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Evidence of Semantic Clustering in Letter-Cued Word Retrieval

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Abstract

Letter-cued word fluency is conceptualized as a phonemically guided word retrieval process. Accordingly, word clusters typically are defined solely by their phonemic similarity. We investigated semantic clustering in two letter-cued (P and S) word fluency task performances by 315 healthy adults, each for 1 min. Singular value decomposition (SVD) and generalized topological overlap measure (GTOM) were applied to verbal outputs to conservatively extract clusters of high frequency words. The results generally confirmed phonemic clustering. However, we also found considerable semantic/associative clusters of words (e.g., pen, pencil, and paper), and some words showed both phonemic and semantic associations within a single cluster (e.g., pair, pear, peach). We conclude that letter-cued fluency is not necessarily a purely phonemic word retrieval process. Strong automatic semantic activation mechanisms play an important role in letter-cued lexical retrieval. Theoretical conceptualizations of the word retrieval process with phonemic cues may also need to be re-examined in light of these analyses.

Keywords

verbal fluency; cued-word retrieval; semantic system; clustering; switching

INTRODUCTION

Verbal fluency tasks typically require examinees to name as many exemplars of a given semantic category (e.g., animals) or words that begin a specified letter cue (e.g., P) as possible in a fixed time interval. In response to semantic category cues (semantic fluency), most people start by naming exemplars of one subcategory and then switch to another after depleting the first (e.g., Bousfield, Sedgewick, & Cohen, 1954; Gruenewald & Lockhead,

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1980). A similar pattern can be seen in letter-cued word retrieval (phonemic fluency), where respondents give some words that begin or end with the same sounds (Troyer, Moscovitch, & Winocur, 1997). These patterns are referred to as *clustering* and *switching* and thought to be sensitive to deficits in semantic system and/or executive controls in various patients with mental illness or brain lesions (Troyer & Moscovitch, 2006; Troyer, Moscovitch, Winocur, Alexander, & Stuss, 1998).

To capture these two characteristics of verbal fluency production for use in clinical settings, Troyer and colleagues (Troyer & Moscovitch, 2006; Troyer et al., 1997) developed a scoring system for frequently used semantic cues (e.g., animal names and supermarket items) and letter cues (e.g., P and S). This system consists of predefined rules that are used to determine whether successively reported words form a cluster. For example, on letter word fluency, successively reported words that rhyme, begin or end with similar sounds, or are homonyms are grouped together as phonemic clusters. On category word fluency, successively reported words from specified subcategories, such as fruits or vegetables as exemplars of supermarket items, define clusters.

An assumption of the scoring system from Troyer et al. (1997) is that people cluster words based only on their semantic relatedness when performing semantic fluency tasks and based only on their phonemic relatedness when doing letter fluency tasks. Troyer et al. adopted this approach in response to studies showing that most clusters involved semantically related words in semantic fluency tasks and phonemically related words in phonemic fluency tasks (e.g., Auriacombe et al., 1993; Raskin, Sliwinski, & Borod, 1992). In semantic fluency, the exclusive reliance on semantic clustering and the use of corresponding clustering rules have been well supported by studies that used data-driven statistical clustering analyses (e.g., Chan et al., 1993; Moelter et al., 2001; Sumiyoshi et al., 2001; Sung et al., 2012).

In phonemic fluency, the assumption that people use only phonemic similarity to cluster words has been more problematic and may be an oversimplification. Using the letter F as a cue, Auriacombe et al. (1993) found that healthy adults produced very few (1.75%) semantic clusters. In contrast, data from Raskin et al. (1992) suggest that nearly one third of the clusters their participants produced in response to the letters F, A, and S were semantic or associative ones. Schwartz, Baldo, Graves, and Brugger (2003) also found data-driven evidence of semantic clustering during phonemic fluency in response to the letters F and A. While most of the clusters seen on letter word fluency tasks are phonemic, these data suggest that semantic clustering may be too common to ignore. It seems that the amount of semantic clustering varies, depending on the specific letter cues researchers use and their scoring rules (Ross et al., 2007). Thus, it is important to find data-driven evidence of semantic clustering for the specific letter fluency tasks without relying on predefined rules that researchers need to determine beforehand.

