

Research Note

Using Network Science Measures to Predict the Lexical Decision Performance of Adults Who Stutter

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Purpose: Methods from network science have examined various aspects of language processing. Clinical populations may also benefit from these novel analyses. Phonological and lexical factors have been examined in adults who stutter (AWS) as potential contributing factors to stuttering, although differences reported are often subtle. We reexamined the performance of AWS and adults who do not stutter (AWNS) from a previously conducted lexical decision task in an attempt to determine if network science measures would provide additional insight into the phonological network of AWS beyond traditional psycholinguistic measures.

Method: Multiple regression was used to examine the influence of several traditional psycholinguistic measures

as well as several new measures from network science on response times.

Results: AWS responded to low-frequency words more slowly than AWNS; responses for both groups were equivalent for high-frequency words. AWS responded to shorter words more slowly than AWNS, producing a reverse word-length effect. For the network measures, degree/neighborhood density and closeness centrality, but not whether a word was inside or outside the giant component, influenced response times similarly between groups.

Conclusions: Network analyses suggest that multiple levels of the phonological network might influence phonological processing, not just the micro-level traditionally considered by mainstream psycholinguistics.

Network science is an emerging discipline that draws on techniques developed in mathematics, sociology, computer science, physics, and other fields to examine complex systems. A *network* consists of *nodes*, which are used to represent an individual entity in the network, and *connections*, which are placed between related nodes. Fundamental to the network science approach is the assumption that the structure of a network influences the dynamics of that network (Watts & Strogatz, 1998). That is, a process might operate efficiently in a network that is structured in one way; however, the same process may operate less efficiently in another network that contains the same number of nodes and connections but is structured differently. Therefore, understanding the structure of a network, such as a network representing the mental lexicon, is critical to understanding how a cognitive process, such as language production, occurs.

The network approach has been used to examine questions in biology, sociology, and technology (Barabási, 2009). In the speech and language sciences, network science has been used to examine semantic representations of words in children with language delays (Beckage, Smith, & Hills, 2011) as well as typically developing children (Hills, Maouene, Maouene, Sheya, & Smith, 2009) and adults (Steyvers & Tenenbaum, 2005). It has also been used to examine the phonological representations of people with aphasia (Vitevitch & Castro, 2015), as well as the language processes of word recognition (Chan & Vitevitch, 2009; Luce & Pisoni, 1998; Vitevitch & Luce, 1998, 1999; Vitevitch & Rodriguez, 2005), word production (Chan & Vitevitch, 2010; Vitevitch, 1997, 2002; Vitevitch & Stamer, 2006), word learning (Goldstein & Vitevitch, 2014; Storkel, 2004), and language-related memory processes (Vitevitch, Chan, & Roodenrys, 2012). The network approach has also been used to examine the symptoms of stuttering (Siew, Pelczarski, Yaruss, & Vitevitch, 2017).

In addition to understanding the organization and efficiency of typical speech and language systems, network science may provide even more benefit in the exploration of speech and language systems in clinical populations such as stuttering. The remainder of this article will focus

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on the phonological network of adults who stutter (AWS) and describe some ways network science can be applied to clinical populations.

The Phonological Network

Vitevitch (2008) used the tools of network science to examine the mental lexicon by creating a network consisting of ~20,000 English words as nodes and placing undirected and unweighted connections between those words that were phonologically similar. Phonological similarity was defined by adding, substituting, or deleting a single phoneme in a word to create another word (Luce & Pisoni, 1998). For example, the nodes for *cat* /kæt/ and *bat* /bæt/ would be connected because of the substitution of one phoneme (the underlined phoneme indicates where the changed phoneme occurred). A small portion of the network is displayed in Figure 1.

