Spoken word recognition and serial recall of words from the giant component and words from lexical islands in the phonological network

Cynthia S. Q. Siew

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Michael S. Vitevitch
Chairperson

_____
Susan Kemper

_____
Joan A. Sereno

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The Thesis Committee for Cynthia S. Q. Siew certifies that this is the approved version of the following thesis:

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Chairperson Michael S. Vitevitch

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Abstract

Network science is a field that applies mathematical techniques to study complex systems, and the tools of network science have been used to analyze the phonological network of language (Vitevitch, 2008). The phonological network consists of a giant component, lexical islands, and several hermits. The giant component represents the largest connected component of the network, whereas lexical islands constitute smaller groups of words that are connected to each other but not to the giant component. To determine if the size of the network component that a word resided in influenced lexical processing, three psycholinguistic tasks (word shadowing, lexical decision, and serial recall) were used to compare the processing of words from the giant component and word from lexical islands. Results showed that words from lexical islands were more quickly recognized and more accurately recalled than words from the giant component. These findings can be accounted for via a spreading activation framework. Implications for models of spoken word recognition and network science are also discussed.

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Introduction

Network science is an emerging interdisciplinary field, which uses mathematical techniques to analyze a diverse array of complex systems such as biological, telecommunication, cognitive, and social networks (Barabási, 2009; Watts, 2004). In these complex networks, nodes represent entities such as people in a social network, Internet web pages, or words of a language, and connections typically represent relationships between any pair of these entities; for instance, friendships among individuals, links between web pages, or phonological or semantic similarity between pairs of words. In recent years network science has been applied to the study of complex cognitive systems, in particular, the semantic and phonological networks of language (Steyvers & Tenenbaum, 2005; Vitevitch, 2008).

In the phonological network of Vitevitch (2008), nodes represented phonological word forms and links (or edges) represented phonological similarity. Two words are phonologically similar if the first word can be transformed to the second word via the substitution, addition or substitution of one phoneme in any position (Landauer & Streeter, 1973; Luce & Pisoni, 1998). Vitevitch (2008) analyzed the phonological network using the tools of network science and found that the network possessed the features of a small-world network: short average path lengths and high clustering coefficients relative to an equally dense random network.

Although short average path lengths and high clustering coefficients (relative to a random network) are typical of most real-world networks (Watts & Strogatz, 1998), the phonological network differed from other real-world networks in two aspects. First, the degree distribution of the phonological network resembled that of a truncated power law (Arbesman et al., 2010b), whereas real-world networks such as the World Wide Web tended to display a scale-free degree distribution (Barabási & Albert, 1999). The presence of scale-free degree distributions in

networks is primarily driven by the presence of "hubs"—nodes that have an exceedingly large number of connections compared to most other nodes (Barabási & Albert, 1999). Barabási and Albert (1999) proposed that networks grow via preferential attachment, where new nodes are more likely to attach to existing nodes with several connections, and showed that these networks tend to display a scale-free degree distribution. Since the phonological network does not display a scale-free degree distribution, this implies that alternative mechanisms such as preferential acquisition and lure of attachment, or a modified preferential attachment model that takes into account the costs of adding new connections, could better account for the observed degree distributions of language networks (Arbesman et al., 2010b; Hills et al., 2009).

Second, the largest connected component (also known as the "giant component") of the phonological network consisted of 6,508 out of 19,340 words, about 33.7% of the entire network. The proportion of words residing in the giant component of the network is small relative to other real-world networks, where typically almost all nodes are connected to form a single connected component (Newman, 2001). Interestingly, this seems to be a feature of the phonological networks of various languages—in a comparative analysis of phonological networks of various languages, it is striking that for the Mandarin network, which has the largest proportion of words residing in the giant component, the proportion of words residing in the giant component is merely 50% (Arbesman et al., 2010b).

The results of these network analyses of the phonological network has led to further investigation of these structural characteristics in spoken word recognition. Studying the structural characteristics of the phonological network has demonstrated that the local structure of words influences various aspects of spoken word recognition and production, as well as short and long-term memory processes (Chan & Vitevitch, 2009; 2010; Vitevitch et al., 2012). Chan

and Vitevitch (2009; 2010) showed that the clustering coefficient, or *C*, of a word has measurable effects on psycholinguistic tasks, such as perceptual identification, lexical decision and picture naming. Clustering coefficient refers to the extent to which phonological neighbors of a word are also neighbors of each other (Watts & Strogatz, 1998). The phonological neighbors of high *C* words tend to be neighbors of each other, whereas the phonological neighbors of low *C* words do not tend to be neighbors of each other. Chan and Vitevitch found in various tasks that low *C* words were responded to more accurately and quickly than high *C* words.

To account for their findings, Chan and Vitevitch (2009) proposed a spreading activation framework. In this account, activation spreads from the target word to its neighbors, and activation from neighbors spread back to the target word. As the neighbors of high *C* words are also neighbors of each other, activation tends to be trapped within this densely connected local neighborhood. This makes it difficult for the target node to "stand out" among its phonological neighbors and be subsequently recognized (Chan & Vitevitch, 2009). In contrast, the activation level of low *C* words tends to be higher than its phonological neighbors as the activation of these phonological neighbors spreads back to the target node and to the rest of the network rather than being trapped within the local neighborhood of the target node. Therefore, the recognition of low *C* words occurs more rapidly than high *C* words.

Note that these findings could not be readily accommodated by existing theories of speech perception and spoken word recognition, as these theories do not explicitly take into account the network structure of the mental lexicon. Indeed, since high and low *C* words were matched on variables that are known to influence lexical processing, current theories would predict that there would be no difference in the response latencies and recognition accuracies between words of high clustering coefficients and words of low clustering coefficients. This has

been corroborated by the results of the simulations of TRACE and Shortlist models of spoken word recognition conducted by Chan and Vitevitch (2009), who showed that these models were unable to account for the finding that low *C* words were recognized more accurately and quickly than high *C* words. This speaks to the potential of network science approaches to contribute invaluable insights beyond that of current perspectives into lexical retrieval mechanisms and further clarify our understanding of these processes.

An important point to emphasize is that the stimuli used in these studies (Chan & Vitevitch, 2009; 2010; Vitevitch et al., 2012) constitute words from the giant component. Recall, however, that the giant component consists of words that make up about 33.7% of the entire mental lexicon. The majority of words are either lexical hermits, that is, words that do not have any phonological neighbors, or reside in lexical islands, which are small groups of words that are connected to each other but disconnected from the giant component. One reason for the existence of lexical islands and hermits in the phonological network is due to the criteria used to denote phonological similarity between pairs of words. In the phonological network constructed by Vitevitch (2008), words were connected only if the first word could be transformed to the second via the substitution, addition, or deletion of 1 phoneme in any position (Luce & Pisoni, 1998). Based on this definition of phonological similarity, longer, multisyllabic words tend to have few or no phonological neighbors and are disconnected from the giant component, such that they either form their own smaller networks (lexical islands), or become lexical hermits.

In complex networks of other domains, an overwhelming majority of nodes are located within the giant component (Newman, 2001). Therefore it is common practice to exclude smaller groups of nodes and individual nodes that are detached from the giant component from further analyses as these nodes are considered to be outliers (e.g., Newman, 2001; Steyvers &

Tenenbaum, 2005). In the phonological network, however, the majority of words constitute lexical islands and hermits. Hence, it does not make sense to treat these words as outliers and exclude them from further investigation; in fact, it is imperative that we extend our investigation to include these words.

Unfortunately, little research has explicitly focused on examining words residing in lexical islands. There is one exception, however. Arbesman et al. (2010a) compared the morphology of lexical islands of English and Spanish, and found that Spanish words belonging to the same lexical island tended to share similar morphology, whereas this was less true of English words that belonged to the same lexical island. It is argued that this result could be a viable explanation for the finding that the typically inhibitory neighborhood effect is not true for Spanish words. For instance, Vitevitch and Rodríguez (2005) found that phonologically similar Spanish words were recognized more quickly than phonologically distinct Spanish words; and it was speculated that the processing of phonologically similar words could be facilitated if these words map onto a similar semantic referent, as in Spanish. The Arbesman et al. (2010a) study is an example of how the analysis of words residing in lexical islands could provide additional insights into the lexical processes underlying spoken word recognition.

The present work represents the first experimental approach aimed at investigating whether there are any processing differences between words residing in the giant component and words residing in lexical islands by comparing their performance on word recognition and short-term memory tasks. For ease of exposition, the term “giant component words” refers to words residing in the giant component of the phonological network, and the term “lexical island words” refers to words residing in lexical islands, which are disconnected from the giant component.

There are three possible outcomes of the present investigation: (a) giant component words are recognized and remembered more rapidly and accurately than lexical island words, (b) lexical island words are recognized and remembered more rapidly and accurately than giant component words, and (c) there are no differences between giant component words and lexical island words. Regardless of the outcome, we stand to gain a clearer understanding of the way in which lexical island words are processed relative to giant component words.

As mentioned, words residing in lexical islands tend to be long and multisyllabic. In contrast, most, if not all, of short, monosyllabic words are found in the giant component (although it should be noted that the giant component consists of *both* short and long words). Given the inverse relationship between word frequency and word length, such that high frequency words tend to be short words and low frequency words tend to be longer words (Zipf, 1935), this suggests that a large proportion of processing activity related to word recognition and lexical retrieval occurs within the giant component. This distribution of words also raises interesting questions about how "detached" words might be retrieved from the lexicon. Although the two sets of words will be matched on various characteristics including word frequency, the fact that processing activity tends to occur within the giant component could afford some processing advantage to giant component words that cannot be accounted for by the individual characteristics of those words alone.

However, the opposite scenario where lexical island words are recognized more quickly and accurately than giant component words is also possible. Recall that lexical islands are essentially smaller networks that are *not* connected to the giant component. If one applies the spreading activation framework as described by Chan and Vitevitch (2009), activation would be more widely dispersed for the giant component words compared to lexical island words, as giant

component words are embedded in a very large network of words where activation ultimately spreads to the entire network, whereas lexical island words are embedded in a small network of words where activation would be trapped within that network.

Here it is important to point out the differences between this speculation and the explanation given by Chan and Vitevitch (2009) to account for the clustering coefficient effect, where low *C* words are more quickly and accurately recognized compared to high *C* words. Although lexical island words may appear to be analogous to high *C* words because the network structure of both types of words seem to lead to more "trapped" activation, the opposite effect is predicted—lexical island words may be processed more quickly and accurately than giant component words because activation spreads back to the target word in a lexical island but may be more dispersed in the giant component.