The goal of this study was to objectively assess semantic clustering during letter word fluency production in response to the letters P and S, as were used by Troyer and colleagues (Troyer & Moscovitch, 2006; Troyer et al., 1997). To achieve this goal, we adopted a two-stage clustering method. The first stage used the singular value decomposition (SVD) procedure, which has been shown to be an effective method for clustering analysis in verbal fluency and other areas of science (Alter, Brown, & Botstein, 2000; Landauer, 2007; Sung et al., 2012). The second stage used a network analysis tool, the generalized topological overlap measure (GTOM; Yip & Horvath, 2007), to conservatively extract finer clusters of associated words identified via SVD. We adapted multilevel clustering analysis for the current study to avoid identifying clusters of words based on predefined rules. Although clustering analysis still requires some degree of judgment by researchers in general, this multilevel data-driven analysis minimizes the possible confounding effects of subjective rules that can vary from study to study. Brief descriptions of SVD and GTOM are provided below.

METHOD

Participants

A community sample of 394 adults was recruited for a study of aging, brain imaging, and cognition from the Baltimore, Maryland, and Hartford, Connecticut, metropolitan regions (Schretlen, Testa, Winicki, Pearlson, & Gordon, 2008). The participants were recruited via random digit dialing or by calling randomly selected listings from the residential telephone directories for the two metropolitan areas. Of these, 315 individuals who did not have a history of bipolar disorder, schizophrenia, current major depression or substance abuse/dependence, any other medical condition that is commonly associated with cognitive impairment, or a score below 24/30 on the Mini-Mental State Exam (Folstein, Folstein, & McHugh, 1975) contributed data to this analysis. The participants ranged in age from 18 to 92 years (M = 54.9; SD = 18.8) and completed a mean of 14.2 years of schooling (SD = 3.1). The sample included slightly more women (179; 56.8%) than men (136; 43.2%) and more Caucasian Americans (250; 79.4%) than African Americans (59; 18.7%) or persons of other racial/ethnic background (6; 1.9%). The Johns Hopkins Medicine Institutional Review Board approved this study, and each person gave written informed consent to participate.

Procedure

All participants completed two letter-cued word fluency tasks (P and S) from the Calibrated Ideational Fluency Assessment (CIFA; Schretlen & Vannorsdall, 2010) as part of a larger neuropsychological assessment. For each letter cue, participants were encouraged to name as many different words as possible beginning with the letters P and S in two consecutive 1-minute intervals. Respondents were told not to say numbers or proper nouns.

Analysis

We first examined the possible effects of age, sex, and education on overall productivity for the two fluency tasks. Neither age nor sex affected the average number of correctly named words based on unequal sample size t-tests with equal variance assumed. Educational attainment, based on a median split of the sample (< 14 vs. ≥ 14 years), affected overall productivity (Table 1). The group with 14 years of education or above generated more P- and S- words than the other group with less education [$t(313) = 5.45$, $p < 0.001$, partial eta-squared (η_p^2) = 0.087 and $t(313) = 5.56$, $p < 0.001$, $\eta_p^2 = 0.090$]. However, the effect sizes for both letter cues were quite small.

Similarly small effects of age, sex, and education on letter word fluency have been reported by others (e.g., Barnes, Tager, Satariano, & Yaffe, 2004; Hughes & Bryan, 2002; Lanting, Haugrud, & Crossley, 2009; Rosselli, Tappen, Williams, Salvatierra, & Zoller, 2009; Singh-Manoux, Richards, & Marmot, 2005). These studies found greater effects of demographic background on category word fluency tasks. Thus, we proceeded to clustering analysis with less concern about the effect of these demographic variables on phonemic fluency performance.

As mentioned earlier, we adapted SVD procedure as the main clustering analysis tool. The key reason for this is that SVD procedure has capability to analyze more fluency data than other clustering techniques do (e.g., multi-dimensional and hierarchical clustering) when they are applied to verbal fluency data (cf. Sung et al., 2012). Also, we wanted to use the same clustering technique as those in our previous studies (e.g., Sung et al., 2012) since it allows direct comparisons of the results if needed.

For clustering analysis, we excluded 239 (5.5%) of 4,347 words named in the P-word condition and 215 (4.7%) of 4,554 words named in the S-word condition because of rule breaks. Clusters of words were identified through a two-stage analysis. In the first stage of two-stage analysis, we applied SVD to extract any possible associations between pairs of the 63 most frequently reported words beginning with P or S (126 words in total), as these had a high probability of being clustered. The number 63 was chosen because each word co-occurred with at least half of the other words in the same condition. Each of these 63 words also was named by at least 5% of the participants. In the second stage, clusters identified via SVD were refined using GTOM, which helps identify clusters in relation to all other words, rather than in relation to just one other word at a time (see below).

