showed that SemD was not a significant predictor when posterior sites were considered. However, when anterior sites and a later time window were examined, a significant effect of SemD was found, with higher scores predicting stronger alpha-beta power decreases. Additional analyses on event-related potential responses around 300–500 ms post-stimulus showed no effects of SemD. These findings provide the first insights into the electrophysiological signature of SemD and corroborate previous reports of stronger alpha-beta power decreases when more lexical-semantic information needs to be retrieved from memory. The null results are discussed in view of a few methodological aspects, which could be explored in future studies.

Keywords: semantic diversity, electroencephalography, spoken word recognition, alpha-beta power

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Introduction

Compare the following two sentences: 1) “He is a very special case”; 2) “The fascists irrigated the tulips”. Although they differ in many respects, the most uncontroversial difference between these sentences lies in their levels of semantic diversity, a semantic richness dimension that indexes the extent to which the contexts containing a word are similar in meaning (Hoffman, Lambon Ralph, & Rogers, 2013): while the first was built from words with high semantic diversity scores, the second was built almost exclusively from words with low scores. This thesis is about the differences in brain activity when we listen to words with high and low levels of semantic diversity. Specifically, it is about whether and how electroencephalographic power in the alpha-beta frequency band is modulated by changes in semantic diversity information associated with nouns that were presented to older English-speaking adults.

The thesis is organized as follows: in the remainder of this section, the arguments for investigating semantic diversity in relation to alpha-beta activity are laid out. In the following section, the methodological steps adopted in the study are described. Then the results from the main analysis are presented followed by the results from post-hoc analyses. Lastly, the findings are discussed including suggestions for future research.

Semantic Diversity

Although word frequency has long been assumed to be the source of statistical information underlying lexical organization, measures that capture the contextual variability of words have challenged this assumption by surpassing frequency in predicting word recognition performance (see Jones, Dye, & Johns, 2017 for a review). The most well-known example is found in Adelman, Brown, and Quesada (2006), where contextual diversity, operationalized as the number of passages (documents) that contained a word in a corpus, outperformed frequency in predicting both lexical decision and word-naming latencies from

the English Lexicon Project database (Balota et al., 2007). The authors explained the superiority of contextual diversity by resorting to the principle of likely need (Anderson & Milson, 1989), which posits that words experienced in many contexts during learning are more likely to be needed in future contexts, making them more readily accessible in the lexicon. This principle is compatible with distributional models of semantic representation, in which a word's meaning is built from the words with which it cooccurs (Jones, Willits, & Dennis, 2015).

Albeit prominent in determining word recognition performance, however, contextual diversity as a simple document count has been shown to be inferior to a measure of contextual diversity that takes into consideration the redundancy in the contexts' general meaning (Jones, Johns, & Recchia, 2012; Hoffman, Rogers, & Lambon Ralph, 2011). Known as semantic diversity, this metric encapsulates more unique variance than document count and word frequency in tasks such as lexical decision, naming, and semantic judgement performed by both young and older adults (Jones et al., 2012; Hoffman, Lambon Ralph, & Rogers, 2013; Hoffman & Woollams, 2015). Thus, the psychological reality of the semantic diversity effect makes it a promising avenue for investigating human lexical-semantic processing.

To understand the effect of semantic diversity (SemD), it is important to know how the measure was developed.¹ As described in Hoffman and colleagues (2013), the process of constructing SemD involved deriving small sets of linguistic contexts from a large text corpus and then using them to produce a co-occurrence matrix with word vectors whose elements corresponded to the frequency of occurrence of the words in different contexts.

¹ Two different metrics called "semantic diversity" were independently developed by Hoffman and colleagues (2011) and Jones and colleagues (2012). They are equivalent, however, as both capture contextual variability while considering the overlap in information between the contexts (Jones et al., 2017). Due to its wider availability, the measure developed by Hoffman and colleagues will be the focus of this study.

Singular value decomposition was then employed to represent each context as a point in a semantic space, wherein the distance between two contexts captured their similarity in content. For each word, the mean similarity between all the contexts in which it appeared was then calculated. Words whose contexts were very similar received a low SemD score, whereas those whose contexts were more diverse received a high SemD score. For example, the more specialized word “aircraft” received a lower SemD score than the word “place”, which can occur in a variety of linguistic contexts.

To further understand the effect of SemD, it would be useful to know the neuronal dynamics underlying it. In this regard, electroencephalographic (EEG) measures could provide valuable information, but no studies so far have assessed the EEG signature of SemD. However, Vergara-Martínez, Comesaña, and Perea (2017) investigated the event-related potential (ERP) signature of a similar measure, contextual diversity, operationalized as the proportion of documents in which a word appeared in the EsPal subtitle database (Duchon, Perea, Sebastián-Gallés, Martí, & Carreiras, 2013). Using a visual lexical decision paradigm, the authors found that words with high contextual diversity scores were associated with faster responses and more negative-going ERP amplitudes at frontal electrodes around 225–450 ms after word presentation compared to words with low contextual diversity scores. Vergara-Martínez and colleagues interpreted these findings as an N400 effect that is elicited as a result of larger semantic networks becoming active for words that appear in many contexts. As the authors further put it, contextually diverse words would be linked to enhanced activity from long term memory because of their richer semantic representations (Vergara-Martínez et al., 2017).