To distinguish between these hypotheses, words were selected from the giant component and lexical islands such that both sets of words were matched on various lexical, phonological and network science characteristics that are known to influence processing. A variety of tasks commonly used in cognitive psychology, which include word naming (Experiment 1), lexical decision (Experiment 2) and serial recall (Experiment 3), were conducted to compare the performance of lexical island words and giant component words on spoken word recognition and short-term memory processes.

Experiment 1

Method

Participants

Twenty native English speakers were recruited from the Introductory Psychology subject pool at the University of Kansas. All participants had no previous history of speech or hearing disorders and received partial course credit for their participation.

Materials

Ninety-six English words were selected as stimuli for this experiment. Half of the stimuli were selected from the giant component of the phonological network and half were selected from lexical islands. Table 1 shows the means and standard deviations of lexical characteristics of words from the giant component and words from lexical islands. A list of the word stimuli and their individual lexical characteristics is included in the Appendix.

Table 1. Summary of lexical characteristics of giant component and lexical island word stimuli.

	Giant component	Lexical islands
Number of phonemes	5.35 (0.53)	5.40 (0.64)
Subjective familiarity	6.60 (0.78)	6.77 (0.43)
Log frequency	1.93 (0.71)	2.11 (0.77)
Neighborhood density	2.73 (0.84)	2.83 (0.72)
Log neighborhood frequency	1.70 (0.53)	1.65 (0.47)
Mean positional probability	0.0533 (0.00852)	0.0542 (0.00760)
Mean biphone probability	0.00562 (0.00180)	0.00590 (0.00194)
Clustering coefficient	0.274 (0.353)	0.236 (0.311)
Onset duration (ms)	58 (3)	58 (4)
Stimuli duration (ms)	556 (92)	583 (70)
Overall file duration (ms)	675 (93)	700 (72)

Word length. Word length refers to the number of phonemes in a given word. Giant component words had a mean word length of 5.35 (SD = 0.53) and lexical island words had a mean word length of 5.40 (SD = 0.64), F (1,94) < 1, p = .73.

Subjective familiarity. Subjective familiarity values were obtained on a 7-point scale, where words with high familiarity scores were perceived to be more familiar (Nusbaum et al., 1984). Giant component words had a mean familiarity value of 6.60 (SD = 0.78) and lexical island words had a mean familiarity value of 6.77 (SD = 0.43), F (1,94) = 1.79, p = .19. Therefore both sets of words were highly familiar.

Word frequency. Word frequency refers to how often a given word occurs in a language. Log-base 10 of the raw frequency counts from Kučera and Francis (1967) were used.

Giant component words had a mean word frequency of 1.93 (*SD* = 0.71) and lexical island words had a mean word frequency of 2.11 (*SD* = 0.77), F (1,94) = 1.45, p = .23.

Neighborhood density. Neighborhood density refers to the number of words that are phonologically similar to a given word (Luce & Pisoni, 1998). Phonological similarity is defined as the substitution, addition, or deletion of one phoneme in a given word to form a phonological neighbor. Giant component words had a mean neighborhood density of 2.73 (*SD* = 0.84) and lexical island words had a mean neighborhood density of 2.83 (*SD* = 0.72), F (1,94) < 1, p = .52.

Neighborhood frequency. Neighborhood frequency is the mean word frequency of a word's phonological neighbors. Word frequency counts were obtained from Kučera and Francis (1967) and converted to log base 10 values. Giant component words had a mean log neighborhood frequency of 1.70 (*SD* = 0.53) and lexical island words had a mean log neighborhood frequency of 1.65 (*SD* = 0.47), F (1,94) < 1, p = .60.

Phonotactic probability. The phonotactic probability of a word refers to the probability that a segment occurs in a certain position of a word (positional segment probability), and the probability that two adjacent segments co-occur (biphone probability; Vitevitch & Luce, 2004). Giant component words had a mean positional segment probability of 0.0533 (*SD* = 0.00852) and lexical island words had a mean positional segment probability of 0.0542 (*SD* = 0.00760), F (1,94) < 1, p = .57. Giant component words had a mean biphone probability of 0.00562 (*SD* = 0.00180) and lexical island words had a mean biphone probability of 0.00590 (*SD* = 0.00194), F (1,94) < 1, p = .48.

Clustering coefficient. The clustering coefficient, C, of a word refers to the extent to which a word's phonological neighbors are also neighbors of each other. C ranges from 0 to 1; when C = 1, this implies that all neighbors of the word are neighbors of each other, and when C

= 0, this implies that no neighbors of the word are neighbors of each other. Giant component words had a mean *C* of 0.274 (*SD* = 0.353) and lexical island words had a mean *C* of 0.236 (*SD* = 0.311), F (1,94) < 1, p = .58.

Duration. The duration of the stimulus sound files was equivalent across both sets of words. The mean overall duration of sound files was 675 ms (*SD* = 93) for giant component words and 700 ms (*SD* = 72) for lexical island words, F (1,94) = 2.18, p = .14. The mean onset duration, measured from the beginning of the sound file to the onset of the stimuli, was 58 ms (*SD* = 3) for giant component words and 58 ms (*SD* = 4) for lexical island words, F (1,94) < 1, p = .59. The mean stimulus duration, measured from the onset to the offset of the word, was 556 ms (*SD* = 92) for giant component words and 583 ms (*SD* = 70) for lexical island words, F (1,94) = 2.64, p = .11.

Procedure

Participants were tested individually. Each participant was seated in front of an iMac computer that was connected to a New Micros response box. Stimuli were presented via BeyerDynamic DT100 headphones at a comfortable listening level and PsyScope 1.2.2 was used to randomize and control the presentation of stimuli. The response box contains a dedicated timing board which provides millisecond accuracy for the recording of response times.

In each trial, the word “READY” appeared on the screen for 500ms. Participants heard one of the randomly selected word stimuli and were instructed to repeat the word as quickly and accurately as possible. Reaction times were measured from stimulus onset to the onset of the participant’s verbal response. Verbal responses were also recorded for offline scoring of accuracy. The next trial began 1s after the participants’ response was made. Prior to the experimental trials, each participant received 5 practice trials to familiarize themselves with the

task, and these trials were not included in the subsequent analyses. There were a total of 96 trials and the experiment lasted 10 minutes.

Results

Both reaction times and accuracy were the dependent variables of interest. Accuracy was manually scored offline by the author. Trials containing mispronunciations of the word or responses that triggered the voice-key prematurely (e.g., coughing, "uh") were coded as incorrect and excluded from the analyses. Trials with reaction times that were less than 500ms or more than 2000ms were considered to be outliers and also excluded. Excluded trials accounted for less than 2.92% of the data.

The convention in psycholinguistic research is to perform two types of analyses on participant and item means, treating participants and items as random factors in each of these analyses respectively. There is increasing awareness within the field, however, that participant analyses fail to take into account the systematic variability due to individual items and item analyses fail to take into account the systematic variability due to participants, such that neither analysis represents an appropriate description of all random sources of variability within the outcome variable (Locker, Hoffman, & Bovaird, 2007). Alternative data analysis approaches such as multilevel modeling and hierarchical regression have been proposed. In particular, hierarchical regression has proven to be especially useful in assessing the variability accounted for by an additional variable, over and above the variability that is already accounted for by other variables in the model, and this technique has been fruitfully applied in recent psycholinguistic studies (e.g., Yap & Balota, 2009).

Although both sets of words have been carefully selected such that they are closely matched on a variety of relevant lexical characteristics, hierarchical regression analyses on item means affords us the ability to determine if the location of the word in the network (i.e., whether the word resides in the giant component or in a lexical island) accounts for significant variability over and above that accounted by traditional lexical characteristics. Therefore, item-level regression analyses were conducted on the mean reaction times and accuracies for the stimuli. A two-step hierarchical approach was used. Number of phonemes, familiarity, frequency, neighborhood density, neighborhood frequency, positional and biphone probabilities, *C*, and stimuli duration were entered in Step 1. Location, a dummy coded variable indicating whether a word resided in the giant component or in a lexical island, was entered in Step 2. If a word belonged to a lexical island, it was coded as '1'; if a word belonged to the giant component, it was coded as '0'. The motivation for partitioning the regression analysis into two steps is to determine if location of the word within the network accounts for additional variance over previously entered variables.

Reaction times

Table 2 presents the results of regression analyses on naming reaction times.

Table 2. Hierarchical regression results for Experiment 1 (reaction times).

Variable	*b*	*SE*	*t*	*P*	R^2	ΔR^2
Reaction times						
Step 1						
Number of phonemes	0.019	10.45	0.20	.84		
Subjective familiarity	-0.061	9.14	-0.68	.50		
Log frequency	-0.22	7.74	-2.44	.02*		
Neighborhood density	-0.032	6.65	-0.39	.69		
Log neighborhood frequency	0.148	10.65	1.76	.08^{+}		
Positional probability	0.344	922.3	2.96	.004**		
Biphone probability	-0.208	4336	-1.65	.10		
Stimuli duration	0.633	0.07	7.00	<.001***		
Clustering coefficient	-0.061	15.56	-0.75	.46		
					0.482***	
Step 2						
Location (dummy variable)	-0.177	10.00	-2.24	.03*		
					0.511***	0.029*

Note: $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

In Step 1, frequency, positional probability and stimulus duration significantly predicted naming reaction times. Frequency was negatively correlated with reaction times, standardized β = -0.22, t (86) = -2.44, $p < .05$, such that high frequency words were responded to more quickly than low frequency words. Positional probability was positively correlated with reaction times, standardized $\beta = 0.344$, t (86) = 2.96, $p < .01$, such that words with high phonotactic probability were responded to less quickly than words with low phonotactic probability. Stimulus duration was positively correlated with reaction times, standardized $\beta = 0.633$, t (86) = 7.00, $p < .001$, such that words of longer durations were responded to less quickly than words of shorter

duration. Together, the variables entered at Step 1 explained 48.2% of the variance in naming reaction times, accounting for a significant proportion of the variance in naming reaction times, $R^2 = .482$, $F\ (9,86) = 8.90$, $p < .001$.

In Step 2, location significantly predicted naming reaction times, standardized $\beta = -0.177$, $t\ (85) = -2.24$, $p < .05$, such that lexical island words were responded to more quickly than giant component words. The influence of location accounted for an additional 2.9% of the variance, $\Delta R^2 = .029$, $F\ (1,85) = 5.03$, $p < .05$. Together, the variables entered at both steps explained 51.1% of the variance in naming reaction times, accounting for a significant proportion of variance in naming reaction times, $R^2 = .511$, $F\ (10,85) = 8.89$, $p < .001$.

Accuracy

Table 3 presents the results of regression analyses on naming accuracies.