SVD analysis—For SVD analysis, we constructed a word-by-participant matrix for each letter cue (i.e., two matrices). In the P-word condition, 939 different words were named by 315 participants, yielding a 939 (rows) by 315 (columns) matrix for SVD analysis. Each cell, c_{ij}, of the matrix had a value of 1 if the j^{th} subject said the i^{th} word or 0 if not (i.e., the matrix is binary with 1s and 0s). In the S-word condition, a 1097-by-315 matrix was constructed the same way. These two matrices served as input matrix for SVD analysis. Although all words were analyzed via SVD, here we report only the results of the analyses for the top 63 words in each letter cue condition for the reason stated in the preceding section.

Briefly, SVD is a general matrix factorization technique of which factor analysis is specific case. (The eigenvalue decomposition, the mathematical basis for factor analysis, is a special case of SVD.) Here we adapted SVD to represent binary word vectors in a multidimensional space whose dimensionality (like factors in factor analysis) will be less than or equal to the number of words in an input matrix. If the dimensionality of an SVD solution is less than the number of words, then the resulting new word vectors in the SVD solution will be grouped together based on the similarity of their cell values in the original input matrix (i.e., the rates of co-occurrence across the participants). Put another way, if two words frequently co-occur, then their vectors in the input matrix will be considered “similar,” suggesting that the two words are semantically or associatively related (see Supplementary Information for a

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simplified example of SVD analysis). SVD will then re-represent those original word vectors into a smaller number of dimensions so that those two vectors are clustered together. The number of dimensions for an SVD solution is usually determined by the researcher based on interpretability of the solution. This approach is similar to factor analysis, where the optimal number of factors is often determined the same way. A cluster of words is identified by examining angles of the re-represented vectors in an SVD solution (Landauer, McNamara, Dennis, & Kintsch, 2007). Thus, the smaller the angle between word vectors, the stronger the association between them.

To determine the initial clusters of words using SVD, we calculated up to 25th dimensional SVD solutions using the PROPACK software for SVD (Larsen, 2004) for Matlab (version R2011a, Mathworks). We assumed that the meaningful dimensionality of a solution would be far less than 25. To repeat, the angles between word vectors of the SVD solution will indicate the association relationship between the words in question. Note that, rather than examining angles, we take the cosine of an angle between any two word vectors since it resembles a correlation measure: cosine values of 1.0, 0.0, and −1.0 indicate that two words are perfectly associated, independent, and mutually exclusive, respectively (Landauer et al., 2007).

Figure 1 shows four selected word examples and their cosine values of vector angles with respect to all 63 words in the SVD solutions. The three different types of lines indicate different dimensional solutions by SVD analysis. After examining the SVD solutions, we determined that two words could be said to be clustered if the cosine of an angle between word vectors is 0.8 or greater in 5-dimensional vector space. For example, from Figure 1-A, we determined that pencil (frequency rank 2) is clustered with itself, paper (3), pen (5), pretty (27), and point (57) since the cosines between pencil and these words in 5-D space were greater or equal to the threshold value, 0.8 (a solid horizontal line in each panel of Figure 1). For the top 63 words, the cosine threshold of 0.8 and dimensionality of 5 showed that all 63 words were associated with at least one other word. These are fairly conservative parameters given that a lower dimensionality and a cosine threshold would make all of the 63 most frequently reported words clustered with many more words.

Generalized Topological Overlap Measure (GTOM)—We next used GTOM to refine the word clusters identified via SVD. The basic idea of GTOM is that if two words are indeed meaningfully associated (e.g., phonemically or semantically), then they are likely to share other words in their clusters. That is, if pencil (2) is truly associated with paper (3), then pencil and paper may share another word, such as pen (5), as a member of their clusters since all are closely associated. Measuring *the degree of word sharing* would help us filter out some undesirable word clusters resulting from the blind application of SVD threshold. For example, SVD analysis may tell us two words are clustered because their cosine value is greater than 0.8. However, it is possible that they may in fact belong in two different clusters without any associative relationship. GTOM will filter out these cases. Thus, one may consider the result of GTOM analysis as a set of word clusters trimmed down from word clusters identified using SVD. The following equation calculates the degree of word sharing, $t_{(ij)}$, by two words, i and j (Yip & Horvath, 2007).

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$$t_{(ij)}=\frac{(\#\quad of\quad shared\quad words\quad between\quad i\quad and\quad j)+a_{(ij)}}{min\,(\#\quad of\quad words\quad clustered\quad with\quad i,\#\quad of\quad words\quad clustered\quad with\quad j)+\left(1-a_{(ij)}\right)}$$

In this equation, $a_{(ij)}$ is 1 if two words *i* and *j* are clustered as a result of SVD analysis and is 0 if they are not. Note that two words may not be clustered as a result of SVD analysis (i.e., $a_{(ij)} = 0$), but they could share other words as their cluster members. The denominator of the equation includes the minimum of numbers of words clustered with the two words of interest, excluding themselves. Note that the degree of word sharing measure $t_{(ij)}$ ranges from 0 to 1.