While expanding our knowledge on this understudied topic, the ERP approach adopted by Vergara-Martínez and colleagues (2017) can only provide part of the event-related electrophysiological picture underlying processing of words with different levels of

contextual variability. Another important part of this picture is given by the analysis of EEG oscillations, a type of ongoing neuronal activity which, unlike ERPs, is not necessarily phase-locked to experimental events (Bastiaansen, Mazaheri, & Jensen, 2011). Brain oscillations reflect synchronous fluctuations between excitatory and inhibitory post-synaptic activity of large groups of neurons, and the power of a given frequency band can be used to assess the degree of synchronized firing in these local neural assemblies, with power decreases being linked to more desynchronization (Hanslmayr, Staudigl, & Fellner, 2012).

The Role of Alpha-Beta Dynamics in Lexical-Semantic Processing

Although all classical frequency bands – delta (1–2 Hz), theta (3–7 Hz), alpha (8–12 Hz), beta (13–30 Hz), and gamma (30–200 Hz) – have been implicated in semantic operations (Hanslmayr & Staudigl, 2014), a pattern has emerged involving the alpha and beta bands, or alpha-beta band, as there is little justification for distinguishing between the two in the memory and language literature (Piai & Zheng, 2019). Specifically, alpha-beta power decreases have been consistently associated with tasks and items involving retrieval of more lexical and conceptual information from memory and are thus relevant when considering the neural dynamics that enable SemD information processing. Examples from the language comprehension literature include the finding that semantically richer words (open class words such as nouns and verbs) are linked to stronger alpha-beta (8 to 21 Hz) power decreases relative to semantically leaner words (closed class words such as prepositions and determiners) during reading, an effect observed at occipital sites around 200–600 ms after word presentation (Bastiaansen, van der Linden, Ter Keurs, Dijkstra, & Hagoort, 2005). In the same vein, stronger alpha (8 to 12 Hz) power decreases are observed for open class words at occipital and frontal channels around 200–700 ms post-stimulus when older individuals perform a similar reading task (Mellem, Bastiaansen, Pilgrim, Medvedev, & Friedman, 2012). Another example is provided by the report of parametric decreases in alpha (8 to 12

Hz) power at anterior sites as items approximate real words in an auditory lexical decision task (Strauß, Kotz, Scharinger, & Obleser, 2014). Additional support for the role of alpha-beta activity in lexical-semantic processing comes from the finding that 8–20 Hz power is reduced during an auditory semantic task (identifying animate nouns in a train of inanimate nouns or vice-versa) compared to a voice task (identifying male voices in a train of words spoken by a female voice or vice-versa), where no access to lexical concepts is required (Shahin, Picton, & Miller, 2009). Finally, the fact that stronger alpha-beta (10 to 20 Hz) power decreases are observed for nouns that follow semantically unrelated primes compared to nouns following related primes in an auditory semantic priming task also suggests that alpha-beta power indexes lexical-semantic operations during spoken word recognition (Brennan, Lignos, Embick, & Roberts, 2014).

Combining these reports with findings from language production and episodic memory research, which also point to stronger alpha-beta power decreases in contexts where more lexical-semantic information can be retrieved (e.g., Piai, Klaus, & Rossetto, 2020; Piai, Meyer, Dronkers, & Knight, 2017; Piai, Rommers, & Knight, 2018; Piai, Roelofs, Rommers, & Maris, 2015; Hanslmayr, Spitzer, & Bäuml, 2009), Piai and Zheng (2019) proposed that alpha-beta power dynamics may reflect more fundamental computations enabling the retrieval of both episodic and lexical-semantic information from memory. A mechanistic account of how this might be the case is given by the “information via desynchronization hypothesis” (Hanslmayr, et al., 2012), according to which the degree of desynchronization in the alpha-beta frequency band represents the richness of information encoded in a memory trace, with more desynchronized firing patterns encoding richer information. However, as Piai and Zheng emphasize, this hypothesis was originally formulated to account for episodic memory encoding processes, and more evidence is needed to extend this explanation to lexical-semantic retrieval operations. Thus, investigating whether SemD information is

reflected in alpha-beta power dynamics could provide valuable support for the existence of common neuronal mechanisms underlying different cognitive functions, bringing us closer to a unified theory of brain and cognition (Piai & Zheng, 2019).

Current Study

Behavioural evidence points to an important role for semantic diversity in lexical organization (Jones et al., 2012; Hoffman et al., 2013; Hoffman et al., 2011; Hoffman & Woollams, 2015). However, the electrophysiological neural correlates of the semantic diversity effect are still unknown. Because alpha-beta power decreases have been implicated in lexical-semantic retrieval processes (e.g., Piai et al., 2020), it is reasonable to assume that semantic diversity information would be reflected in alpha-beta activity, but this remains an open question. In this study, I address this gap by asking whether and how differences in semantic diversity scores modulate alpha-beta power dynamics during spoken word recognition.