Table 3. Hierarchical regression results for Experiment 1 (accuracy rates).

Variable	*b*	*SE*	*t*	*P*	R^2	ΔR^2
Accuracy						
Step 1						
Number of phonemes	0.080	0.89	0.66	.51		
Subjective familiarity	0.328	0.78	2.84	.006**		
Log frequency	0.053	0.66	0.46	.65		
Neighborhood density	-0.021	0.57	-0.20	.84		
Log neighborhood frequency	0.054	0.91	0.50	.62		
Positional probability	0.084	79.13	0.56	.58		
Biphone probability	-0.128	372	-0.79	.43		
Stimuli duration	0.017	0.006	-0.15	.88		
Clustering coefficient	0.081	1.34	0.78	.44		
					0.148	
Step 2						
Location (dummy variable)	0.112	0.88	1.08	.28		
					0.16	0.012

Note: $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

In Step 1, only familiarity significantly predicted naming accuracies, standardized $\beta = 0.328$, t (86) = 2.84, $p < .01$, such that more familiar words were responded to more accurately than less familiar words. Together, the variables entered at Step 1 explained 14.8% of the variance in naming accuracies, which did not account for a significant proportion of variance in naming accuracies, $R^2 = .148$, F (9,86) = 1.66, $p = .11$.

In Step 2, location did not significantly predict naming accuracy, standardized $\beta = 0.112$, t (85) = 1.08, $p = .28$, nor did it explain a significant proportion of variance, $\Delta R^2 = .012$, F (1,85) = 1.17, $p = .28$. Together, the variables entered at both steps explained 16.0% of the variance in

naming accuracies, which did not account for a significant proportion of variance in naming accuracies, $R^2 = .160$, $F\ (10,85) = 1.62$, $p = .12$.

Table 4 shows the subject and item reaction time and accuracy means for the lexical island and giant component words. Reaction times for lexical island words (*M* = 956 ms, *SD* = 55 ms) were faster than reaction times for giant component words (*M* = 968 ms, *SD* = 72 ms), and this was consistent across subject means as well.

Accuracies were very high across both lexical island and giant component conditions, although slightly higher accuracy rates were observed for the lexical island words (*M* = 97.71%, *SD* = 3.41%) as compared to giant component words (*M* = 94.46%, *SD* = 4.94%). This was consistent across subject means as well. The fact that accuracy rates are close to ceiling could explain why the location of word within the network did not significantly affect accuracy rates. This also suggests that there was no speed-accuracy trade-off in the performance of the task.

Table 4. Subject and item means for giant component and lexical island words in Experiment 1.

	Lexical island words	Giant component words
Subject means		
Reaction times (ms)	955 (107)	967 (110)
Accuracy (%)	97.71 (3.09)	96.46 (4.06)
Item means		
Reaction times (ms)	956 (55)	968 (72)
Accuracy (%)	97.71 (3.41)	96.46 (4.94)

The results of the word naming task is compatible with the hypothesis that lexical island words are processed more quickly than giant component words. As mentioned in the Introduction, the spreading activation framework can be used to account for the present results. Lexical island words are more quickly recognized than giant component words because activation is trapped within the network structure of a lexical island, whereas for giant component words, activation spreads to the rest of the network. This would allow lexical island words to have higher activation levels compared to giant component words and are therefore more easily retrieved and produced in the word naming task. In order to establish that this finding is consistent across different kinds of experimental tasks and is not an artifact of a specific experimental paradigm, a second experiment employing auditory lexical decision was conducted using the same stimuli.

Experiment 2

Method

Participants

Twenty native English speakers were recruited from the Introductory Psychology subject pool as described in Experiment 1. All participants were right-handed and had no previous history of speech or hearing disorders. None of the participants in the present experiment took part in Experiment 1.

Materials

The word stimuli for the present experiment consisted of the same 96 words used in Experiment 1. In addition, a list of 96 phonotactically legal nonwords was constructed by replacing a phoneme (at any position except the first and last positions) of the word stimuli with another phoneme. For instance, the nonword *porcel* (/poɹsl/) was created by replacing /ɑ/ in *parcel* (/pɑɹsl/) with /o/. The phonological transcriptions of nonwords are listed in the Appendix.

The nonwords were recorded by the same male speaker in a similar manner as in Experiment 1. The same method for editing and digitizing the word stimuli was used to create individual sound files for each nonword.

Duration. The duration of the stimulus sound files was equivalent across both words and nonwords. The mean overall duration of sound files was 687 ms (SD = 84) for words and 665 ms (SD = 75) for nonwords, F (1,190) = 3.70, p = .06. The mean onset duration, measured from the beginning of the sound file to the onset of the stimuli, was 58 ms (SD = 3) for words and 57 ms (SD = 5) for nonwords, F (1,190) < 1, p = .40. The mean stimulus duration, measured from the

onset to the offset of the word, was 569 ms (*SD* = 82) for words and 550 ms (*SD* = 75) for nonwords, F (1,190) = 2.84, p = .09.

Procedure

Participants were tested in groups no larger than three. As in Experiment 1, each participant was seated in front of an iMac computer that was connected to a New Micros response box. Stimuli were presented via BeyerDynamic DT100 headphones at a comfortable listening level and PsyScope 1.2.2 was used to randomize and control the presentation of stimuli. The response box contains a dedicated timing board which provides millisecond accuracy for the recording of response times.

In each trial, the word "READY" appeared on the screen for 500ms. Participants heard one of the randomly selected stimuli and were instructed to decide, as quickly and accurately as possible, whether the item heard was a real English word or a nonword. If the item was a word, participants pressed the button labeled 'WORD' with their right (dominant) index finger. If the item was a nonword, participants pressed the button labeled 'NONWORD' with their left index finger. Reaction times were measured from stimulus onset to the onset of the participant's button press. The next trial began 1s after the participants' response was made. Prior to the experimental trials, each participant received 8 practice trials to become familiar with the task, and these trials were not included in the subsequent analyses. There were a total of 192 trials and the experiment lasted 15 minutes.

Results

Both reaction times and accuracy were the dependent variables of interest. In lexical decision, only accurate responses for word stimuli were analyzed. Trials with reaction times that

were less than 500ms or more than 2000ms were excluded. Excluded trials accounted for less than 9.53% of the data. As in Experiment 1, hierarchical regression analyses were conducted on the item means.

Reaction times

Table 5 presents the results of regression analyses on lexical decision reaction times.

Table 5. Hierarchical regression results for Experiment 2 (reaction times).

Variable	*b*	*SE*	*t*	*p*	R^2	ΔR^2
Reaction times						
Step 1						
Number of phonemes	0.039	17.05	0.4	.69		
Subjective familiarity	-0.475	14.91	-5.12	<.001***		
Log frequency	-0.158	12.62	-1.7	.09^{+}		
Neighborhood density	-0.089	10.90	-1.06	.29		
Log neighborhood frequency	0.027	17.37	0.31	.76		
Positional probability	0.284	1505	2.37	.02*		
Biphone probability	-0.07	7074	-0.53	.60		
Stimuli duration	0.341	0.11	3.66	<.001***		
Clustering coefficient	-0.113	25.38	-1.36	.18		
					0.452***	
Step 2						
Location	-0.203	16.2	-2.52	.01*		
					0.490***	0.038*

Note: $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

In Step 1, familiarity, positional probability and stimulus duration significantly predicted lexical decision reaction times. Familiarity was negatively correlated with reaction times,

standardized $\beta = -0.475$, t (86) = -5.12, $p < .001$, such that more familiar words were responded to more quickly than less familiar words. Positional probability was positively correlated with reaction times, standardized $\beta = 0.284$, t (86) = 2.37, $p < .05$, such that words with high phonotactic probability were responded to less quickly than words with low phonotactic probability. Stimulus duration was positively correlated with reaction times, standardized $\beta = 0.341$, t (86) = 3.66, $p < .001$, such that words of longer durations were responded to less quickly than words of shorter durations. Together, the variables entered at Step 1 explained 45.2% of the variance in lexical decision reaction times, accounting for a significant proportion of the variance in lexical decision reaction times, $R^2 = .452$, F (9,86) = 7.86, $p < .001$.

In Step 2, location significantly predicted lexical decision reaction times, standardized $\beta = -0.203$, t (85) = -2.52, $p = .01$, such that lexical island words were responded to more quickly than giant component words, and accounted for an additional 3.8% of the variance, $\Delta R^2 = .038$, F (1,85) = 6.35, $p < .05$. Together, the variables entered at both steps explained 49.0% of the variance in lexical decision reaction times, accounting for a significant proportion of variance in lexical decision reaction times, $R^2 = .490$, F (10,85) = 8.15, $p < .001$.

Accuracy

Table 6 presents the results of regression analyses on lexical decision accuracies.

Table 6. Hierarchical regression results for Experiment 2 (accuracy rates).

Variable	*b*	*SE*	*t*	*p*	R^2	ΔR^2
Accuracy						
Step 1						
Number of phonemes	-0.013	2.03	-0.15	.88		
Subjective familiarity	0.616	1.77	7.83	<.001***		
Log frequency	0.192	1.50	2.44	.02*		
Neighborhood density	-0.061	1.29	-0.86	.39		
Log neighborhood frequency	-0.050	2.07	-0.68	.50		
Positional probability	0.027	178.9	0.27	.79		
Biphone probability	-0.032	841.3	-0.29	.77		
Stimuli duration	0.157	0.01	1.99	.05$^+$		
Clustering coefficient	0.073	3.02	1.04	.30		
					0.606***	
Step 2						
Location (dummy variable)	0.058	1.99	0.82	.41		
					0.609***	0.003

Note: $^+$ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

In Step 1, familiarity and frequency significantly predicted lexical decision accuracies. Familiarity was positively correlated with accuracies, standardized $\beta = 0.616$, t (86) = 7.83, $p <$ .001, such that more familiar words were responded to more accurately than less familiar words. Frequency was also positively correlated with accuracies, standardized $\beta = 0.192$, t (86) = 2.44, p < .05, such that high frequency words were responded to more accurately than low frequency words. Together, the variables entered at Step 1 explained 60.6% of the variance in lexical decision accuracies, accounting for a significant proportion of variance in lexical decision accuracies, $R^2 = .606$, F (9,86) = 14.69, $p < .001$.

In Step 2, location did not significantly predict lexical decision accuracy, standardized $\beta = 0.058$, $t\,(85) = 0.82$, $p = .41$, nor did it explain a significant proportion of variance, $\Delta R^2 = .003$, $F\,(1,85) = 0.62$, $p = .44$. Together, the variables entered at both steps explained 60.6% of the variance in lexical decision accuracies, accounting for a significant proportion of variance in lexical decision accuracies, $R^2 = .606$, $F\,(10,85) = 13.24$, $p < .001$.