A number of measures can be made at various levels of the network that have important implications for lexical processing (see Appendix A). For a review of network measures examined in the phonological network, see Vitevitch, Goldstein, Siew, and Castro (2014). Some network science measures assess the macro-level, or aspects of the whole network, whereas other measures assess the micro-level, or aspects of individual nodes in the network. An example of a measure of the whole network is the observation of Vitevitch (2008), who found that the approximately 20,000 nodes within the phonological network resided in one of three locations: the giant component, in one of many possible smaller components called islands, or as an isolated hermit. The giant component consisted of a large group of nodes ($n = 6,508$) that were highly connected to each other. Another 2,567 nodes resided in islands in the network, which consisted of smaller groupings of nodes that were connected to each other, but not to the giant component. For example, Vitevitch (2008) described the “island of the shunned,” because all words in that island contained the sequence of segments /ʃʌn/, such as *faction*, *fiction*, and *fission*. Lastly, hermits ($n = 10,265$) were those nodes in the network that were not connected to any other node in the network (e.g., *spinach*).

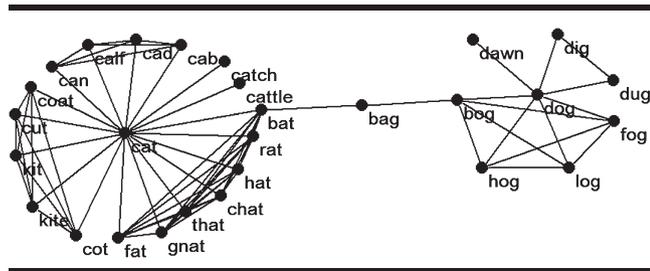
An example of a measure that assesses individual nodes in the network is *degree*. Degree refers to the number of connections that a node has. In the phonological

network, this measure refers to the number of words that sound like the target word (as defined by the one-phoneme metric), which is better known in the psycholinguistic literature as *neighborhood density* (Luce & Pisoni, 1998). Henceforth, we will use the term *degree/neighborhood density* to reflect the fact that two different fields are describing the same concept. A node that has high degree/neighborhood density is connected to many other nodes (e.g., *cat* in Figure 1), whereas a node that has low degree/neighborhood density is connected to few other nodes (e.g., *dog* in Figure 1). It has long been known in speech perception (Luce & Pisoni, 1998) that as the degree/neighborhood density of a word increases, the slower and less accurately that word is responded to.

Finally, some network measures assess the *meso-level*, or aspects of the network that lie somewhere between an individual (*micro-level*) and the whole network (*macro-level*). One such measure is *closeness centrality*, which measures the distance from one node to all other nodes in the network (following the shortest path between any two nodes being considered). For a given node, closeness centrality takes into consideration only those nodes that reside within its particular connected component (i.e., the giant component or an island) as these are the only possible nodes that it could be connected to. Hermit nodes, which are not connected to any other node, would have a closeness centrality value of 0. A node that has a closeness centrality value close to 1 tends to be close to other nodes in the network. That is, one can get from that node to any other node in the network by traversing relatively few connections. On the other hand, a node that has a closeness centrality value close to 0 tends to be far away from other nodes in the network. In this case, one must traverse many connections to get from that node to any other node in the network.

Vitevitch and Castro (2015) found in a picture-naming task (often used to examine speech production) that individuals with aphasia and healthy controls named words with high closeness centrality (i.e., words that are close to other words in the lexicon) less accurately than words with low closeness centrality (i.e., words that are far away from other words in the lexicon). They proposed that more competition during word retrieval occurs for words with high closeness centrality because of their many close connections, whereas words with low closeness centrality would be easier to produce because they are more distant from other nodes in the network.

Figure 1. A small portion of the phonological network examined by Vitevitch (2008).



The Present Study

Evidence suggests that children and AWS have subtle, subclinical differences in their phonological processing abilities as compared with typically fluent peers (e.g., Byrd, McGill, & Usler, 2015; Byrd, Vally, Anderson, & Sussman, 2012; Newman & Bernstein Ratner, 2007; Pelczarski & Yaruss, 2014, 2016; Sasisekaran & De Nil, 2006; Sasisekaran & Byrd, 2013; cf. Bosshardt & Fransen, 1996; Hennessey, Nang, & Beilby, 2008), yet these differences are not yet well understood and not always revealed during

traditional behavioral tasks. Vitevitch and Castro (2015) examined archival data of picture-naming performance from individuals with aphasia and healthy controls to illustrate how network science measures can be used to better understand the process of speech production in clinical populations. In the present study, we conducted a similar analysis of previously collected data from a lexical decision task with AWS and adults who do not stutter (AWNS) to determine if network science measures may provide additional insight into the organization and structure of a potentially less efficient phonological system.