To this end, I analysed a subset of EEG data recorded while older English-speaking participants performed a word-picture verification task in which they listened to nouns with different semantic diversity scores. Time-averaged alpha-beta power values locked to word presentation were used as the dependent variable in linear mixed models whose fixed effects included semantic diversity and other lexical and semantic variables to control for potential confounds.

Based on the reviewed literature, I hypothesised that alpha-beta power would reflect semantic diversity information during spoken word recognition. Thus, I predicted that semantic diversity would have a significant effect in models predicting alpha-beta power during word presentation. Moreover, given the information via desynchronization hypothesis, I predicted that semantic diversity scores would be inversely related to alpha-beta power,

with stronger power decreases being linked to semantically richer words (i.e., words with higher scores).

Method

Participants

Participants were thirteen older adults (six females; mean age = 63 years, $SD = 7$; mean years of education = 17, $SD = 3$), all of whom were native speakers of American English and had no history of dementia, psychiatric conditions, substance abuse or multiple neurological events. The study protocol accorded with the declaration of Helsinki and was approved by the Committee for Protection of Human Subjects of the University of California, Berkeley. Written informed consent was provided by all participants after they were explained the nature of the study. For their participation, they received monetary compensation.

Materials

The materials used in this study were part of the word-picture verification task employed by Todorova, Neville, and Piai (in press). For the task, the authors selected 70 pictures from the BOSS database (Brodeur, Dionne-Dostie, Montreuil, & Lepage, 2010) along with their basic-level names. For each picture, they then created three conditions. In the congruent condition, the prime word was the picture's basic-level name (e.g., *dog* for a picture showing a poodle). In the semantically related condition, prime words associated with the pictures' basic level names (forward association strength from 0.1 to 0.9) were selected from Nelson, McEvoy, and Schreiber's (2004) norms (e.g., *cat* for the picture of a dog). The same prime words were reassigned to semantically and phonologically unrelated pictures to form the unrelated condition. The primes, which were all English nouns, were recorded in a soundproof booth by a native American English speaker and were normalized to 77 dB sound-pressure level. Importantly, in the present study, only EEG data related to the word

processing part of this task were analysed due to the lack of name agreement norms for the pictures. In addition, only nouns that had not been classified as homographs by Nelson and colleagues were considered, as homonymy and polysemy have been shown to affect word recognition performance in different ways (Rodd, Gaskell, & Marslen-Wilson, 2002). Finally, only nouns for which SemD information was available were included in the analyses. Hence, out of the 140 nouns originally present in the word-picture verification task from Todorova et al. (70 from the congruent condition and 70 from the other two conditions), 96 were selected for the current study (see the Appendix for a list of word stimuli with their corresponding SemD scores).

Procedure

Presentation software (Neurobehavioral Systems, Albany, CA) was used to control stimulus presentation and response recording. Participants were tested one by one in a sound-attenuated booth. The structure of the trials was as follows: first, a fixation cross was displayed for one second. Then, a word was presented via loudspeakers while the cross was still on the screen. After a silent period of one second, a picture was displayed for two seconds, during which time participants responded to the question “do the word and the picture match?”. Responses were given with a left-hand button press, using the index finger for “yes” and the middle finger for “no”. After this two-second period, three asterisks appeared indicating the end of the trial for a variable interval of 1.2 to 1.9 s. An example of the trial structure in each of the three conditions is given in Figure 1. In total, there were 280 trials, 70 for the related condition, 70 for the unrelated condition, and 140 for the congruent condition. The trials were pseudorandomized using Mix (van Casteren & Davis, 2006), with maximum repetition of pictures, conditions and words set to two.

Figure 1

Trial Structure and Example Materials for Related (Left), Unrelated (Middle) and Congruent (Right) Conditions

EEG Recording and Preprocessing

Scalp EEG was recorded from 64 Ag/AgCl active electrodes (BIOSEMI, Amsterdam, Netherlands) mounted in an elastic cap according to the extended 10–20 system, with a sampling rate of 1024 Hz. The vertical electrooculogram was recorded from Fp1 and an electrode positioned below the left eye, and the horizontal electrooculogram was recorded from electrodes placed on the left and right temples.

Preprocessing and analysis of the EEG data were done with FieldTrip (Oostenveld, Fries, Maris & Schoffelen, 2011) version 20200115 in Matlab R2018a (Mathworks, MA, USA). The following preprocessing steps were performed: 1) all electrodes were re-referenced offline to the average of the right and left mastoids; 2) data were segmented into epochs of 1.5 s time-locked to word presentation, including a 500 ms pre-stimulus baseline; 3) baseline correction was applied, with the mean baseline value being subtracted from the signal; 4) a low-pass filter of 40 Hz was applied; 5) peripheral channels with excessive noise were excluded from further analysis, with only frontal, frontocentral, central, centroparietal and parietal channels remaining (see Figure 2 below); 6) given the pervasive presence of eye-blinks across all datasets, rejection of systematic artefacts was done with independent component analysis (Jung et al., 2000, as implemented in FieldTrip); 7) remaining artefacts were rejected based on visual inspection of each trial; 8) channels with drift were removed

and interpolated back based on the weighted average of the channels' neighbours. These preprocessing steps were performed exclusively on trials for which correct responses had been provided (mean = 186 trials per participant, SD = 12.24). An average of 9.38 % (SD = 6.02) of trials was rejected.

