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Quantifying flexibility in thought: The resiliency of semantic networks differs across the lifespan

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ABSTRACT

Older adults tend to have a broader vocabulary compared to younger adults – indicating a richer storage of semantic knowledge – but their retrieval abilities decline with age. Recent advances in quantitative methods based on network science have investigated the effect of aging on semantic memory structure. However, it is yet to be determined how this aging effect on semantic memory structure relates to its overall flexibility. Percolation analysis provides a quantitative measure of the flexibility of a semantic network, by examining how a semantic memory network is resistant to "attacks" or breaking apart. In this study, we incorporated percolation analyses to examine how semantic networks of younger and older adults break apart to investigate potential age-related differences in language production. We applied the percolation analysis to 3 independent sets of data (total $N = 78$ younger, 78 older adults) from which we generated semantic networks based on verbal fluency performance. Across all 3 datasets, the percolation integrals of the younger adults were larger than older adults, indicating that older adults' semantic networks were less flexible and broke down faster than the younger adults'. Our findings provide quantitative evidence for diminished flexibility in older adults' semantic networks, despite the stability of semantic knowledge across the lifespan. This may be one contributing factor to age-related differences in language production.

1. Introduction

Aging is associated with cognitive decline, and this decline is seen in a number of areas of cognition, such as speed, inhibition, and language production. Older adults need to adapt to these age-related deficits to better navigate everyday tasks – yet as individuals age, they tend to become less flexible and have increased difficulty adapting to new environments (i.e., declines in processing speed and cognitive control; Hasher, Lustig, & Zacks, 2008; Salthouse, 2010). In contrast, one ability that remains remarkably stable across the lifespan is semantic knowledge or semantic memory (e.g., Park et al., 2002). However, semantic abilities are most often measured through vocabulary, and vocabulary inventories are typically un-timed, possibly minimizing age-related differences. Moreover, vocabulary inventories only assess knowledge of a relatively small sample of words, vastly underestimating the depth, breadth, and complexity of semantic knowledge. Words and their semantic features have structure and inter-relations among them (e.g., they can be represented as networks; Siew, Wulff, Beckage, & Kenett, 2019), which vocabulary inventories cannot capture. In the current study, we quantitatively examine, for the first time, the effect of aging on flexible thinking, by applying computational methods to estimate the *flexibility of* semantic memory structure of younger and older adults across three different samples. Specifically, we apply network science methods to estimate the semantic networks of these samples and examine the flexibility via a percolation analysis, which measures network resilience, or flexibility, by the process in which it breaks apart (Kenett et al., 2018), to further assess age-related decline.

2. Aging, flexibility, and semantic memory

Compared to the content of semantic knowledge, the structure of semantic knowledge may be even more relevant in aging, as older adults tend to have an equal or broader vocabulary compared to younger adults, indicating a richer storage of semantic knowledge (Kavé & Halamish, 2015; Kemper & Sumner, 2001; Park et al., 2002; Verhaeghen, 2003). Indeed, older adults show comparable performance to younger adults in a variety of semantic measures, including generating word associations (Bowles, Williams, & Poon, 1983; Burke & Peters,

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1986) and semantic priming effects (Burke, White, & Diaz, 1987; Madden, Pierce, & Allen, 1993). Although this greater repository of knowledge could be advantageous, having more words to select from could also increase semantic selection difficulty. Indeed, recent work differentiates knowledge and executive aspects of semantics (Hoffman, Loginova, & Russell, 2018; Rodd, Gaskell, & Marslen-Wilson, 2004; Rogers, Patterson, Jefferies, & Lambone-Ralph, 2015). The controlled semantic cognition framework suggests that semantic cognition involves the interaction between conceptual knowledge and the control processes that guide retrieval (Rogers et al., 2015). Specifically, age-related decline has been observed when there is high semantic competition – older adults are less accurate than younger individuals (Hoffman, 2018) – indicating that older adults are most impaired in situations with heightened semantic selection demands. These results suggest that decline in executive control *processes* hinder older adults in semantic tasks that require fine-grained retrieval or selection of concepts. However, such decline may also be related to the *structure* of the semantic system, such that a less efficient structure of concepts within the semantic system could contribute to retrieval difficulties (Klimesch, 1987).

Recent advances in computational methods, such as network science, are providing a means to study the development and change of the semantic system during typical aging (Dubossarsky, De Deyne, & Hills, 2017; Wulff, De Deyne, Jones, Mata, & Consortium, 2019; Wulff, Hills, & Mata, 2018). Network science provides a unifying framework to examine different aspects of semantic cognition, such as structural organization and search processes; it is based on graph theory, allowing the study of complex systems (such as semantic memory) as networks (Barabási, 2016). A network is comprised of nodes, that represent the basic unit of the system (e.g., concepts in semantic memory), and links (or edges), that signify the relations between them (e.g., semantic similarity). Over the past two decades, a growing number of studies have used computational methods to represent and study cognitive systems as networks (Baronchelli, Ferrer-i-Cancho, Pastor-Satorras, Chater, & Christiansen, 2013; Borge-Holthoefer & Arenas, 2010; Castro & Siew, 2020; Siew et al., 2019). For example, network science has tested the hypothesis that highly creative individuals have increased flexibility in their semantic memory structure (Kenett, Anaki, & Faust, 2014; Kenett & Faust, 2019), identified mechanisms of language development (Hills, Maouene, Maouene, Sheya, & Smith, 2009; Steyvers & Tenenbaum, 2005), shed novel light on statistical learning (Karuza, Kahn, Thompson-Schill, & Bassett, 2017), shown how specific linguistic network properties influence memory retrieval (Kenett, Levi, Anaki, & Faust, 2017; Kumar, Balota, & Steyvers, 2019; Vitevitch, Chan, & Goldstein, 2014; Vitevitch, Chan, & Roodenrys, 2012), and provided insight into the structure of semantic memory of second language in bilinguals (Borodkin, Kenett, Faust, & Mashal, 2016).