Table 7 shows the subject and item reaction time and accuracy means for the lexical island and giant component words. Reaction times for lexical island words (*M* = 978ms, *SD* = 83ms) were faster than reaction times for giant component words (*M* = 1019ms, *SD* = 114ms), and this was consistent across subject means as well.

Accuracies were very high across both lexical island and giant component conditions, although higher accuracy rates were observed for the lexical island words (*M* = 93.02%, *SD* = 8.92%) as compared to giant component words (*M* = 87.92%, *SD* = 17.74%). This was consistent across subject means as well.

Table 7. Subject and item means for giant component and lexical island words in Experiment 2.

	Lexical island words	Giant component words
Subject means		
Reaction times (ms)	974 (71)	1006 (92)
Accuracy (%)	93.02 (5.33)	87.92 (6.43)
Item means		
Reaction times (ms)	978 (83)	1019 (114)
Accuracy (%)	93.02 (8.92)	87.92 (17.74)

The results of the lexical decision task are similar to that of the word naming task in Experiment 1—lexical island words are more quickly processed and recognized as compared to giant component words.

It is important to reemphasize that the giant component and lexical islands words were closely matched on a variety of variables that are known to influence lexical processing. Current models of spoken word recognition would not predict any differences between these two sets of words. Nevertheless, the results of Experiments 1 and 2 have shown that lexical island words are more quickly processed than giant component words in both word shadowing and lexical decision tasks. These results strongly suggest that there is psychological reality to the idea that phonological word-forms in the mental lexicon are indeed organized as a complex network, which includes a giant component, several lexical islands, and hermits. Since both sets of words were matched on lexical and network science variables including degree and *C*, the present results showed that the processing differences observed between the two sets of words could be attributed to whether the word resided in the giant component or in one of the lexical islands.

This further suggests that the size of the network component that a word resides in has an important influence in lexical processing, beyond that of the individual lexical and network characteristics of words.

In the next experiment, a serial recall task will be employed to investigate whether an advantage for recalling lexical island words as compared to giant component words exists. Using a serial recall task offers another way to compare giant component and lexical island words on a different aspect of lexical processing, especially as it has been argued that short-term memory processes involves similar processes that occur in speech perception (Ellis, 1980; Schweickert, 1993). In addition, given that the dependent variable of interest in the serial recall task is recall accuracy, the serial recall task may reveal differences in accuracy rates between giant component and lexical island words that were not observed in Experiments 1 and 2. Based on the results of Experiments 1 and 2, one would expect that lexical island words would be more accurately recalled than giant component words.

Experiment 3

In a serial recall task participants are presented with a sequence of items and have to recall items in the same serial order. The serial recall task is a widely used experimental paradigm that cognitive psychologists use to explore the limits of short-term memory and its underlying cognitive processes (Baddeley et al., 1975; Ebbinghaus et al., 1913; Hulme et al., 1991). As there is a strong correlation between short-term memory span (the number of items that are recalled in its correct order) and the rate at which words are articulated (e.g., Hulme et al., 1991), researchers argue that there exists a speech-based component that influences the speed at which information in the short-term memory store is refreshed and therefore short-term

memory involves processes that are common to speech perception (Schweickert, 1993). Hence, the serial recall task complements the psycholinguistic tasks that are predominantly used to investigate lexical processing, as demonstrated by Vitevitch et al. (2012) who employed the serial recall task to examine the effect of clustering coefficient on short-term memory. Note that although short-term memory processes are typically thought to influence serial recall performance, there is evidence that suggests that long-term memory contributes to serial recall ability as well (Hulme et al., 1997; Tehan & Humphreys, 1988; Watkins, 1977).

Method

Participants

Thirty-two native English speakers were recruited from the Introductory Psychology subject pool. All participants had no previous history of speech or hearing disorders and received partial course credit for their participation. These participants did not participate in Experiments 1 and 2.

Materials

The word stimuli for the present experiment consisted of the same 96 words used in Experiment 1. The words in each condition were pseudo-randomly assigned to ensure that no phonological neighbors appeared in the same list. 8 lists consisting of 6 giant component words each and 8 lists consisting of 6 lexical island words each were created. In addition, two different samples of the 16 lists (Versions A & B) were created to minimize order effects.

Procedure

Participants were tested individually. Each participant was randomly assigned to one of the two versions of the word lists; 16 participants were assigned to Version A and 16 participants

were assigned to Version B. As in the previous experiments, each participant was seated in front of an iMac computer. Stimuli were presented via BeyerDynamic DT100 headphones at a comfortable listening level and PsyScope 1.2.2 was used to randomize and control the presentation of stimuli.

In each trial, the word "READY" appeared on the screen for 500ms. Participants were presented with one of the 16 randomly selected lists over headphones, at a rate of approximately 1 word per second. At the end of each list, the prompt "RECALL" appeared on the screen and participants recalled out loud the list of words in the same order as they were presented. Participants were instructed to say "pass" if they could not recall the word in any particular position. Verbal responses were recorded for offline scoring of accuracy. The next trial began when participants finished recalling the words and pressed the spacebar. Prior the experimental trials, each participant received 4 practice trials to become familiar with the task, and these trials were not included in the subsequent analyses. There were a total of 16 trials and the experiment lasted 15 minutes.

Results

In contrast to the previous two experiments, recall accuracy was the dependent variable of interest in this experiment. Accuracy was manually scored offline by the author. Trials which contained mispronunciations of the word, or in which the participant said "pass" (or some indication of recall failure, e.g. "skip" or "don't know") were coded as incorrect trials.

A 2 × 6 two-way within-participants ANOVA was conducted. The independent variables are location (2; lexical island or giant component) and serial position (6; 1 through 6). The dependent variable was the participants' mean accuracy rate in each condition. The location ×

position interaction was significant, F (5,155) = 3.32, $p < .01$. To ensure that the significant interaction was not due to specific ordering effects of either Version A or Version B, list was included as a third independent variable in the ANOVA. Since the three-way interaction was not significant, this implied that the nature of the significant two-way interaction observed between location and position was consistent across both lists.

To further interpret the nature of the significant location × position interaction, tests of simple main effects of location were conducted at each level of position. At position 1, the simple main effect of location was significant, F (1,31) = 9.83, $p < .01$. At positions 2 to 6, the simple main effect of location was not significant, Fs < 1.70, ps > .20.

As shown in the accuracy rates in Table 8 below, recall for words belonging to lexical islands was significantly better than words belonging to the giant component, but only for words in the first position of the serial recall curve. Recall for words belonging to lexical islands or giant component did not significantly differ across the other positions along the serial recall curve.

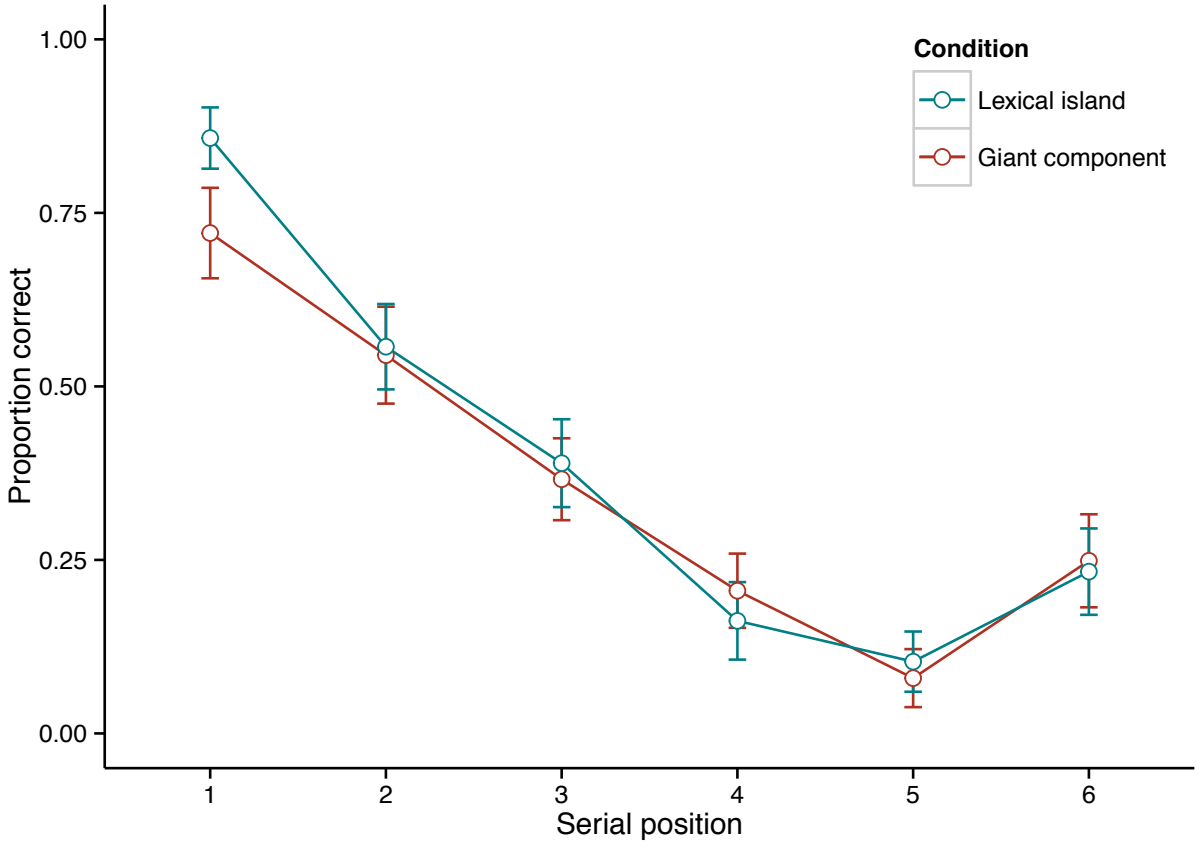

Figure 1. Serial recall curve showing proportion of accurate recall of giant component and lexical island words at each serial position.

Table 8. Accuracy rates for giant component and lexical island words in Experiment 3.

	Serial Position					
	1	2	3	4	5	6
Lexical island words	0.855 (0.135)	0.555 (0.218)	0.387 (0.218)	0.160 (0.136)	0.102 (0.116)	0.230 (0.206)
Giant component words	0.719 (0.211)	0.543 (0.251)	0.363 (0.211)	0.203 (0.200)	0.078 (0.113)	0.246 (0.243)

Note: Standard deviations are in parentheses.