Figure 2

Selected channels (green) highlighted in the layout of a Biosemi 64-channel head cap

EEG Data Analysis

The first step to obtaining the average alpha-beta power values that would be used in the statistical analyses was to define specific frequencies, electrodes, and time intervals over which to average the power values. To this end, time-frequency representations of power were computed for each participant at frequencies ranging from 10 to 30 Hz, using a sliding time window of 200 ms advancing in steps of 50 ms and of 1 Hz. The data in each time window were multiplied with a Hanning taper to reduce spectral leakage. After normalising the signal according to a relative baseline method, the time-frequency spectrum averaged over participants was plotted for inspection. Based on previous findings, alpha-beta power was expected to reflect lexical-semantic processes most prominently at posterior sites (Bastiaansen et al., 2005; Obleser & Weisz, 2011; Mellem et al., 2012; Shahin et al., 2009).

Visual inspection confirmed this trend, as the strongest power decreases were centred at parietal and centroparietal electrodes (P1, P2, P3, P4, CP4, and CP5). The strongest decreases were further circumscribed to the 10–20 Hz frequency range and the 400–600 ms time window. These intervals were thus selected for further analysis. Importantly, this selection did not bias the main analysis of the effect of SemD on alpha-beta power, as the time-frequency representations were obtained for the average of all trials, independently of their SemD scores, and were therefore unrelated to the statistical tests that would be subsequently performed. Next, time-averaged power was calculated for each electrode at the single trial level with the fast Fourier transform (FFT) over the time window mentioned above. Lastly, these power values were averaged over the frequency window of 10 to 20 Hz for left and right posterior channels separately. As a result, each participant had two average alpha-beta power values per trial, one for the left and one for the right hemisphere.

Design and Statistical Analysis

The experimental design included the within-participant independent variable semantic diversity, obtained from Hoffman et al. (2013), and the within-participant dependent variable alpha-beta power (10–20 Hz) at posterior electrodes between 400 and 600 ms post-word onset. Additionally, to avoid potential confounds from lexical and semantic measures that have been shown to affect word recognition processes (Pexman, 2012; Vitevitch, Siew, & Castro, 2018), the following controlled variables were included: concreteness rating (1-7 scale), retrieved from Nelson et al. (2004); word length (in number of letters); familiarity rating (1-9 scale), retrieved from McRae, Cree, Seidenberg, and McNorgan (2005); natural logarithm of word frequency of occurrence in the British National Corpus, retrieved from McRae and colleagues (2005); and phonological neighbourhood density (i.e., the number of alternative words that can be made by changing one phoneme in the target word), obtained with the Irvine Phonotactic Online Dictionary (version 2.0; www.iphod.com). Moreover, the

factor “hemisphere” (with levels “left” and “right”) was included in the analysis to account for possible differential effects of SemD as a function of topographical location.

Linear mixed models were used for the statistical analysis with the lme4 package (version 1.1.21; Bates, Mächler, Bolker, & Walker, 2015) in R (version 3.6.1; www.r-project.org). A full random effect structure was attempted, with by-participant and by-item random intercepts as well as by-participant random slopes for the effect of each predictor. In case the model failed to converge, random slopes with the lowest variance were excluded (Barr, Levy, Scheepers, & Tily, 2013). The first converging model included random slopes for the effect of SemD and frequency. The ANOVA function was then used to perform a likelihood ratio test comparing a model with random slopes for frequency and SemD and a model without the effect associated with the least amount of variance (frequency). The results of the test indicated that random slopes for the effect of frequency failed to significantly improve fit. Hence, the final model included only random intercepts for participants and items, and random slopes for the effect of SemD for participants. Fixed effects included the continuous variables SemD, familiarity, concreteness, phonological neighbourhood density, length, and frequency, which were all centred to reduce collinearity. In addition, the categorical variable “hemisphere” was sum-coded and included in an interaction term with SemD. Visual inspection of residual plots indicated that model assumptions of linearity, homoskedasticity, and normality of residuals were satisfied after the dependent variable alpha-beta power was logarithmically transformed. In addition, variance inflation factors (VIF) of all predictors indicated absence of multicollinearity ($VIF < 2$; see Rogerson, 2011 for a suggestion of five as the acceptable maximum level). The Satterthwaite approximation was used to compute p-values for the fixed effects using the lmerTest package version 3.1-2 (Kuznetsova, Brockhoff, & Christensen, 2017).

Results

To observe signal characteristics in the intervals of interest, alpha-beta power changes relative to baseline were computed for each time point for high- and low-SemD words separately, based on a median split² (Figure 3).

Figure 3

Relative Power Changes Averaged over Posterior Channels and the Topographical Distribution of these Changes per SemD Condition

Note: Time-resolved spectra are shown between 500 ms pre-stimulus presentation and 1 s post-stimulus presentation, at frequencies between 10 and 30 Hz. Power at each frequency was estimated

² Words whose SemD score was above the median were classified as high-SemD, while words with scores below the median were classified as low-SemD.

with a Hanning-tapered window of 200 ms advancing in steps of 50 ms and of 1 Hz. Topographical distributions are shown for the period between 400 and 600 ms after word onset.