An example might help clarify the equation. As shown in Figure 1-A, SVD analysis showed that pencil (2) clustered with, excluding itself, paper (3), pen (5), pretty (27), and point (57). Likewise, point (57) clustered with pencil (2), pen (5), pin (21), pony (47), and past (51). Therefore, the number of words clustered with pencil is 4, and it is 5 for point. Since pencil and point were clustered with each other as a result of SVD analysis, $a_{(pencil,\ point)}$ is 1. The number of words shared by pencil and point is 1; pen (5) is the only word shared between them, excluding themselves. Putting these values into the equation gives us

$$t_{(pencil,point)}=\frac{1+1}{min\,(4,5)+(1-1)}=\frac{2}{4}=0.5.$$

For the purpose of the current study, we set the GTOM threshold for $t_{(ij)}$ measure to 1.0, the maximum possible value, again, to conservatively refine the word clusters (although we also examined other threshold values). A GTOM value of 1.0 means that two words are clustered with exactly the same words or one is clustered only with a subset of words that cluster with the other word. All other cases will give us GTOM values less than 1.0.

RESULTS

The results of the two-staged clustering analysis are shown in Figures 2 and 3 for the P- and the S-word conditions separately. In these figures, the solid lines connecting two words indicate that the words are clustered at a GTOM threshold of 1.0. Broken lines indicate connections that emerge when the threshold is lowered to 0.9. Note that the distance shown between words and the location of the words within the figures do not have any meaning.

In Figure 2, we can easily see some semantically or associatively related words within each identified cluster. These include [pen, pencil, paper], [pineapple, pumpkin, potato], [peach, pear, plum], [push, pull], [put, pants], and so on. The same is true of word clusters in response to the letter S, as shown in Figure 3. Identified semantic clusters include [sweat, sugar, salt, sour], [sun, summer], [stand, sit], [socks, shirt, shoe], [stop, start], [sit, stand] and so on. It seems that the associations between words are much stronger in the S-word condition, where words tended to be fully connected within a cluster.

Notably, many clusters are not exclusively phonemic or semantic but are a mix. This mixing leads to some word groupings that are seemingly unrelated. For example, it is not easy to discern any phonemic or semantic associations between pair and plum (Figure 2), but the word pear represents a bridge between them. Similarly, the cluster of [socks, shoe, shirt] has no obvious semantic association with the clusters [salt, sea, ship] and [sour, sweat, salt (duplicated), sugar]. But one may be able to draw a phonemic association between them through [shirt, ship], [shoe, sugar], or [sour, socks], whose first two letters have the same or similar initial sounds.

With a GTOM threshold of 0.9, new associations emerge between words within a cluster (broken lines in Figures 2 and 3), rather than between clusters. Finally, many of the top 63 words did not cluster with other words when the GTOM threshold was set to 0.9 or 1.0, probably because of their conservatism.

DISCUSSION

We report a conservative and objective data-driven method of examining the utility of the phonemic association rules proposed by Troyer and colleagues for the letter fluency task. We found clear evidence that words can be associated not only by phonemic characteristics, but also by semantic associations (or a mixture of the two) in two letter-cued word fluency tasks. This suggests that — unlike the semantic process for category fluency — the hidden cognitive mechanism responsible for phonemic fluency performance may not be a homogenous process, and instead may involve qualitatively different cognitive processes. Also, considering that only the 63 most frequently reported words were examined here, it is likely that semantic clustering of responses to two letter cues (P and S) is not a rare phenomenon. These findings support the assertion by Abwender, Swan, Bowerman, and Connolly (2001) and Schwartz et al. (2003) that relying exclusively on phonemic rules to identify clustering on letter word fluency tasks might not fully capture the mental processes that support lexical retrieval on such tasks.

Implication for clustering and switching measurements

Our results suggest that key verbal fluency parameters, such as cluster size (number of words in a cluster), number of clusters, and number of switches between clusters (Troyer et al., 1997), may underestimate or overestimate the true nature of word clustering in letter word fluency productions. For example, the word string [pair, pear, plum, peach] has one multiword cluster (pair, pear) defined by phonemic similarity, but it also contains a semantic cluster (pear, plum, peach), and the present results suggest that the entire string can be conceptualized as a single cluster with multiply determined associations. Determining which of these best captures the underlying cognitive processes may be essential to the task of elucidating the neural circuitry that supports this approach to lexical retrieval. Conversely, since Troyer et al. (1997) define switching based on shifts between both single- and multiple-word clusters, their system will overestimate the true number of switches on letter word fluency because it does not count semantically related words as valid clusters (see Abwender et al., 2001 for a specific example).