Method

Data from a previously conducted lexical decision task were obtained from a larger study designed to examine the phonological processing abilities of AWS and AWNS (Pelczarski, 2011). Participants included 19 AWS paired by sex, age, and education level to 19 AWNS. Groups each consisted of 14 men and 5 women who ranged in age from 22 to 45 years (mean age AWS, $M = 32.68$; mean age AWNS, $M = 33.21$). Inclusionary criteria for the AWS group included self-identification as a person who stutters, a severity rating of at least mild from the Stuttering Severity Instrument–Fourth Edition (Riley, 2009), and demonstration of at least 3% stuttered speech. Stuttering severity for the AWS ranged from mild to severe, and those who did not meet the inclusionary criteria were included in the AWNS group.

In addition to the matching criteria, participants were administered standardized tests of expressive and receptive vocabulary (Expressive Vocabulary Test [EVT], Williams, 1997; Peabody Picture Vocabulary Test–Third Edition, [PPVT-III], Dunn & Dunn, 1997) to ensure that vocabulary size was not a confounding factor. Groups performed similarly on the vocabulary measures (EVT: $t = .829$; $p = .163$; PPVT-III: $t = .946$; $p = .357$), suggesting that the participants were well matched in this regard.

Stimuli for the lexical decision task consisted of words and nonwords balanced according to length, word frequency, and phonotactic probability. They were digitally recorded

by a standard American English-speaking woman and presented with E-Prime (Schneider, Eschman, & Zuccolotto, 2002). Participants listened to the stimuli via headphones and were instructed to use a single finger to press a button for “word” or “nonword” and to return the finger to a central home-base location between trials. Reaction times were obtained via button press and recorded in milliseconds in E-Prime.

Thirty real words were examined in the present network analysis (see Appendix B). Nonwords by definition do not exist in the lexicon and therefore were not examined here.

A multiple regression model was used to predict reaction time during the lexical decision task using R software (R Core Team, 2016). This type of analysis allows us to examine the effect of one particular measure while controlling for a number of other possible variables. Following Vitevitch and Castro (2015), a model-building procedure was done to determine if participant group and/or network measures explained additional variance in reaction time beyond traditionally studied psycholinguistic variables (see Table 1). An analysis of variance between models was done to determine if the addition of predictors significantly add to the model. In the initial regression model, we included well-known linguistic variables of word length (i.e., number of phonemes) and word frequency (i.e., the frequency with which a word occurs in the language). In the next model, we included a variable reflecting participant group, in this case AWS and AWNS. The participant variable did not add significantly to the model but was kept because of its relevance to the research question. In the third model, we included the network science measures found to have significant effects in Vitevitch and Castro (2015): degree/neighborhood density, closeness centrality, and location within the network. These network measures added significantly to the model and were kept.

Finally, two models were tested that included interaction terms between participant group and the other variables. A model with interactions between participant group and the traditional psycholinguistic variables was found to be significant, and those interaction terms were kept.

Table 1. Model-building procedure and significance predicting reaction time.^a

Variable	Adjusted R^2	Analysis of Variance (p)
Model 1: Traditional psycholinguistic variables Len + WF	.1436	
Model 2: Add participant group Len + WF + Group	.1427	.82
Model 3: Add network measures Len + WF + Group + Deg + CC + Comp	.1707	< .001
Model 4: Add interactions between group and psycholinguistic variables Len + WF + Group + Deg + CC + Comp + Group × Len + Group × WF	.1769	< .01
Model 5: Add interactions between group and network measures Len + WF + Group + Deg + CC + Comp + Group × Len + Group × WF + Group × Deg + Group × CC + Group × Comp	.1747	.88

Note. Len = word length; WF = log word frequency; Deg = degree/neighborhood density; CC = closeness centrality; Comp = component.