Serial recall of lexical island words was more accurate than recall of giant component words, although this was only observed for words in the initial serial position. Based on the existing memory literature, there are three different explanations that can account for the present findings.

The first explanation draws on much older findings reported in the memory literature, which showed that items presented in early serial positions were retrieved from long-term memory, whereas items presented in late serial positions were retrieved from short-term memory (Craik, 1968; Watkins, 1977). Given that an advantage for lexical island words was only observed in the first serial position (i.e., a primacy effect), this would suggest that long-term memory plays a role in the superior serial recall performance of lexical island words in the first serial position. Given that the mental lexicon is part of long-term memory, it is perhaps not surprising that effects were observed for where in the lexicon a word resides (i.e., islands vs the giant component).

More recently, Hulme et al. (1997; see also Hulme et al., 1991; Schweickert, 1993) showed that the success of short-term serial recall depends on two components: a speech-based component whereby recall accuracy or short-term memory span depends on the same processes that underlie speech production and perception, and long-term memory, which specifically includes the process of redintegration. The second account of the present results involves the same spreading activation mechanism process used to account for the results of Experiments 1 and 2 as they relate to speech perception and lexical processing, whereas the third account of the present results involves the process of redintegration.

Based on the spreading activation account, lexical island words are better recalled than giant component words because activation only spreads to other words within the same lexical island. Activation tends to become trapped within the island, whereas the activation of a giant component word would spread to the rest of the giant component. Therefore, the spreading activation account used to account for the findings of Experiments 1 and 2 can also be used to explain the differences in serial recall performance observed between lexical island and giant component words.

A third, alternative account involving redintegration of representations by *long-term* memory could also account for the present finding. Redintegration occurs when the representations held in short-term memory are partially degraded. This degraded representation is then compared to phonological representations that are stored in long-term memory in order to "clean up" the representations in short-term memory and enable successful retrieval of the target word (Hulme et al., 1991; Roodenrys et al., 2002). Furthermore, redintegration can also be described in terms of the spreading activation mechanism used to account for the results of Experiments 1 and 2, which is consistent with the proposal that redintegration is a by-product of

speech perception processes (Hulme et al., 1997). The study by Vitevitch et al. (2012) comparing the recall accuracies of high and low *C* words in a serial recall task is an example of how the spreading activation mechanism can be useful in explaining the redintegration process.

Vitevitch et al. (2012) found that high *C* words were recalled more accurately than low *C* words in a serial recall task, although this was true only for words presented in the final positions. To account for their findings, an explanation based on the redintegration phenomenon as described by Hulme et al. (1997) was proposed. According to Hulme et al. (1997; Roodenrys et al., 2002), redintegration occurs when the representations held in short-term memory are partially degraded. These degraded representations are then compared to phonological representations that are stored in long-term memory in order to "clean up" the representations in short-term memory (Hulme et al., 1997). Due to the fact that the neighbors of high *C* words tend to be neighbors of each other, activation tends to remain within the local neighborhood, and spreads back to the degraded target word, thus resulting in redintegration and superior recall performance (Vitevitch et al., 2012). On the other hand, for low *C* words, activation tends to be dissipated to the rest of the network, and the lack of activation remaining within the neighborhood leads to a lack of scaffolding for the degraded representations, such that redintegration for low *C* words is not as successful and low *C* words are not recalled as accurately.

This phenomenon can also be applied to explain the finding in Experiment 3, where lexical island words were better recalled than giant component words in a serial recall task. As lexical islands are separate from the rest of the phonological network, activation of the target word tends to be trapped within the lexical island. This leads to more successful redintegration for lexical island words as compared to giant component words, because the circulation of

activation within the island can better "clean up" the degraded representations, whereas for giant component words, the diffusion of activation to the rest of the network does not facilitate the redintegration of the degraded target word.

It is important to point out, however, that Vitevitch et al. (2012) observed that recall performance for high and low C words began to diverge toward the end of the word list. This is consistent with the hypothesis that redintegration occurs for words presented later in the list as representations tend to become more degraded in the later part of the word list (Hulme et al., 1997; Roodenrys et al., 2002).

In the present study, however, better performance was observed for lexical island words in the *first* serial position. Nevertheless, redintegration remains a plausible explanation for the following reasons. First, the words used in the present study were longer than those used in Vitevitch et al. (2012) (mean number of phonemes = 5.38, *SD* = 0.58), as words in lexical islands generally tend to be multisyllabic. In contrast, the stimuli in Vitevitch et al. (2012) were monosyllabic and were of the CVC pattern (i.e., all words were 3 phonemes long). It could be argued that the longer words used in the present experiment led to degradation occurring even at the earliest serial positions, so it is plausible that redintegration could have taken place for words in the earliest serial position.

This possibility is supported by prior research on the word length effect in serial recall performance—the well-established finding whereby superior serial recall was observed for short words compared to longer words (Baddeley et al., 1975; Hulme et al., 2006; but see Service, 1998). Although alternative explanations exist for the word length effect (e.g., Caplan et al., 1992; Service, 1998), the most widely accepted account relates to the articulatory loop in Baddeley and Hitch's (1975) model of working memory—because it takes longer to articulate

multisyllabic words than monosyllabic words, the representations of multisyllabic words begin to decay to a greater extent and multisyllabic words are recalled less accurately than monosyllabic words (Baddeley et al., 1975, Tehan & Tolan, 2007). Therefore, it is plausible to surmise that the longer stimuli used in the present experiment could have been subject to rapid degradation or decay, which allowed redintegration to occur for lexical island words even at the first serial position.

In addition, it may take time for redintegration effects to emerge, especially for words that are presented in later positions. The spreading of activation does not happen instantaneously; it is a process that occurs over time and differences in activation levels emerge after some time. In fact, researchers who have attempted to model spreading activation in networks have simulated the spreading of activation as an accumulative process that occurs over a number of discrete time steps (Vitevitch et al., 2011; see also Anderson, 1983). In the present experiment, words were presented at a rate of 1 word per second and participants began recalling the word list immediately after the word list was presented. A future study could address whether decreasing the presentation rate of the stimuli, or increasing the interstimulus interval of the serial recall task would allow redintegration effects to emerge for words presented at the final positions of the word list.

In summary, three different accounts exist that can explain the results of Experiment 3. The first one posits that the primacy effect for lexical island words in the early positions compared to giant component words reflect the involvement of long-term memory. The other two accounts draw on the hypothesis that the serial recall of words depends on processes that influence two different kinds of representations—direct retrieval from short-term memory via the

same processes that underlie lexical processing, and indirect retrieval via redintegration that occurs among long-term memory representations (Schweickert, 1993).

Although the present thesis does not explicitly distinguish between each of the three accounts, future studies could differentiate among them by measuring each participant's speech rate for each set of words and using speech rate as a covariate to control for the influence of short-term memory, which is shown to be highly correlated with the rate at which participants are able to articulate the items (as in Hulme et al., 1991). If an effect of word location remains even after the effect of speech rate is accounted for (i.e., lexical island words are still recalled more accurately than giant component words after controlling for speech rate), then this would indicate that long-term memory representations, as exemplified by the redintegration process, do influence serial recall performance.

Finally, although the mechanisms of the last two possible explanations are very similar because they both involve spreading activation, they are qualitatively different because redintegration focuses on the *recovery* of degraded representations in long-term memory whereas direct retrieval from short-term memory relies on the *difference* in activation levels of short-term memory representations during on-line lexical processing. The key distinction between the two explanations is that redintegration occurs only when the representations are partially degraded. Hulme et al. (1997) suggested that the likelihood of redintegration increases for long words and low frequency words because the representations of these words degrade more rapidly; in particular, the likelihood of redintegration increases to a greater extent if long words and low frequency words are found towards the end of the word list. To distinguish between the two accounts, an experiment manipulating word length or word frequency within words that reside in either lexical islands or the giant component could be conducted. The crucial result would be

whether a word's location within the phonological network interacts with, or is additive with word length or frequency across serial positions. An interaction would suggest that the difference in serial recall performance between lexical island and giant component words may be partly due to redintegration processes that occur among long-term memory representations, whereas additivity would suggest that the difference in serial recall performance between lexical island and giant component words is primarily due to spreading activation processes that occur among short-term memory representations.

General Discussion

Across three experiments, a processing advantage was observed for lexical island words compared to giant component words. Compared to giant component words, lexical island words were produced more quickly in a word shadowing task, recognized more quickly in a lexicon decision task, and recalled more accurately in a serial recall task. As these two sets of words were matched on a number of lexical, phonological, and network characteristics known to influence lexical processing, the present set of findings strongly suggest that the size of the network component that words happen to reside in plays a role in influencing lexical retrieval in spoken word recognition and short-term memory. Specifically, the processing of words belonging to smaller components of the phonological network (i.e., lexical island words) was facilitated relative to words belong to the largest component of the phonological network (i.e., giant component words).

Spreading activation framework

As discussed in the Introduction, Chan and Vitevitch (2009) introduced a spreading activation framework to account for their finding that high *C* words were more quickly and

accurately recognized than low *C* words. Recall that high *C* words have phonological neighbors that are also neighbors of each other, whereas the neighbors of low *C* words do not tend to be neighbors of each other. When the target word is activated, activation spreads from the target word to its neighbors. Activation then spreads from these words back to the target word, and also to their own neighbors. The crucial difference lies in the extent of interconnectivity that resides in the local neighborhoods of these words, which affects the activation levels of the target words. For high *C* words, a higher proportion of activation remains within this local neighborhood since the neighbors of the targets are also neighbors of each other. Relative to high *C* words, a lower proportion of activation is "trapped" in the local neighborhoods of low *C* words, and most of the activation spreads to the rest of the network. Therefore, it is easier to recognize low *C* words, because they tend to "stand out" from their neighbors (in terms of activation levels) whereas the activation levels of high *C* words and their neighbors tend to be more similar to each other, making it difficult to recognize high C words.

This spreading activation framework can also be applied to account for the processing advantage observed for lexical island words compared to giant component words. The process begins similarly for both sets of words. Activation spreads from the target word to its neighbors, and from its neighbors back to the target node and to their own neighbors. This process continues over time, until most of the initial activation has dissipated to the rest of the network. This is where the difference in the component size becomes important. The sizes of lexical islands are very small compared to the size of the giant component; the largest island consists of 53 words and the giant component consists of 6,508 words. As lexical islands constitute small sections of the phonological network that are independent of and separate from the giant component, this implies that activation tends to become "trapped" within lexical islands as the spread of

activation is bounded by the size of the lexical island. As for giant component words, activation would ultimately spread to the rest of the giant component. This would result in lexical island words having higher activation levels compared to giant component words, thus accounting for the participants' superior performance for lexical island words on various experimental tasks.