Accurate estimation of clustering and switching is important for both theoretical and clinical reasons, and inaccuracies are more likely to occur on letter word fluency tasks. This means that when researchers observe apparent differences in clustering and switching between phonemic and semantic fluency tasks, their theoretical inferences about the true nature of cognitive mechanisms responsible for fluency performance are more likely to be wrong. Also, clinically, inaccurate assessment of letter fluency capabilities of patents with different mental diseases could lead to wrong conclusions about the diseases in question.

In fact, many studies have found that both healthy persons and various patient populations show different levels of performance on letter and category word fluency tasks (e.g., Bozikas, Kosmidis, & Karavatos, 2005; Fossati, Guillaume, Ergis, & Allialaire, 2003; Haugrud, Crossley, & Vrbancic, 2011; Ho et al., 2002; Kave, Heled, Vakil, & Agranov, 2011). For example, Fossati et al. (2003) found that persons with depression produced fewer switches and fewer total words on category (animal names) than letter (P, V, R) word fluency. Kave et al. (2011) found that persons with traumatic brain injuries showed greater impairment on category than letter word fluency tasks in terms of both switching and clustering. Bozikas et al. (2005) also reported a similar pattern of disassociation between semantic and phonemic fluency performance by adults with schizophrenia. These studies all used the scoring system of Troyer et al. (1997) or related systems. Our results call the validity of their conclusions into question.

One reason to be particularly concerned about such studies, in light of our results, is that they have not considered the possibility that impaired semantic clustering could contribute to reduced productivity on letter word fluency tasks. For example, two of the tidiest clusters we found are [pen, pencil, paper] and [shoe, shirt, socks]. Armed with only phonemic association rules, researchers will fail to identify the semantic elements of these clusters that some patient groups might fail to demonstrate on phonemic fluency tests. In other words, paper and socks are each semantically, but not phonemically associated with the other words in their respective clusters. Thus, ignoring the semantic component in these clusters could lead researchers to incorrectly conclude that there is a significant disassociation between two fluency performances. This possibility is not unreasonable to imagine, especially when the participants show significantly impaired semantic fluency in the very same studies.

Our findings clearly do not negate all the conclusions of studies that found disassociations between phonemic and semantic fluency performance. As long as the impairment is primarily confined to semantic associations in both semantic and phonemic fluency tests, the argument that there is disproportionate deficit in two types of fluency task would remain valid even with more refined measures. Interestingly, if this is the case, then it also raises a question about the claim that temporal lobe functioning is the key determinant of clustering in both letter and category word fluency (Troyer & Moscovitch, 2006; Troyer et al., 1997). If one could identify disassociations between semantic and phonemic clustering within a single phonemic fluency test in some group, such as persons with schizophrenia, then it is reasonable to hypothesize that different brain mechanisms support semantic and phonemic clustering (e.g., Abwender et al., 2001; Ross et al., 2007). To our knowledge, such disassociation in patients with schizophrenia has not been examined.

Finally, the current study has limitations. One is that we did not report any statistical tests to identify clustering solution for SVD analysis. The reason is that there is no well-accepted statistical test that allows one to choose specific dimensional solutions for SVD (Quesada, 2007). As in factor analysis, the dimensionality of a SVD solution typically is based on the interpretability of a solution. One approach to this issue is to adapt an additional analysis that helps one identify cluster solutions conservatively. That is the approach adopted here and by others (Chan et al., 1993; Moelter et al., 2001).

Another challenge of the current study is to set the appropriate parameters and thresholds for clustering analysis in SVD and GTOM. Again, because there are no universally accepted criteria or thresholds for defining clusters through these analyses, which can vary depending on the type of data and the purpose of analysis, we identified clusters based on very conservative rules. This approach is to minimize the possibility of finding results based on setting arbitrary parameters. Some might consider this a limitation of the present study, but we believe it strengthens the validity of the obtained results, since using more liberal thresholds would have yielded a larger number of phonemic and semantic clusters than we found and analyzed.