^aThe final model used in the present analysis was Model 4.

However, a model with interactions between participant group and the network measures was not significant, and those interaction terms were removed. It may be possible that there were not sufficient enough data to find significant interactions. The final model contained word length, word frequency, participant group, degree/neighborhood density, closeness centrality, component, interaction between group and word length, and interaction between group and word frequency.

Word length was centered at one phoneme and ranged from two to 11 phonemes ($M = 5.8$, $SD = 2.64$). *Word frequency* counts came from Kučera and Francis (1967; we added 1 to each value and then performed a \log_{10} transformation) and ranged from 0.3 to 6.06 ($M = 3.04$, $SD = 1.17$). For group, we coded AWNS as 0 and AWS as 1. *Degree/neighborhood density* (we added 1 to each value and performed a \log_{10} transformation; Vitevitch, 2008) ranged from 0 to 1.51 ($M = 0.54$, $SD = 0.54$). *Closeness centrality* ranged from 0 to 1 ($M = 0.22$, $SD = 0.30$). For *component*, words in the giant component were coded as 0 and words outside the giant component (i.e., islands and hermits) were coded as 1.

Results

As reported in Pelczarski (2011), AWS and AWNS distinguished real words from nonwords in the lexical decision task with equal accuracy for the real words ($\chi^2 = 0.131$; $p = .936$) and for the nonwords ($\chi^2 = 0.171$; $p = .917$). Although AWS have been reported to have generally slower nonspeech motor movements (for a review, see Bloodstein & Bernstein Ratner, 2007), both groups were comparable in terms of reaction times ($t = 1.15$; $p = .272$). Traditional statistical analyses did not reveal any between-group differences; however, the analyses we report below revealed several interesting findings.

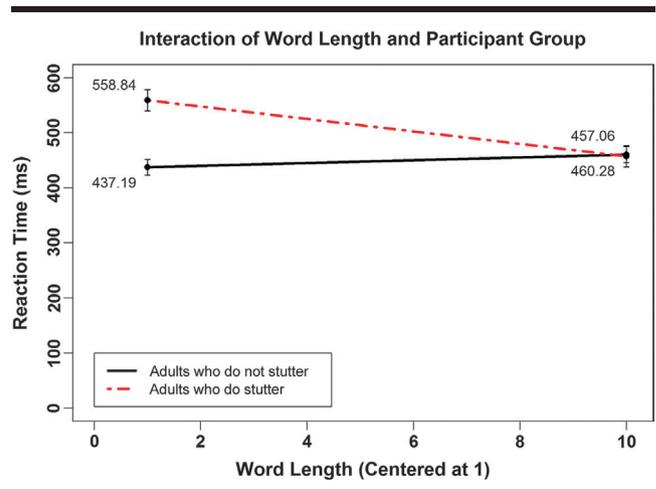
Table 2 lists each variable in the final model and its regression coefficient, standard error, and p value. The main effects of word length, word frequency, and group should be interpreted in the context of the significant interactions. Using the online utility developed by Preacher, Curran, and Bauer (2006), the interactions were plotted in Figures 2 and 3. The interaction of word length and

Table 2. Statistical results predicting reaction time on a lexical decision task performed by adults who stutter (AWS) and do not stutter.