The time-frequency plots show that stronger power decreases were present for high-SemD words around 10–20 Hz and 400–600 ms (top row of Figure 3). In turn, the topographical plots depicting the distribution of power changes suggest that the largest differences between conditions were located at frontal and frontocentral electrode sites (bottom row of Figure 3). Although these differences might reflect the influence of other lexical and semantic variables, this possibility seems unlikely, as SemD had a small correlation with the controlled variables in this study: the strongest correlation was with frequency, but it was still weak (Spearman's $\rho = .23$).

Despite these apparent differences, however, results from the linear mixed model showed that none of the lexical or semantic variables significantly predicted (log) alpha-beta power (Table 1). The interaction between hemisphere and SemD was also not significant, indicating that the effect of SemD did not vary according to topographical location. The factor hemisphere, on the other hand, was a significant predictor, with channels on the left being linked to stronger power decreases than channels on the right.

Table 1

Linear Mixed Model Results: Main Analysis

Log alpha-beta power (posterior, 400–600 ms)				
<i>Predictors</i>	<i>Estimates</i>	<i>CI</i>	<i>t value</i>	<i>p</i>
SemD	0.11	-0.18 – 0.41	0.75	0.454
Hemisphere – Left	-0.05	-0.08 – -0.02	-3.74	0.001
Concreteness	0.02	-0.01 – 0.05	1.52	0.129
Log Frequency	-0.01	-0.08 – 0.07	-0.14	0.888
Length	-0.00	-0.03 – 0.03	-0.06	0.955
Familiarity	0.00	-0.01 – 0.01	0.63	0.532

Phon. Neigh.	-0.00	-0.00 – 0.00	-1.20	0.231
Density				
SemD : Hemisphere	-0.01	-0.14 – 0.12	-0.13	0.899
Random Effects	Variance			
Residual	0.78			
Intercepts _{items}	0.02			
Intercepts _{participants}	0.16			
Slopes _{SemD/participants}	0.39			
N _{participants}	13			
N _{items}	96			
Observations	4392			
Marginal R ² /	0.005 / 0.031			
Conditional R ²				

Note: Results in boldface are significant at the $p < .05$ level.

Post-hoc Analyses

Alpha-Beta Power at Anterior Sites

Although factors other than those controlled in this study might have contributed to the topographical distribution of power changes depicted in Figure 3, it is reasonable to assume that anterior sites might have been more sensitive to SemD information than posterior sites. Importantly, this pattern would be consistent with previous studies, as lexical-semantic effects on alpha-beta power have also been found at frontal locations (e.g. Mellem et al., 2012; Strauß et al., 2014). In addition, when selecting the regions of interest for the initial analysis, a similar magnitude of power decreases was observed across most electrodes (Figure 4), which means that anterior channels could potentially reflect lexical-semantic operations as well. For these reasons, exploratory analyses focusing on anterior electrodes seemed warranted. However, because lexical-semantic effects on alpha-beta power have only been reported at *left* anterior locations, these analyses were restricted to the left hemisphere (channels F1, F3, FC1, and FC3).

Figure 4

Time-Frequency Plots Averaged over Participants and Trials for All Channels Included in the Analysis

With the dependent variable now being alpha-beta (10–20 Hz) power at left anterior sites around 400–600 ms post-word onset, a new linear mixed model was fit containing SemD and the controlled variables (all centred) as fixed effects. A full random structure was attempted, but the model either failed to converge or produced singularity errors until only random intercepts for participants remained. To satisfy model assumptions of normality of residuals, the dependent variable was again logarithmically transformed. All other model assumptions were met.

The results showed a significant effect of phonological neighbourhood density ($t = -2.85$; $p = .004$), with power decreases being stronger for words with more phonological neighbours (Table 2). Additionally, the model included a marginally significant effect of SemD ($t = 1.82$, $p = .069$), with increased power for words with higher SemD scores.

Table 2*Linear Mixed Model Results: Post-hoc Analysis on Left Anterior Sites*

Log alpha-beta power (anterior, 400–600 ms)				
<i>Predictors</i>	<i>Estimates</i>	<i>CI</i>	<i>t value</i>	<i>p</i>
SemD	0.16	-0.01 – 0.33	1.82	0.069
Concreteness	0.01	-0.02 – 0.04	0.40	0.689
Log Frequency	-0.00	-0.06 – 0.06	-0.00	0.999
Length	-0.02	-0.04 – 0.01	-1.53	0.125
Familiarity	0.00	-0.01 – 0.01	0.68	0.498
Phon. Neigh. Density	-0.00	-0.00 – -0.00	-2.85	0.004
Random Effects		Variance		
Residual	0.55			
Intercept _{participants}	0.47			
N _{participants}	13			
Observations	2196			
Marginal R ² / Conditional R ²	0.003 / 0.464			

Note: Results in boldface are significant at the $p < .05$ level.