Finally, we have not reported different clustering patterns by demographic variables such as sex, age, and education, although their effects on overall productivity were examined. The main reason for this is that their effects on letter word fluency performance are very limited as noted earlier. Another reason is that the current analysis deals with qualitative aspects of phonemic fluency performance, namely, semantic/associative clusters in phonemic fluency. Examining putative effects of demographic characteristics on the content of word clusters deserves further study in separate investigation.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

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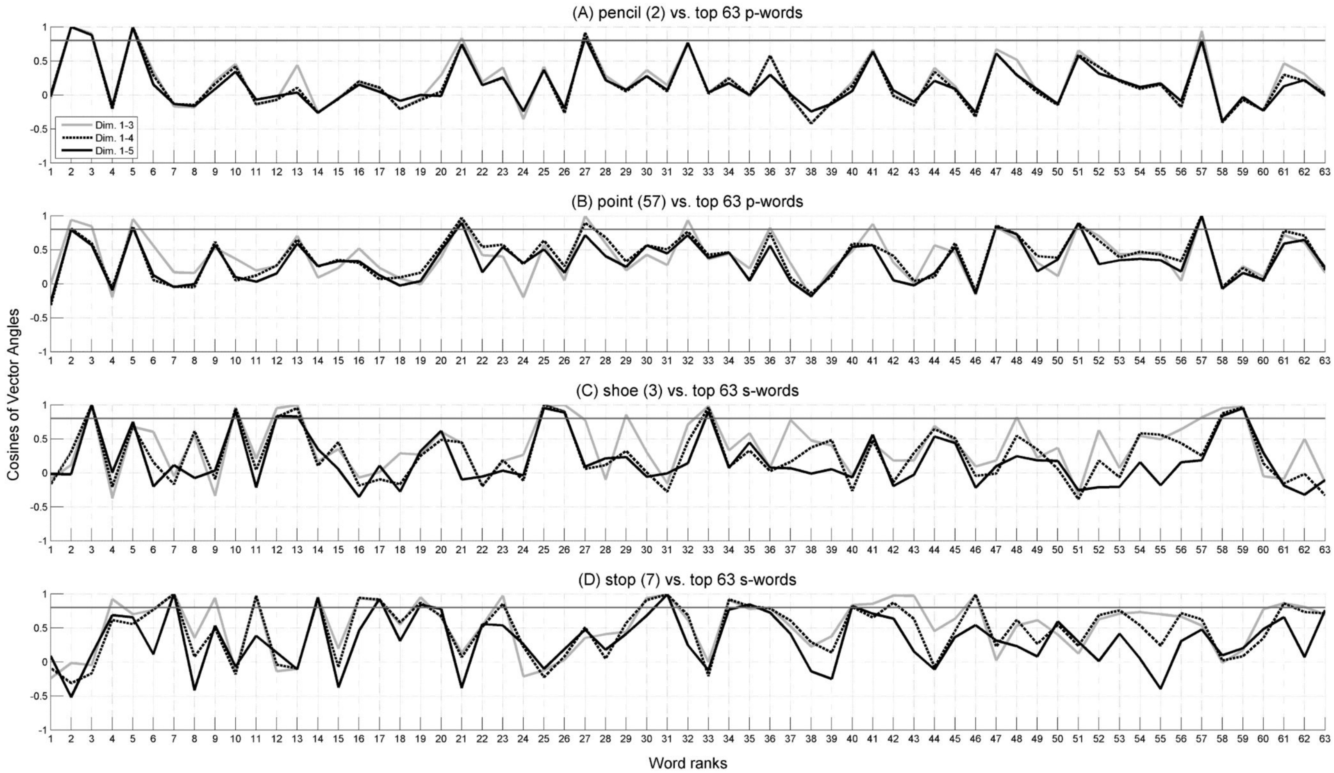

Figure 1.

Cosines of angles between four selected word vectors (pencil, point, shoe, and stop) and the top 63 word vectors plotted in three different dimensional spaces (Dim. 1-3, 1-4, and 1-5). (A) Pencil (rank 2) against top 63 P-words. (B) Point (57) against top 63 P-words. (C) Shoe (3) against top 63 S-words. (D) Stop (7) against top 63 S-words. The solid horizontal line across each panel indicates a cosine value of 0.8, which was used for cluster threshold in SVD analysis (see text). Counting by 5, in rank order the 63 P-words are: people (1), pencil, paper, purple, pen (5), place, pot, pan, play, person (10), push, pull, pear, put, pea (15), pat, please, pickle, pink, peach (20), pin, pig, pineapple, plum, pet (25), pie, pretty, pick, pepper, potato (30), pumpkin, part, pants, park, pipe (35), party, power, pop, poor, plate (40), phone, pill, peanut, peace, picture (45), pole, pony, proper, pale, paint (50), past, pillow, perfect, pit, pack (55), pimple, point, plant, pass, palm (60), pair, pool, purpose. Counting by 5, in rank order the 63 S-words are: sun (1), sand, shoe, sit, saw (5), simple, stop, snake, stand, salt (10), silly, sugar, sea, see, snow (15), sad, sew, sorry, soup, soap (20), sandwich, street, sing, sin, shirt (25), ship, same, swim, sex, single (30), start, sound, socks, super, said (35), school, sat, silver, sail, stupid (40), store, sign, smile, sky, soda (45), slow, summer, say, sink, show (50), son, salad, song, slide, snail (55), soft, safe, sour, sweet, send (60), slip, something, sight.