Variable	Coefficient	Standard error	p value
Word length	2.31	5.58	.68
Word frequency	-43.75	7.63	<.001
Group (AWS)	121.64	45.06	<.001
Degree/neighborhood density	115.77	27.79	<.001
Closeness centrality	-80.09	26.17	.002
Component (outside GC)	-3.73	29.09	.90
Length \times Group	-12.49	5.12	.01
Log Word Frequency \times Group	-22.05	10.53	.04

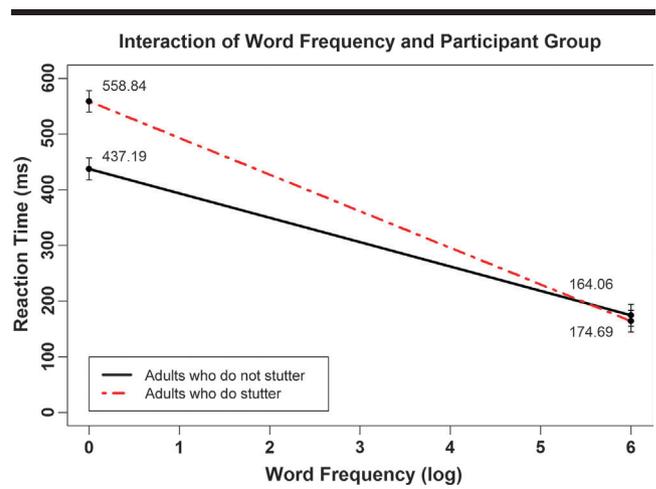
Note. GC = giant component.

Figure 2. Interaction of word length and group predicting reaction time on a lexical decision task. The two groups are adults who stutter and adults who do not stutter. Word length ranges in the data set from two to 11 phonemes but is plotted as one to 10 because of centering. The predicted reaction time given the interaction is plotted at each endpoint. The 95% confidence interval of the slope for each regression line is displayed at each endpoint.



group showed that AWS responded significantly more slowly than AWNS when words are short (e.g., at one phoneme: $p < .001$) but not when words are longer (e.g., at 10 phonemes: $p = .94$). Specifically, the region of significance suggests that the point of significance between the two groups in word length lies at approximately four phonemes. That is, AWS responded significantly more slowly than AWNS when words were four phonemes or fewer, but there was no significant difference between the two groups when words were longer than four phonemes. In addition, the individual slope for AWNS is not

Figure 3. Interaction of word frequency and group predicting reaction time on a lexical decision task. The two groups are adults who stutter and adults who do not stutter. Word frequency ranges in the data set from 0.30 to 6.06. The predicted reaction time given the interaction is plotted at each endpoint. The 95% confidence interval of the slope for each regression line is displayed at each endpoint.



significant ($p = .68$), whereas the individual slope for AWS is marginally significant ($p = .07$).

The interaction of word frequency and group showed that AWS responded significantly more slowly in the lexical decision task than AWNS when words are of low frequency (e.g., at 0.5: $p < .01$) but not when words are of higher word frequency (e.g., at 6: $p = .77$). Specifically, the region of significance suggests that the point of significance between the two groups in word frequency lies at approximately 3.2. That is, AWS responded significantly more slowly than AWNS when words have a frequency value of 3.2 or less, with no significant difference between the two groups when words have a frequency value greater than 3.2. In addition, the individual slope for AWNS and AWS is significant (both $ps < .001$). That is, for both groups, as word frequency increases, reaction times decrease, replicating a long-known influence of word frequency on lexical processing (Whaley, 1978).

A main effect of degree/neighborhood density was found in the present study such that as degree/neighborhood density increased, reaction time also increased. That is, words with higher degree/neighborhood density were responded to more slowly in the lexical decision task than words with low degree/neighborhood density. This finding replicates previous studies of spoken word recognition (e.g., Luce & Pisoni, 1998).

A main effect of closeness centrality was also observed, such that as closeness centrality increased, reaction time decreased. Recall that closeness centrality measures the distance from one node to all other nodes in the network (following the shortest path between any two nodes being considered). Therefore, words with high closeness centrality (or words that are close to many words in the network) were responded to more quickly than words with low closeness centrality (or words that are far from many other words in the network). Finally, although Vitevitch and Castro (2015) found that during a picture-naming task, individuals with aphasia and healthy controls produced words found outside of the giant component more accurately than words in the giant component, there was no significant effect of a word being inside/outside the giant component in the present analysis.