The significance of the effect of phonological neighbourhood density and the fact that none of the semantic variables were significant suggest that in the time window between 400 and 600 ms participants might have been at early stages of lexical selection (Winsler, Midgley, Grainger, & Holcomb, 2018). This idea is even more plausible when considering that the mean duration of the prime words was 671 ms, which implies that around 400–600 ms conceptual retrieval associated with a unique lexical entry might not have been at play for many items. Because SemD should affect later stages of lexical access associated with semantic processing (Hoffman et al., 2015; Vergara-Martínez et al., 2017), additional analyses based on alpha-beta power values from a later time interval seemed granted.

At the same time, the marginally significant effect of SemD in the opposite direction as predicted (i.e., stronger power increases rather than decreases for higher SemD scores)

suggests that repetition priming effects might have affected the results, as brain activity is often reduced upon repeated encounter with a given stimulus (Henson, 2003) and alpha-beta power increases index a deactivated cortical area or an inhibited cortical network (Neuper & Pfurtscheller, 2001). Moreover, semantic richness dimensions such as SemD may be especially impacted by repetition priming effects, with enhanced reductions in brain activity for semantically richer (high-SemD) words (Rabovsky, Sommer, & Rahman, 2011). Therefore, it seemed important for further analyses to include only the first trial in which each word appeared in order to avoid repetition priming effects.

To address both these issues, an additional model was fit predicting alpha-beta power at left anterior sites around 600–800 ms post-stimulus onset, based on a dataset containing only the first trial in which the prime words appeared for each participant. Inspection of residual plots and variance inflation factors once again indicated that model assumptions were met after logarithmically transforming the dependent variable. The random structure included only by-participant random intercepts, as more complex structures failed to converge. Fixed effects included SemD and the other lexical and semantic controlled variables, which were again centred to reduce collinearity.

The results of the linear mixed model (Table 3) showed a significant effect of SemD on (log) alpha-beta power, with stronger decreases in power being linked to higher SemD scores ($t = -2.41$; $p = .016$), in accordance with predictions.

Table 3

Linear Mixed Model Results: Post-hoc Analysis on the 600-800 ms Time Window Based on Non-repeated Items

<i>Predictors</i>	Log alpha-beta power (anterior, 600–800 ms)			
	<i>Estimates</i>	<i>CI</i>	<i>t value</i>	<i>p</i>
SemD	-0.29	-0.53 – -0.05	-2.41	0.016
Concreteness	-0.01	-0.05 – 0.03	-0.40	0.687

Log Frequency	-0.03	-0.12 – 0.06	-0.65	0.514
Length	0.01	-0.03 – 0.04	0.49	0.621
Familiarity	-0.01	-0.02 – 0.01	-0.82	0.412
Phon. Neigh. Density	0.00	-0.00 – 0.00	0.45	0.649
Random Effects	Variance			
Residuals	0.58			
Intercept _{participants}	0.44			
N _{participants}	13			
Observations	1224			
Marginal R ² /	0.004 / 0.432			
Conditional R ²				

Note: Results in boldface are significant at the $p < .05$ level.

ERP Analysis

A few lexical decision studies have found that the N400 ERP component can be modulated by measures of contextual variability such as number of senses and contextual diversity (Taler, Kousaie, & Zunini, 2013; Vergara-Martínez et al., 2017). Albeit scarce and inconsistent, these reports suggest that SemD might also affect N400 responses. Therefore, an additional post-hoc analysis was performed to verify whether SemD modulated N400 amplitudes in the word-picture verification task employed in this study. The analyses followed the same preprocessing steps that were described in the “EEG Recording and Preprocessing” section and were also done with Fieldtrip (Oostenveld et al., 2011) in Matlab (Mathworks, MA, USA). Because the focus was on the N400 component, only the time window between 300 and 500 ms was considered. Separate average ERPs were extracted for this time window for each scalp quadrant (left anterior, left posterior, right anterior, and right posterior). These average ERP values per quadrant were then used as the dependent variable in a linear mixed model whose fixed effects included all lexical and semantic variables as well as the sum-coded factors “coronal” (with levels “anterior” and “posterior”) and “sagittal” (with levels “left” and “right”), which were part of interaction terms with SemD.

Random effects included by-participant and by-item random intercepts and by-participant random slopes for the effect of SemD, as the inclusion of random slopes for the effect of other predictors either led to convergence errors or failed to significantly improve model fit. Only the first trial per word per participant was included in the analysis to discard repetition priming effects. All model assumptions were met except for normality of residuals. This remained the case even after different types of transformations were applied to the dependent variable. Although not ideal, this situation might be relatively innocuous, however, as Gaussian models have been shown to be remarkably robust to deviations of normality (Knief & Forstmeier, 2018).

Results of the linear mixed model showed that none of the lexical and semantic variables significantly influenced the ERPs in the selected time interval (Table 4). Furthermore, the interactions between SemD and the two variables indexing topographical locations were not significant, meaning that the (null) effect of SemD was the same in all scalp quadrants.