At first sight, this explanation may appear to contradict the explanation described earlier to account for difference between high and low *C* words, especially as the reason for *poorer* performance for high *C* words appears identical to the reason for *superior* performance for lexical island words: a higher proportion of "trapped" activation. It is important to emphasize here that in the case of clustering coefficient, activation is trapped within a word's *local neighborhood*. For the lexical island words, activation is trapped *within the lexical island* that these words resided in. In fact, as lexical island words and giant component words were matched on the number of phonological neighbors and *C*, it can be further assumed that the local neighborhood characteristics of lexical island and giant component words are equivalent. That is, at the initial time steps, the amount of activation remaining within the target word's local neighborhood can be assumed to be comparable across both sets of words. For giant component words, activation will ultimately spread to the rest of the giant component. On the other hand, for lexical island words, activation will be trapped within the island, and spread back to the target word, thus boosting activation levels of lexical island words relative to giant component words.

In Experiment 3, a serial recall task was conducted in order to investigate a different aspect of lexical processing – the representations of lexical island and giant component words in short-term memory. As mentioned, this finding can be accounted for by a number of various cognitive mechanisms. However, the most parsimonious account would be the one whereby the same spreading activation mechanism used to account for the findings of Experiments 1 and 2

can also be applied to account for the finding that lexical island words are more accurately recalled than giant component words. Lexical island words are better recalled than giant component words because activation only spreads to other words within the same lexical island and tend to be trapped within the island, whereas the activation of a giant component word would spread to the rest of the giant component. This account would also be consistent with the idea that the processes that underlie short-term memory are similar to the processes that support speech perception and speech production (Schweickert, 1993).

Implications for theories and models of spoken word recognition

The past 60 years or so of speech perception research has witnessed the proliferation of a number of models of spoken word recognition. The more widely known models include the Cohort Model (Marslen-Wilson, 1987; the latest adaptation being the Distributed Cohort Model, Gaskell & Marslen-Wilson, 1997), TRACE, the interactive-activation model proposed by McClelland and Elman (1986), Shortlist B (Norris & McQueen, 2008), Neighborhood Activation Model (NAM; Luce & Pisoni, 1998) and PARSYN, the computational instantiation of NAM (Luce, Goldinger, Auer & Vitevitch, 2000). Although these models have vastly different theoretical assumptions and architectural premises, they have been highly successful in accounting for and modeling several well-established effects of word frequency, phonological neighborhood density and phonotactic probability.

Recall that lexical island and giant component words selected for the present set of experiments were closely matched on a variety of lexical characteristics that are known to influence spoken word recognition. Therefore, the two sets of words differed only whether they resided within the giant component or within lexical islands of the phonological network. Current models of spoken word recognition, such as Cohort Model, TRACE, Shortlist B and

Neighborhood Activation Model, would not predict any differences between the two sets of words as they have similar lexical characteristics.

Nevertheless, this paper presents converging evidence from three experiments showing that lexical island words are recognized more quickly and recalled more accurately than giant component words. Without explicitly incorporating the overall network structure of the phonological network, it is difficult to see how any of these theories or models could account for the present findings, as well as clustering coefficient effects reported in Chan and Vitevitch (2009; 2010) and the redintegration of high C words reported in Vitevitch et al. (2012). The present findings present significant challenges to current theories and models of spoken word recognition, as they strongly suggest that the overall network structure of the phonological network, as well as the *size* of the network component, play an important role in cognitive processes of word recognition and short- and long-term memory.

Implications for network science

In the network science literature, an overwhelming amount of work has focused on analyzing and investigating large-scale complex networks that consist of thousands of nodes (e.g., Internet (Yook et al., 2002); the human brain (Bullmore & Sporns, 2009); online social networks (Adamic & Adar, 2003)), although networks of a smaller scale have also been studied (e.g., Zachary's karate club; Zachary, 1977). The present work presents evidence suggesting that the size of the network may represent an important factor to consider when investigating networks. In particular, small networks may be susceptible to boundary effects, as described by Kohonen (1982) in his study of self-organizing feature maps. These maps are a type of unsupervised artificial neural network that are created based on local interactions between nodes and used to cluster high-dimensional input into lower-dimensional groups. Kohonen (1982)

showed that for nodes residing at the edges of 2-dimensional networks, their weight vectors tend to be “contracted” as these nodes do not have as many neighbors that they could interact with as compared to nodes found in the center of the map. The boundary effect is the phenomenon that nodes at the edges exert a kind of “pressure” on a map that causes distortions to its final form near the edges of the 2-dimensional map.

Due to the small sizes of lexical islands, most lexical island words tend to be found near or at the edges of the network as compared to giant component words which tend to be embedded more deeply within the giant component. A word that is more deeply embedded in the network would have activation spreading in a more symmetrical fashion around itself, whereas a word located at or near the edge of the network, might have a more asymmetrical distribution of activation spreading around itself, leading to the distortion observed for the mechanisms and processes that occur at the edges of the network. Future work could investigate these speculations by specifically comparing words found at the edges of networks and words that are more deeply embedded within the giant component to investigate whether the location of these words indeed leads to differences in processing.

The size of the network could also have implications for the spread of information within a network. Although it may be easier for information to spread to all nodes in a small, highly clustered network compared to a large network (Newman, 2000), the small size of the network could lead to a form of information saturation or devaluation as redundant information continues to circulate somewhat indefinitely in a small network, akin to how the same pieces of gossip which circulate within a tight knit clique of friends quickly begin to lose their informational value. Therefore, although the same mechanisms and network principles can be applied to both large and small network components, the difference in size in the components could result in

qualitatively different outcomes in real life contexts. The results of the present set of experiments suggest that network scientists and other researchers using network science techniques in their respective areas should also consider how the size of networks (or network components) could affect processing in these systems.

Future work and conclusions

In this paper, three experiments were conducted to investigate whether words residing in lexical islands were processed differently compared to words residing in the giant component of the phonological network. Across all experiments it was consistently shown that lexical island words were recognized more quickly and recalled more accurately than giant component words, even though both sets of words were matched on a variety of lexical, phonological, and network characteristics that are known to influence spoken word processing. An account of how a spreading activation framework applied to network components of different sizes could lead to higher activation levels for lexical island as compared to giant component words was offered. In addition, it was speculated that "boundary effects" could have emerged more strongly for lexical island words as most of these words constitute the edges of these smaller networks, and there is a possibility that mechanisms that occur at the edges of networks become warped or distorted (Kohonen, 1982). It should be noted, however, that these are simply verbal, post-hoc explanations for the present findings. This paves the way for future work to validate these explanations by using computer simulations to model spreading activation in networks of varying sizes and of nodes residing at the edges of a network (as in Vitevitch et al., 2011) or by investigating the influence of other types of network characteristics on lexical processing.

The results of these experiments have shown that the size of the network component that words happen to reside in plays an important role in spoken word recognition and memory

processes, over and beyond the lexical and network characteristics of individual words. Importantly, these findings also contribute to the growing body of research showing that network structure of the mental lexicon has measurable and considerable influences on cognitive processes (e.g., Hills et al., 2009; De Deyne et al., 2012), and is testament to the growing recognition of the notion that the mental lexicon can be modeled as a complex network, and that the nature of its overall network structure can proffer meaningful insights into the mechanisms of these processes.

References

Adamic, L. A., & Adar, E. (2003). Friends and neighbors on the web. *Social Networks, 25*(3), 211-230.

Arbesman, S., Strogatz, S. H., & Vitevitch, M. S. (2010a). Comparative analysis of networks of phonologically similar words in English and Spanish. *Entropy, 12*(3), 327-337.

Arbesman, S., Strogatz, S. H., & Vitevitch, M. S. (2010b). The structure of phonological networks across multiple languages. *International Journal of Bifurcation and Chaos, 20*(3), 679-685.

Baddeley, A. D., & Hitch, G. J. (1975). Working memory. *Psychology of Learning and Motivation, 8*, 47-89.

Baddeley, A. D., Thomson, N., & Buchanan, M. (1975). Word length and the structure of short-term memory. *Journal of Verbal Learning and Verbal Behavior, 14*(6), 575-589.

Barabási, A. L. (2009). Scale-free networks: a decade and beyond. *Science, 325*(5939), 412-413.

Barabási, A. L., & Albert, R. (1999). Emergence of scaling in random networks. *Science, 286*(5439), 509-512.

Bullmore, E., & Sporns, O. (2009). Complex brain networks: graph theoretical analysis of structural and functional systems. *Nature Reviews Neuroscience, 10*(3), 186-198.

Caplan, D., Rochon, E., & Waters, G. S. (1992). Articulatory and phonological determinants of word length effects in span tasks. *Quarterly Journal of Experimental Psychology, 45*(2), 177-192.

Chan, K. Y., & Vitevitch, M. S. (2009). The influence of the phonological neighborhood clustering coefficient on spoken word recognition. *Journal of Experimental Psychology: Human Perception and Performance, 35*(6), 1934-1949.

Chan, K. Y., & Vitevitch, M. S. (2010). Network structure influences speech production. *Cognitive Science, 34*(4), 685-697.

Craik, F. I. M. (1968). Two components in free recall. *Journal of Verbal Learning and Verbal Behavior, 7*(6), 996-1004.

De Deyne, S., Navarro, D. J., Perfors, A., & Storms, G. (2012). *Strong structure in weak semantic similarity: A graph based account.* Paper presented at the Proceedings of the 34th Annual Conference of the Cognitive Science Society.

Ebbinghaus, H., Ruger, H. A., & Bussenius, C. E. (1913). Memory: A contribution to experimental psychology. New York: Teachers College, Columbia University.

Gaskell, M. G., & Marslen-Wilson, W. D. (1997). Integrating form and meaning: A distributed model of speech perception. *Language and Cognitive Processes, 12*(5-6), 613-656.

Hills, T. T., Maouene, M., Maouene, J., Sheya, A., & Smith, L. (2009). Longitudinal analysis of early semantic networks: Preferential attachment or preferential acquisition? *Psychological Science, 20*(6), 729-739.

Hulme, C., Neath, I., Stuart, G., Shostak, L., Surprenant, A. M., & Brown, G. D. A. (2006). The distinctiveness of the word-length effect. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 32*(3), 586-594.

Hulme, C., Roodenrys, S., Schweickert, R., Brown, G. D. A., Martin, S., & Stuart, G. (1997). Word-frequency effects on short-term memory tasks: Evidence for a redintegration process in immediate serial recall. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 23*(5), 1217-1232.

Kohonen, T. (1982). Self-organized formation of topologically correct feature maps. *Biological Cybernetics, 43*(1), 59-69.