Discussion

Several main effects were revealed in this analysis. Expected effects for closeness centrality and neighborhood frequency were found for both groups; however, the two main effects for word length and word frequency that distinguished the groups will be discussed first. AWS demonstrated a reverse word-length effect, wherein longer reaction times were observed for shorter stimuli than for longer stimuli. AWNS did not show this effect. Reverse word-length effects have been reported previously in studies using immediate serial recall in situations in which phonological maintenance is challenging (e.g., in unpredictable lists of words and nonwords). Jefferies, Frankish, and Noble (2011) suggested that longer words are remembered better because the phonological code is bolstered through access to

preexisting representations in the lexicon (i.e., redintegration), particularly when there is difficulty in the phonological maintenance system. Delayed or disordered phonological encoding and phonological memory abilities in AWS could be considered a situation in which phonological maintenance is difficult. Some researchers have argued that difficulties in phonological encoding of children and AWS may be mediated at times by support from long-term lexical representations (Pelczarski, 2011; Pelczarski & Yaruss, 2016), although more research is needed in this area.

Word frequency was the second significant main effect. AWS responded more slowly to low-frequency words than high-frequency words as compared with AWNS, suggesting that the planning or retrieval of phonetic codes for less frequently spoken words may be delayed. Low-frequency words in particular seem to be more susceptible to disfluencies in AWS. Several studies have reported that stuttering occurred more frequently on low-frequency words than high-frequency words in adults (Hubbard & Prins, 1994; Newman & Bernstein Ratner, 2007; Soderberg, 1966) and in children (Anderson, 2007; Palen & Peterson, 1982; Ratner, Newman, & Streckas, 2009). The slower reaction times for low-frequency words in a lexical decision task provides further evidence that some aspect of phonological processing is delayed in AWS.

The effect of neighborhood density was present in both groups and did not distinguish between speaker groups. Recall that degree/neighborhood density refers to the number of words that sound similar to a target word. A word with high degree/neighborhood density has many words that sound similar to it, whereas a word with low degree/neighborhood density has few words that sound similar to it. The findings of the present study replicate previous findings (e.g., Luce & Pisoni, 1998), such that as degree/neighborhood density increases, word recognition is slower and less accurate in both AWS and AWNS.

Less work has examined the influence of closeness centrality on word recognition. Recall that closeness centrality is a measure that identifies “important” nodes in the system. Words with high closeness centrality tend to be close to other words in the network, whereas words with low closeness centrality tend to be far from other words in the network. Iyengar, Madhavan, Zweig, and Natarajan (2012) used an off-line word-morph task to examine the influence of closeness centrality. In the word-morph task, participants had to “morph” one word (e.g., *bay*) into another word (e.g., *egg*) by changing one letter at a time. Participants completed the game more quickly when they used “landmark” words, which upon subsequent analysis by Iyengar et al., turned out to be words with high closeness centrality (e.g., *aid*). In the present study, we found that as closeness centrality increased, reaction time decreased for both AWS and AWNS. The “landmark” words with high closeness centrality seem to stand out more among the other words in this word recognition task, making lexical discrimination easier during spoken word recognition.

It is important to note that the meso-level measure of closeness centrality findings seems to be in contradiction to

those found for the micro-level measure degree/neighborhood density. In the case of degree/neighborhood density, having many connections was detrimental (i.e., slower reaction times). However, with closeness centrality, words that were more connected to the entire network (i.e., words with high closeness centrality) had an advantage (i.e., faster reaction times). The difference between these two measures is critical. Degree/neighborhood density takes into consideration only those nodes that are immediately connected to the target node, whereas closeness centrality takes into consideration all nodes in the network. It may be the case that being more connected to the entire network (i.e., high closeness centrality) may make the initial search for a lexical item quicker. That is, words with high closeness centrality are easily identifiable “landmarks” among the mass of words in the lexicon. But once one zooms in to the more local neighborhood of a particular word, having more immediate connections (i.e., degree/neighborhood density) may make discrimination of the target from those neighbors more difficult.