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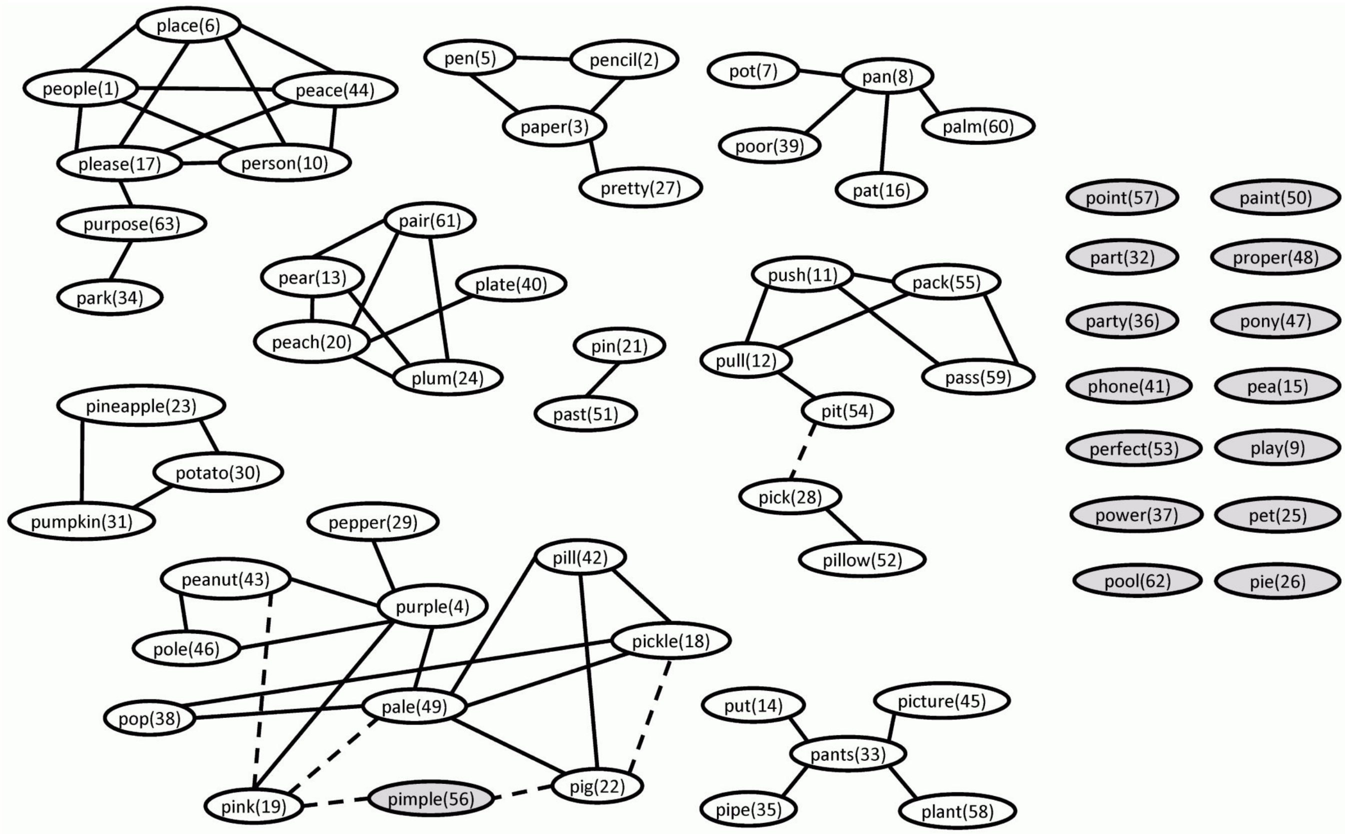

Figure 2.

P-word clusters identified via GTOM with 1.0 and 0.9 thresholds. Solid connecting lines indicate that the GTOM threshold value between two words connected is 1.0. Broken lines indicate additional connections between words when the GTOM threshold is lowered to 0.9. Gray shading indicates that words are isolated or become isolated as the threshold changes. Numbers within parentheses indicate the frequency rank of the word (1 through 63).