Kučera, H., & Francis, W. N. (1967). *Computational analysis of present-day American English*. Providence, RI: Brown University Press.

Landauer, T. K., & Streeter, L. A. (1973). Structural differences between common and rare words: Failure of equivalence assumptions for theories of word recognition. *Journal of Verbal Learning and Verbal Behavior, 12*(2), 119-131.

Locker, L., Hoffman, L., & Bovaird, J. A. (2007). On the use of multilevel modeling as an alternative to items analysis in psycholinguistic research. *Behavior Research Methods, 39*(4), 723-730.

Luce, P. A., Goldinger, S. D., Auer, E. T., & Vitevitch, M. S. (2000). Phonetic priming, neighborhood activation, and PARSYN. *Attention, Perception, & Psychophysics, 62*(3), 615-625.

Luce, P. A., & Pisoni, D. B. (1998). Recognizing spoken words: The neighborhood activation model. *Ear and Hearing, 19*(1), 1-36.

Marslen-Wilson, W. D. (1987). Functional parallelism in spoken word-recognition. *Cognition, 25*(1), 71-102.

McClelland, J. L., & Elman, J. L. (1986). The TRACE model of speech perception. *Cognitive Psychology, 18*(1), 1-86.

Newman, M. E. J. (2000). Models of the small world. *Journal of Statistical Physics, 101*(3-4), 819-841.

Newman, M. E. J. (2001). The structure of scientific collaboration networks. *Proceedings of the National Academy of Sciences, 98*(2), 404-409.

Norris, D., & McQueen, J. M. (2008). Shortlist B: A Bayesian model of continuous speech recognition. *Psychological Review, 115*(2), 357-395.

Nusbaum, H. C., Pisoni, D. B., & Davis, C. K. (1984). Sizing up the Hoosier mental lexicon: Measuring the familiarity of 20,000 words. *Research on Speech Perception Progress Report, 10*, 357-376.

Roodenrys, S., Hulme, C., Lethbridge, A., Hinton, M., & Nimmo, L. M. (2002). Word-frequency and phonological-neighborhood effects on verbal short-term memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 28*(6), 1019-1034.

Schweickert, R. (1993). A multinomial processing tree model for degradation and redintegration in immediate recall. *Memory & Cognition, 21*(2), 168-175.

Service, E. (1998). The effect of word length on immediate serial recall depends on phonological complexity, not articulatory duration. *The Quarterly Journal of Experimental Psychology: Section A, 51*(2), 283-304.

Steyvers, M., & Tenenbaum, J. B. (2005). The large-scale structure of semantic networks: Statistical analyses and a model of semantic growth. *Cognitive Science, 29*(1), 41-78.

Tehan, G., & Humphreys, M. S. (1988). Articulatory loop explanations of memory span and pronunciation rate correspondences: A cautionary note. *Bulletin of the Psychonomic Society, 26*, 293-296.

Tehan, G., & Tolan, G. A. (2007). Word length effects in long-term memory. *Journal of Memory and Language, 56*(1), 35-48.

Vitevitch, M. S. (2008). What can graph theory tell us about word learning and lexical retrieval? *Journal of Speech, Language and Hearing Research, 51*(2), 408-422.

Vitevitch, M. S., Chan, K. Y., & Roodenrys, S. (2012). Complex network structure influences processing in long-term and short-term memory. *Journal of Memory and Language, 67*(1), 30-44.

Vitevitch, M. S., Ercal, G., & Adagarla, B. (2011). Simulating retrieval from a highly clustered network: Implications for spoken word recognition. *Frontiers in Psychology, 2*, 369.

Vitevitch, M. S., & Luce, P. A. (2004). A web-based interface to calculate phonotactic probability for words and nonwords in English. *Behavior Research Methods, 36*(3), 481-487.

Vitevitch, M. S., & Rodríguez, E. (2005). Neighborhood density effects in spoken word recognition in Spanish. *Journal of Multilingual Communication Disorders, 3*(1), 64-73.

Watkins, M. J. (1977). The intricacy of memory span. *Memory & Cognition, 5*(5), 529-534.

Watts, D. J. (2004). The" new" science of networks. *Annual Review of Sociology, 30*, 243-270.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. *Nature, 393*(6684), 440-442.

Yap, M. J., & Balota, D. A. (2009). Visual word recognition of multisyllabic words. *Journal of Memory and Language, 60*(4), 502-529.

Yook, S. H., Jeong, H., & Barabási, A. L. (2002). Modeling the Internet's large-scale topology. *Proceedings of the National Academy of Sciences, 99*(21), 13382-13386.

Zachary, W. W. (1977). An information flow model for conflict and fission in small groups. *Journal of Anthropological Research, 33*(4), 452-473.

Zipf, G. K. (1935). *The psycho-biology of language*. Boston, MA: Houghton-Mifflin.

Appendices

Lexical island words

Word	Klattese	Number of phonemes	Subjective familiarity	Log frequency (KF67)	Neighborhood density	Log neighborhood frequency	Positional probability	Biphone probability	Clustering Coefficient	Onset duration	Stimuli duration	Offset duration	Overall file duration
beckon	bEk|n	5	6.58	1.00	3	1.85	0.0590	0.00690	0.333	56.6	425.2	61.0	542.8
mission	mIS|n	5	7.00	2.89	2	2.22	0.0557	0.00630	0.000	55.1	478.9	63.8	597.9
portion	porS|n	6	7.00	2.79	3	1.00	0.0582	0.00840	0.000	59.5	566.0	59.5	685.0
taken	tek|n	5	6.50	3.45	4	1.76	0.0489	0.00510	0.500	59.5	486.2	60.9	606.6
concede	kxnsid	6	6.67	1.90	3	1.66	0.0596	0.00830	1.000	53.7	644.4	62.5	760.5
concern	kxnsRn	6	6.92	2.99	2	1.39	0.0616	0.00760	0.000	61.0	661.8	69.7	792.4
confine	kxnfYn	6	6.92	1.30	3	1.26	0.0569	0.00640	0.333	59.5	671.9	55.2	786.6
consign	kxnsYn	6	6.17	1.30	4	1.57	0.0626	0.00800	0.167	63.9	702.4	72.5	838.8
coffin	kcfxn	5	7.00	1.85	3	2.06	0.0568	0.00540	1.000	56.6	532.6	61.0	650.2
deafen	dEfxn	5	6.17	1.00	1	1.00	0.0599	0.00680	0.000	62.4	460.0	58.1	580.5
siphon	sYfxn	5	4.42	1.00	3	1.20	0.0623	0.00570	0.000	61.0	582.0	56.6	699.5
soften	scfxn	5	6.92	1.60	4	1.85	0.0587	0.00510	0.500	66.8	621.1	63.8	751.7
banish	b@nIS	5	6.33	1.60	3	1.23	0.0581	0.00710	0.333	58.0	603.7	63.8	725.6
furnish	fRnIS	5	7.00	2.46	3	1.53	0.0462	0.00300	0.000	52.2	714.0	49.3	815.6
manage	m@nIJ	5	6.92	2.30	3	2.31	0.0584	0.00810	0.000	59.5	582.0	56.5	698.0
marriage	m@rIJ	5	7.00	2.98	2	2.17	0.0548	0.00640	0.000	52.2	586.3	55.2	693.7
domain	domen	5	6.83	1.95	2	1.00	0.0480	0.00160	0.000	61.0	560.2	55.2	676.3
regain	rIgen	5	6.75	1.00	3	2.00	0.0508	0.00570	0.333	56.6	577.6	56.6	690.8
remain	rImen	5	7.00	2.97	3	1.35	0.0571	0.00670	0.333	58.0	626.9	63.8	748.8
retain	rIten	5	6.75	2.04	4	2.06	0.0604	0.00660	0.167	61.0	641.5	66.8	769.2
partition	pXtIS|n	7	6.67	1.78	3	1.87	0.0521	0.00760	0.333	66.8	650.2	61.0	777.9
permission	pXmIS|n	7	7.00	2.43	2	1.39	0.0497	0.00710	1.000	55.1	638.5	58.0	751.7
petition	pxtIS|n	7	7.00	2.18	3	2.05	0.0568	0.00790	0.000	55.1	626.9	55.1	737.2
position	pxzIS|n	7	6.92	3.38	4	2.04	0.0503	0.00700	0.167	58.0	667.6	66.8	792.4
central	sEntrL	6	7.00	3.21	3	1.36	0.0719	0.01000	0.000	52.2	583.4	52.3	687.9
locus	lok|s	5	6.00	1.30	3	1.79	0.0468	0.00460	0.000	61.0	615.3	63.8	740.1
notice	not|s	5	7.00	2.77	2	1.98	0.0473	0.00510	0.000	61.0	560.2	58.1	679.2
report	rIport	6	7.00	3.24	4	1.42	0.0590	0.00630	0.167	61.0	600.8	55.1	716.9
lizard	lIzXd	5	7.00	1.00	4	1.33	0.0468	0.00340	0.500	58.0	522.4	58.0	638.5
nervous	nRvxs	5	7.00	2.38	3	1.99	0.0414	0.00310	0.333	61.0	626.9	52.2	740.1
service	sRvxs	5	6.50	3.50	2	2.84	0.0571	0.00380	0.000	61.0	716.9	55.1	833.0
warrant	wcrxnt	6	6.75	2.30	3	1.77	0.0618	0.00840	0.000	49.3	577.6	52.3	679.2
happen	h@pxn	5	7.00	2.80	2	1.00	0.0622	0.00740	1.000	55.1	522.4	60.9	638.5
margin	marJ|n	6	7.00	2.00	3	1.33	0.0559	0.00850	0.333	58.0	551.5	58.1	667.6
peasant	pEzNt	5	6.92	1.85	4	2.04	0.0534	0.00210	0.167	58.0	487.6	55.1	600.8
revolve	rIvalv	6	6.67	1.00	3	1.60	0.0402	0.00480	0.333	55.1	690.8	61.0	806.9
gallop	g@lxp	5	6.83	1.60	2	1.00	0.0557	0.00580	1.000	52.2	481.8	52.2	586.3
nominee	namxni	6	7.00	1.48	3	1.35	0.0560	0.00750	0.333	55.1	629.8	60.9	745.9
felon	fEl|n	5	6.67	1.00	3	1.51	0.0621	0.00760	0.000	55.1	638.5	69.7	763.4
village	vIlIJ	5	6.92	2.86	3	1.26	0.0503	0.00580	0.333	58.0	568.9	61.0	687.9

cunning	k^nIG	5	6.75	1.70	3	3.05	0.0578	0.00550	0.333	58.0	473.1	66.7	597.9
retail	ritel	5	7.00	2.30	3	1.72	0.0415	0.00230	0.000	52.2	566.0	58.1	676.3
memory	mEmXi	5	7.00	2.88	2	1.00	0.0541	0.00400	0.000	58.0	507.9	52.2	618.2
trophy	trofi	5	6.92	1.90	3	1.00	0.0421	0.00500	0.000	52.2	560.2	58.1	670.5
treasure	trEZX	5	7.00	1.60	2	1.95	0.0412	0.00520	0.000	58.0	496.3	55.1	609.5
solemn	salxm	5	6.83	2.08	2	1.39	0.0689	0.00600	0.000	52.2	603.7	52.2	708.2
radio	redio	5	7.00	3.08	2	1.35	0.0361	0.00250	0.000	58.0	548.6	58.1	664.7
plaza	pl@zx	5	7.00	1.30	2	2.17	0.0502	0.00350	0.000	55.1	545.7	61.0	661.8