Lastly, the location of a node in the network allows for an examination of the network at the macro-level. Recall that Vitevitch (2008) found that nodes could reside in the interconnected giant component, in a small connected island distinct from the giant component, or as a hermit not connected to any other node in the network. Previous studies (Siew & Vitevitch, 2016; Vitevitch & Castro, 2015) have found that words located outside of the giant component (i.e., island and hermit words) have a processing advantage over words located in the giant component in both word recognition and production tasks. The present study, however, did not find a significant effect, which may have been due to a lack of power (i.e., fewer words in the present analysis) to detect the influence if it was present.

The phonological encoding of AWS is frequently referred to as being “disordered” or “delayed,” but it is challenging to determine exactly what aspect of phonological encoding is aberrant using purely behavioral tasks. The subtle phonological processing differences AWS display could be due to a disorganized or weakened phonological network structure, to a less robust/stable phonological representation, or even to a delayed or disrupted retrieval of the phonological code. Although the AWS and AWNS behaved differently in response to different psycholinguistic variables, network analyses of the current data revealed expected network effects (degree/neighborhood density and closeness centrality) for both groups, suggesting that the structure of the phonological network in AWS is similar to its typically fluent counterparts. This brings us one step closer to more fully understanding the nature of the phonological encoding differences between AWS and AWNS by potentially ruling out structural differences in the phonological network. This finding contrasts with findings from studies of the semantic network, where structural differences between typically developing and late-talkers are observed (Beckage et al., 2011). Future studies using network science measures may help us further explore whether the robustness of the phonological representations or the efficiency of phonological retrieval may be disrupted in

AWS. This discovery would not have been possible with traditional psycholinguistic measures.

The present study allows us to move beyond the reductionist approach of contemporary psycholinguistics, which focuses only on examination of the individual word (e.g., how frequently a word is used). The present findings clearly illustrate the importance of examining measures that can account for differences in speech processing above and beyond what traditional psycholinguistic measures can account for. Specifically, the use of the network science approach—a more holistic approach—enables us to examine the relationships and interactions among entities. It is in these relationships and interactions that we might gain a better understanding of speech and language processes in a variety of clinical populations.

Furthermore, the network science approach allows us to examine multiple levels of a system. Again, traditional psycholinguistics tends to focus on characteristics of the individual word, or what the network science approach refers to as the micro-level. In contrast, the network science approach also allows for an examination of the meso- and macro-levels of a system. Importantly, as shown in the present study, different structural characteristics at different levels of the system may have different influences on processing. As noted by Watts and Strogatz (1998), the structure of the network has important implications for how processing occurs in that network. Therefore, we must consider how words are connected in the entire network and at various levels of the network to better understand speech processing. In this study, we found that a micro-level measure (i.e., degree/neighborhood density) and a meso-level measure (i.e., closeness centrality) influenced word recognition processes. The latter influence would not have been found had only traditional psycholinguistic methods and measures been employed. Although the macro-level measure (i.e., component) was not found to be significant in this study, further research ensuring greater variability of this measure may provide different results.

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Appendix A

List of network measures discussed in the text

Network measure	Scale	Definition	Formula
Degree/neighborhood density	Micro-level	The number of connections immediately connected to a node	k_i , the number of nodes to which node i is connected
Closeness centrality	Meso-level	The distance from one node to all other possible nodes in the network following the shortest path between any two nodes being considered; this value ranges from 0 to 1	Closeness (i) = $1/\sum_j d_{ij}$, where i is the node of interest, j is another node in the network, d_{ij} is the shortest distance between the two nodes
Location in network	Macro-level	The location of a node in the overall network	A node can reside in one of three locations: the <i>giant component</i> , a smaller component called an <i>island</i> , or as an isolated <i>hermit</i>

Appendix B

List of real words used in the lexical decision task in Pelczarski (2011)

edge	pout	petty	human	popular	community
oat	ring	ready	effervesce	pajamas	palpitation
to	gravel	island	physical	contract	experience
fit	middle	fuchsia	company	computer	organization
house	people	science	museum	equipment	quintuplet