Table 4

Linear Mixed Model Results: Post-hoc ERP Analysis

Event-related potentials (300–500 ms)				
<i>Predictors</i>	<i>Estimates</i>	<i>CI</i>	<i>t value</i>	<i>p</i>
SemD	1.44	-0.78 – 3.67	1.27	0.204
Coronal – Anterior	0.90	0.71 – 1.10	9.12	<0.001
Sagittal – Left	-0.07	-0.27 – 0.12	-0.74	0.458
Familiarity	-0.01	-0.11 – 0.09	-0.25	0.802
Concreteness	-0.02	-0.23 – 0.19	-0.17	0.862
Length	-0.06	-0.35 – 0.23	-0.42	0.673
Log Frequency	-0.66	-1.40 – 0.09	-1.73	0.083
Phon. Neigh. Density	-0.01	-0.03 – 0.01	-0.89	0.374
SemD : Coronal	-0.19	-1.18 – 0.80	-0.37	0.709

SemD : Sagittal -0.05 -1.04 – 0.94 -0.10 0.920

Random Effects Variance

Residuals 47.99

Intercept_{items} 2.38

Intercept_{participants} 2.83

Slopes_{SemD/participant} 3.74

N_{participants} 13

N_{items} 96

Observations 4896

Marginal R² / 0.020 / 0.068

Conditional R²

Note: Results in boldface are significant at the $p < .05$ level.

To illustrate signal characteristics associated with different SemD scores in this analysis, Figure 5 shows ERPs averaged over participants and trials for high- and low- SemD words separately, based on a median split. Although differences between conditions may be seen starting around 400 ms in some frontal and central channels, these differences are small and spatially constricted.

Figure 5*Grand-average ERPs per SemD Condition*

Note: The signal is shown for all channels included in the statistical analysis from the baseline period (-500 to 0 ms) until 1 s after word onset.

Discussion

This study sought to shed some light onto the neural dynamics underlying the SemD effect by assessing whether and how changes in SemD scores are reflected in alpha-beta power activity during a word-picture verification task performed by older adults. Alpha-beta power was predicted to index SemD information such that stronger decreases would be linked to words with higher SemD scores. Contrary to predictions, alpha-beta power was not modulated by SemD or any other lexical or semantic variable when posterior sites were considered. This pattern is at variance with previous investigations that report significant effects of lexical-semantic manipulations on alpha-beta power at posterior locations (Bastiaansen et al., 2005; Obleser & Weisz, 2011; Mellem et al., 2012; Shahin et al., 2009). Part of this inconsistency might be due to differences in participants' age, as most of these

studies recruited younger individuals, and the distribution of spectral alpha power and alpha incidence may shift from posterior to anterior sites in older adults (Kolev, Yordanova, Basar-Eroglu, & Basar, 2002). However, Mellem et al. (2012) did find effects of lexical-semantic manipulations on alpha power at posterior channels when older adults performed a reading task. In this case, the visual modality of word presentation might account for the disparities, as alpha power decreases are stronger over posterior sites when participants process or expect visual stimuli compared to auditory stimuli (Bastiaansen, Böcker, Brunia, Munck, & Spekreijse, 2001). The power decreases observed at posterior sites in the current study might have therefore been related to visual processes, as participants were looking at a fixation cross and expecting the target pictures while they listened to the prime words. Nevertheless, because the EEG data are spatially smeared, these interpretations should be considered with caution.

Conversely, a post-hoc analysis focusing on anterior electrodes and the 600–800 ms time window indicated that SemD significantly modulated alpha-beta power even after controlling for other lexical and semantic variables. In line with predictions, this model linked stronger power decreases to words with higher SemD scores. These results are consistent with previous reports of significant effects of lexical-semantic manipulations on alpha-beta power during language comprehension (e.g., Brennan et al., 2014). Furthermore, the inverse relationship between alpha-beta power and SemD scores is aligned with Vergara-Martínez et al.'s (2017) findings of enhanced activity from long-term memory for words with greater variability in their semantic representation. It is also consistent with the hypothesis that stronger alpha-beta power decreases enable more information to be retrieved from memory, regardless of whether it is episodic or lexical-semantic in nature (Hanslmayr et al., 2012; Piai et al., 2020).

Moreover, the significant effect of SemD above and beyond other lexical and semantic measures corroborates the prominence of contextual diversity in lexical organization, which had been suggested by behavioural studies (Jones et al., 2017). However, this study can only speak to the effects of SemD in older adults, who have been found to be particularly sensitive to the variability in contextual usage of words (Johns, Sheppard, Jones, & Taler, 2016). This additional sensitivity is thought to result from the accumulated linguistic experience that older individuals possess, which would refine the contextual information associated with the words in their lexicon and would make this information more readily available in their lexical system (Johns et al., 2016). Hence, future work could focus on whether and how SemD information is differentially reflected in alpha-beta power dynamics as a function of age.