Giant component words

Word	Klattese	Number of phonemes	Subjective familiarity	Log frequency (KF67)	Neighborhood density	Log neighborhood frequency	Positional probability	Biphone probability	Clustering coefficient	Onset duration	Stimuli duration	Offset duration	Overall file duration
parcel	parsL	5	6.33	1.00	3	1.45	0.0600	0.00695	0.333	55.1	487.6	63.8	606.6
ceiling	silIG	5	7.00	2.49	2	1.82	0.0538	0.00485	0.000	61.0	592.1	55.1	708.2
driven	drIvxn	6	7.00	2.64	3	1.00	0.0596	0.00786	1.000	61.0	444.1	52.3	557.3
temple	tEmpL	5	6.73	2.58	4	1.67	0.0459	0.00532	0.667	58.0	403.4	60.9	522.4
comic	kamIk	5	6.67	1.95	3	1.52	0.0578	0.00853	0.333	58.0	566.0	66.8	690.8
century	sEnCXi	6	7.00	3.32	2	1.72	0.0620	0.00644	0.000	56.6	560.2	59.5	676.3
panther	p@nTX	5	7.00	1.00	3	1.00	0.0615	0.00595	0.333	58.0	519.5	66.8	644.3
facet	f@s|t	5	5.58	1.30	4	1.55	0.0653	0.00595	0.000	56.8	448.4	59.5	564.7
cumber	k^mbX	5	4.82	1.00	4	2.21	0.0485	0.00385	0.500	58.0	409.3	55.2	522.4
stutter	st^tX	5	6.67	1.00	1	1.00	0.0548	0.00687	0.000	56.6	535.5	66.8	658.9
rollick	ralIk	5	3.58	1.00	3	1.36	0.0542	0.00543	0.000	52.2	492.0	58.1	602.3
scepter	sEptX	5	4.92	1.00	3	2.26	0.0690	0.00545	1.000	63.9	545.7	61.0	670.5
brittle	brItL	5	7.00	1.48	3	1.44	0.0587	0.00638	0.000	55.1	326.5	68.2	449.9
filing	fYlIG	5	7.00	2.28	3	1.88	0.0431	0.00455	0.333	59.5	603.7	68.2	731.4
scant	sk@nt	5	6.92	1.70	3	2.14	0.0569	0.00535	0.000	59.5	592.1	59.5	711.1
mountain	mWntN	5	7.00	2.52	2	2.34	0.0517	0.00575	0.000	58.0	597.9	66.7	722.7
spiral	spYrL	5	6.92	1.90	2	1.35	0.0408	0.00280	0.000	58.0	661.8	61.0	780.8
drench	drEnC	5	6.92	1.00	3	1.81	0.0443	0.00475	1.000	55.1	563.1	58.1	676.3
repeat	rIpit	5	7.00	2.42	3	1.48	0.0612	0.00607	0.000	56.6	564.5	58.1	679.2
grunt	gr^nt	5	7.00	1.30	4	2.00	0.0510	0.00462	0.500	58.0	490.5	60.9	609.5
coroner	kcrxnX	6	6.92	1.70	3	1.41	0.0609	0.00656	0.333	55.1	563.1	66.8	685.0
remind	rImYnd	6	7.00	2.18	2	1.48	0.0532	0.00638	0.000	55.3	586.3	59.5	701.1
defend	dxfEnd	6	7.00	2.32	3	2.49	0.0419	0.00368	0.000	56.8	615.3	60.9	733.0
mention	mEnC|n	6	7.00	2.70	4	1.95	0.0607	0.00814	0.500	61.0	577.6	66.8	705.3
receive	rIsiv	5	7.00	2.88	4	1.55	0.0560	0.00920	0.167	53.9	635.6	63.9	753.4
limber	lImbX	5	7.00	1.30	3	2.04	0.0482	0.00475	0.000	58.0	550.0	58.0	666.0
hardly	hardli	6	7.00	3.03	1	2.62	0.0519	0.00548	0.000	56.8	600.8	47.6	695.3
minute	mIn|t	5	7.00	2.72	4	1.21	0.0743	0.00855	0.167	56.8	378.8	50.8	486.3
squid	skwId	5	7.00	1.00	4	1.39	0.0433	0.00330	0.000	55.3	589.2	61.0	705.5
straighten	stretN	6	7.00	1.85	1	3.08	0.0509	0.00590	0.000	56.8	644.4	63.9	765.0
supposed	sxpozd	6	6.82	2.81	1	2.99	0.0417	0.00180	0.000	53.9	878.0	65.3	997.2
collect	kxlEkt	6	7.00	2.20	3	1.91	0.0623	0.00692	0.333	55.3	547.1	61.0	663.7
mustard	m^stXd	6	7.00	2.30	2	1.24	0.0573	0.00820	0.000	58.0	552.9	59.5	670.4
cartridge	kartrIJ	7	6.50	1.78	3	1.10	0.0611	0.00895	0.333	61.0	586.3	60.9	708.2
languor	l@GgX	5	4.67	1.00	3	2.60	0.0364	0.00313	0.333	63.9	492.0	65.3	621.1
dribble	drIbL	5	6.83	1.00	3	1.23	0.0445	0.00525	0.333	63.9	445.5	56.6	566.0
magnet	m@gn|t	6	6.75	1.48	2	1.00	0.0578	0.00576	0.000	55.1	554.4	52.3	661.8
parable	p@rxbL	6	5.67	1.48	3	1.16	0.0602	0.00692	0.333	55.1	531.2	63.9	650.2
remit	rImIt	5	4.92	1.00	3	1.50	0.0648	0.00718	0.000	59.5	561.6	63.9	685.0
reverse	rIvRs	5	7.00	2.26	3	1.26	0.0466	0.00558	0.000	63.9	714.0	55.1	833.0
knowledge	nalIJ	5	6.83	3.16	2	2.21	0.0434	0.00493	0.000	58.0	647.3	58.1	763.3
device	dxvYs	5	7.00	2.74	3	2.19	0.0370	0.00205	1.000	61.0	615.3	63.8	740.1

chapter	C@ptX	5	6.83	2.87	2	1.42	0.0516	0.00418	0.000	59.5	554.4	65.3	679.2
hamper	h@mpX	5	7.00	1.70	3	1.32	0.0495	0.00565	0.333	53.7	496.3	62.4	612.4
temporal	tEmpXL	6	6.33	1.70	2	2.33	0.0447	0.00482	1.000	53.9	542.8	58.1	654.7
colleague	kalig	5	7.00	1.95	2	1.15	0.0562	0.00718	1.000	63.9	631.3	66.8	761.9
danger	denJX	5	7.00	2.85	2	1.15	0.0463	0.00198	1.000	59.5	502.1	62.4	624.0
salvage	s@lvIJ	6	6.83	1.70	2	1.67	0.0542	0.00378	0.000	62.4	685.0	65.3	812.7

Nonwords

Nonword	IPA	Nonword	IPA
beton	bɛtɨn	porcel	poɹsl
mizzion	mɪʒɨn	ceilong	siloŋ
pontion	ponʃɨn	druven	dɹuvən
tapen	tepɨn	tample	timpl
conzede	kənzid	cowic	kɑwɪk
conbern	kənbɚn	cendury	sɛndɚi
comfine	kəmfaɪn	panker	pænkɚ
conlign	kənlaɪn	fapet	fæsot
cothin	kɔθən	cumler	kʌmlɚ
deamen	dɛmən	stoitter	stɔɪtɚ
suphon	sufən	romick	ɹɑmɪk
saften	sʌfən	sepger	sɛpgɚ
bonish	bonɪʃ	brimmle	bɹɪml
fugish	fɚgɪʃ	fileg	faɪleŋ
magage	mægɪʤ	scaft	skæft
madiage	mædɪʤ	moontain	mʊntn
dogain	dogen	spooral	spʊɹl
reshain	ɹɪʃen	drenth	dɹɛntʃ
redain	ɹɪden	repout	ɹɪpaʊt
refain	ɹɪfen	glunt	glʌnt
partution	pɚtʊʃɨn	corofer	kɔɹədɚ
pernission	pɚnɪʃɨn	rehind	ɹɪhaɪnd
perition	pəɹɪʃɨn	dejend	dəjɛnd
polition	pəlɪʃɨn	mendion	mɛndɨn
cendral	sɛndɹl	rebeive	ɹɪbiv
lercus	lɚkɨs	lomber	lombɚ
nopice	nopɨs	harply	hɑɹpli
rekort	ɹɪkoɹt	minupe	mɪnot
lipard	lɪpɚd	sqad	spwɪd
navous	nʌvəs	stroten	stɹotn
sernice	sɚnəs	summosed	səmozd
weerant	wɪɹənt	colluct	kəlukt
halen	hælən	musgard	mʌsgɚd
mardin	mɑɹdɨn	curtridge	kuɹtɹɪʤ
peasart	pɛzɹt	langdor	læŋdɚ
repolve	ɹɪpɑlv	driggle	dɹɪgl
goillop	gɔɪləp	magzet	mægzɨt
nomidee	nɑmədi	paradle	pæɹədl
fenon	fɛnɨn	remut	ɹɪmʌt
vittage	vɪtɪʤ	relerse	ɹɪlɚs
cuzzing	kʌʒɪŋ	knowpedge	nɑpɪʤ
rezail	ɹizel	degice	dəgaɪs
medory	mɛdɚi	chapmer	tʃæpmɚ
tromy	tɹomi	hamler	hæmlɚ
trosure	tɹoʒɚ	temtoral	tɛmtɚl
somemn	sɑməm	comeague	kɑmig

ravio	ɹevio	dadger	deddʒɚ
plara	plæɹə	salgage	sælgɪdʒ