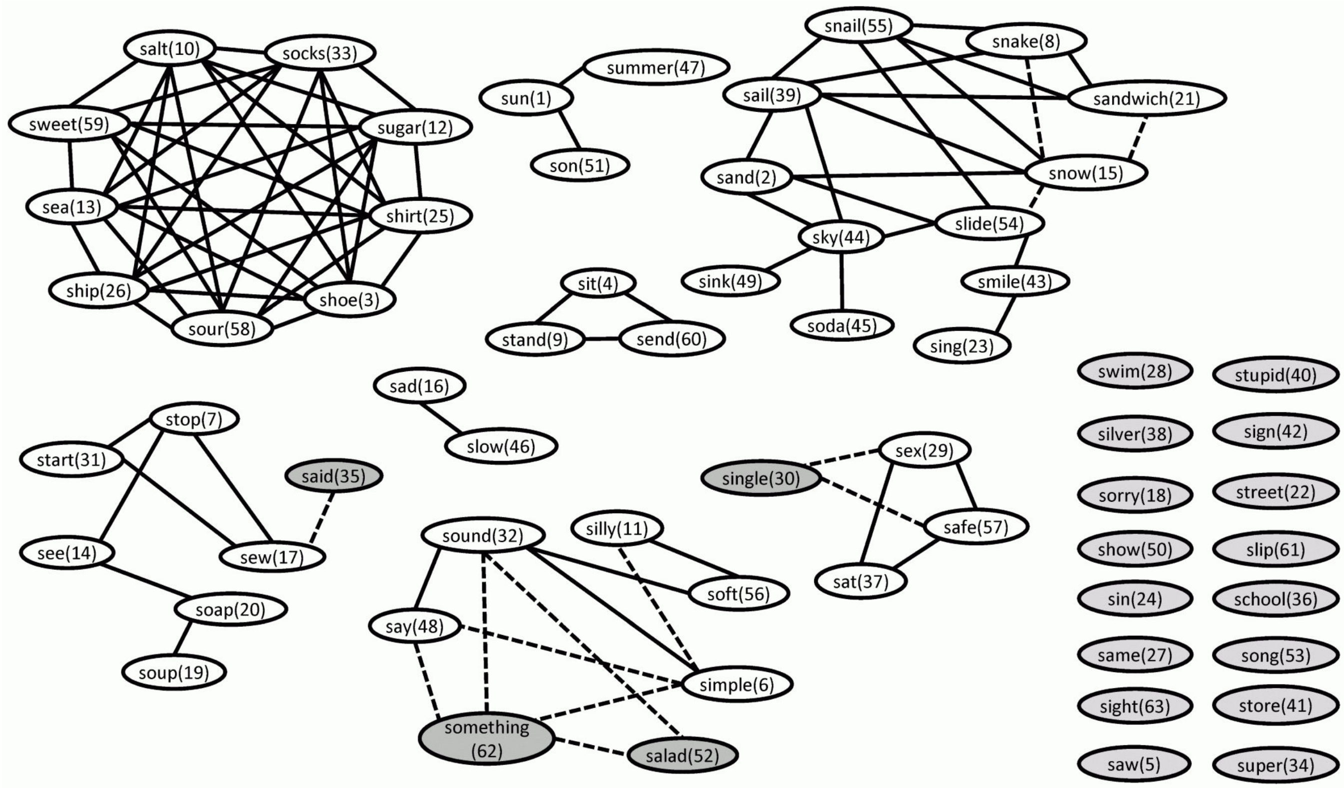

Figure 3.

S-word clusters identified via GTOM with 1.0 and 0.9 thresholds. As in Figure 2, solid connecting lines indicate that the GTOM threshold value between two words connected is 1.0. Broken lines indicate additional connections between words when the threshold is lowered to 0.9. Numbers within parentheses are the frequency rank of the word (1 through 63).

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Table 1

Means and standard deviations of numbers of correctly named words, by sex, age, and education sub-groups

	Sub-groups	**P-words** ***Mean*** **(*SD*)**	**S-words** ***Mean*** **(*SD*)**
Age (years)	> 60 (n = 135)	13.0 (5.0)	14.0 (5.4)
	≤ 60 (n = 180)	14.4 (4.6)	15.1 (5.0)
Sex	Men (n = 136)	13.6 (5.1)	14.3 (5.3)
	Women (n = 179)	13.9 (4.6)	14.6 (5.2)
Education (years)	≥ 14[a] (n = 170)	15.3 (5.0)*	16.0 (5.2)*
	< 14 (n = 145)	12.5 (4.3)	13.0 (4.8)

[a]Median split

*sub-group differences within each letter cue: $p < 0.001$