In turn, the ERP analysis showed that none of the lexical or semantic variables significantly modulated ERP responses in the 300–500 ms time interval. These findings are inconsistent with Vergara-Martínez and colleagues (2017), who observed larger ERP amplitudes around 225–450 ms for words with higher contextual diversity scores using a lexical decision paradigm. To understand why no effects were found in this study, it is relevant to note that the word-picture verification task employed here greatly differs from a lexical decision task. Indeed, the former is more akin to a semantic judgement task insofar as it requires participants to access deeper semantic aspects of the words in order to decide whether they match the concepts associated with the pictures. The behavioural responses observed in this task further support this idea, as reaction times to semantically related pairs were slower than to unrelated pairs (Todorova et al., in press), the opposite of what is found in lexical decision tasks, where primes reduce response latencies to semantically related words compared to unrelated words (Holcomb & Neville, 2007). The reason why task differences matter in this case is given by Zunini, Renout and Taler (2016), who report a

modulatory effect of task on the relationship between semantic richness dimensions and N400 amplitudes. Specifically, while in a lexical decision task smaller amplitudes were found for semantically richer words (words with more associates or semantic neighbours), no amplitude differences were found in a semantic categorization task even though the stimuli were identical. Thus, it is possible that task characteristics contributed to the null effect of SemD on the ERP amplitudes observed in this study. In addition, age differences might have played a role, as the participants in Vergara-Martínez and colleagues were young adults, who, on average, show earlier N400 peak latencies as well as larger and less variable amplitudes compared to older participants (Kutas & Iragui, 1998). Future investigations could confirm these possibilities by contrasting the effects of SemD on ERP responses in different tasks and age groups.

It is important that these interpretations be seen in light of a few limitations, which relate to the fact that the word-picture verification task was not originally designed to detect the effects of SemD. First, name agreement norms for the pictures were not available, which precluded the assessment of how SemD affected participants' reaction times, as this would require knowing the SemD scores associated with the picture names. These behavioural data would have been useful because no studies have assessed how SemD impacts performance in word-picture verification, and this information could have helped interpret the EEG data. Second, the prime words used in the task did not cover a wide a range of SemD scores: while in the norms by Hoffman and colleagues (2013) they varied from 0.11 to 2.41, the scores in this study ranged from 0.73 to 1.97. Thus, EEG data related to more extreme SemD scores could not be analysed, reducing the power to detect SemD effects. Third, very few items were available at the tails of the SemD distribution, with only three items scoring below 1.2, and only six above 1.8. Consequently, the EEG data related to these items might have been too noisy, further decreasing the power to detect SemD effects. Fourth, the signal-to-noise ratio

might have been jeopardised by the relatively few unique items for which SemD information was available (96 or fewer depending on how accurate participants' responses were). Lastly, the length of the words varied and the words' uniqueness points were not available, which means that at any given time point different words might have been at different stages of lexical access, further compromising the capacity to isolate the SemD effect.

Despite these limitations, this study has offered the first insights into the neuronal mechanisms enabling the effect of SemD, which is an important determinant of word recognition performance (Jones et al., 2017). In addition, it has provided the first evidence that changes in the contextual variability of words can be reflected in alpha-beta power dynamics, thus expanding our knowledge about the role of alpha-beta activity in lexical-semantic processing and making us one step closer to having unified mechanistic accounts of brain and cognition. Because of their exploratory nature, however, these findings are encouraged to be confirmed in future investigations in a more targeted manner.

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Appendix

List of the 96 Words Selected for this Study along with Their SemD scores

Word	SemD	Word	SemD	Word	SemD
man	1.9798668	button	1.6245175	cow	1.4576783
eye	1.9400496	teeth	1.6192905	oar	1.4551464
book	1.8309699	cat	1.6076471	pants	1.4255844
baker	1.8111016	honey	1.6057852	tissue	1.4250730
table	1.8107101	bacon	1.5969238	baby	1.4221989
leaves	1.8046361	clown	1.5852736	crib	1.4212346
moss	1.7993276	butterfly	1.5783128	shirt	1.4164335
lion	1.7983124	pencil	1.5651182	bird	1.4131663
broom	1.7946238	church	1.5566357	squirrel	1.3918353
circus	1.7730113	bread	1.5550672	beans	1.3887328
hammer	1.7502720	anchor	1.5544553	cheese	1.3853295
woman	1.7309430	tree	1.5524781	cake	1.3753417
shepherd	1.7145303	carrot	1.5387272	necklace	1.3742835
television	1.6929522	bottle	1.5378661	vase	1.3704680
glove	1.6880763	rice	1.5349264	boat	1.3639429
car	1.6877118	wrist	1.5267039	library	1.3546931
wood	1.6858976	cookie	1.5265107	antenna	1.3493555
dentist	1.6858698	apple	1.5234023	beach	1.3478130
bee	1.6764397	shoes	1.5092966	cigarette	1.3416993
carpenter	1.6745315	milk	1.5075448	feathers	1.3143615
arrow	1.6680877	acorn	1.5043837	rug	1.3085775
shield	1.6669261	ink	1.5024970	butter	1.3022745
nose	1.6576670	glasses	1.4923354	horse	1.2880513
leg	1.6567524	airport	1.4902961	bishop	1.2643120
tiger	1.6553784	carpet	1.4888222	dog	1.2630090
orange	1.6546391	hair	1.4868252	dagger	1.2362549
chalk	1.6471694	sand	1.4788731	spoon	1.2177242
knife	1.6396403	rabbit	1.4787185	ashtray	1.2065143
chair	1.6384495	apron	1.4738396	caterpillar	1.2026408
bus	1.6380723	bullet	1.4665617	lettuce	1.1120762
banana	1.6377311	jug	1.4650063	tomato	1.0438906
cook	1.6249514	ankle	1.4610768	guitar	0.7309955