Several recent studies have applied network science methodologies to test theories about how semantic memory structure might facilitate flexible thinking, such as creative cognition (Kenett & Faust, 2019). These studies have shown how differences in semantic memory structure relate to individual differences in creativity, both at the group level (Kenett et al., 2014; Kenett, Beaty, Silvia, Anaki, & Faust, 2016) and at the individual level (Benedek et al., 2017; Bernard, Kenett, Ovando-Tellez, Benedek, & Volle, 2019; He et al., 2020). In addition, the semantic memory structure of highly creative individuals is characterized by a more flexible structure—i.e., higher connectivity and lower overall distances between concepts—likely permitting more efficient spreading of activation processes across a broader semantic space, leading to the generation of more novel ideas as activation tends to reach nodes in the network that are farther apart from each other (Kenett et al., 2018; Kenett & Faust, 2019). Therefore, these studies link flexible semantic memory structure with adaptable, creative thinking for younger adults. However, the connection between semantic structure and such flexible cognition has not been examined in the context of cognitive aging. Understanding how semantic networks change over the lifespan may help to explain the reduced cognitive flexibility that is often observed in aging (Dubossarsky et al., 2017; Wulff et al., 2019).

Recent studies comparing the structure of semantic networks across the lifespan provide converging evidence that the size of semantic networks continuously expands (Wulff et al., 2019). These studies report structural properties of the lexicon that vary across different age cohorts (Dubossarsky et al., 2017; Wulff et al., 2018; Zortea, Menegola, Villavicencio, & Salles, 2014) and find that concepts in older adults' semantic memory are more modular (i.e., concepts have sparser semantic neighborhoods, which means that concepts in the network are less connected) and more segregated (any pair of concepts in the network is "further apart") than those of younger adults. Dubossarsky et al. (2017) assessed how semantic networks differ across the lifespan (i.e. 10–84 years) using free association data from 8,000 participants. The authors found non-linearities in semantic memory properties across the lifespan, such that semantic memory is sparsely organized in children, increases in density towards midlife, then is increasingly sparse among older adults (Dubossarsky et al., 2017). These findings, although cross-sectional in nature, are consistent with the idea of aging being associated with changes in the structure of the semantic system, providing insight into the structure of the lexicon across the lifespan. However, while additional studies related highly structured, segregated semantic memory structure to higher intelligence (Kenett, Beaty, et al., 2016), network segregation has also been related to decreased flexible thinking among younger adults (Faust & Kenett, 2014; Kenett, Gold, & Faust, 2016; Siew, 2013). In relation to typical aging, it is yet to be determined how these changes in semantic memory structure relate to changes in flexible thinking.

Recently, percolation theory, a computational approach that measures the resilience of complex networks by the process of removing nodes or edges, has been applied to semantic network research as a quantitative way of studying its flexibility (Borge-Holthoefer, Moreno, & Arenas, 2011; Kenett et al., 2018; Stella, 2020). These studies are based on the assumption that the more a system is resilient to attack, the more flexible it is (Cohen & Havlin, 2010; Saberi, 2015). Percolation analyses quantify the flexibility of complex networks under simulated targeted or random attacks, by analyzing the effect of removing nodes or links between nodes whose strength falls below an increasing threshold (Farkas, Ábel, Palla, & Vicsek, 2007; Palla, Derényi, Farkas, & Vicsek, 2005).

A handful of empirical cognitive studies have applied percolation theory to study the resilience, or flexibility, of semantic memory structure in younger adults and clinical populations (Borge-Holthoefer et al., 2011; Kenett et al., 2018; Stella, 2020). Kenett et al. (2018) applied a percolation analysis on the semantic network of low- and high-creative individuals (Kenett et al., 2014). Across these two groups, the semantic network of the high-creative individuals was more connected and less segregated than that of the low-creative group. Thus, the authors indirectly inferred that the high-creative group had a more flexible semantic memory structure (Kenett et al., 2014). In conducting a percolation analysis on the semantic networks of these two groups, Kenett et al. (2018) found that the semantic network of the high-creative group broke apart more slowly in response to the network attacks, compared to the low-creative group. Thus, the authors argue that this finding indicates that the semantic network of the high-creative group is more flexible than that of the low-creative group (Kenett et al., 2018). Thus, the authors demonstrated how a higher connected, less segregated semantic memory network structure relates to heightened flexible thinking, and how percolation theory can be used to provide a quantitative measure of cognitive flexibility.

3. Present study

While previous studies have found that older adults show stable or increased reserves of semantic knowledge (e.g., Burke & Shafto, 2008; Kavé & Halamish, 2015; Park et al., 2002), recent evidence indicates that the structure of semantic memory networks appears to differ across

the lifespan. Advances in network science have enabled investigating the effect of aging on semantic memory structure, showing that the semantic network of older adults is more segregated compared to younger adults (Dubossarsky et al., 2017; Wulff et al., 2019; Wulff et al., 2018). Here we expand upon this recent work by applying network science and percolation analyses to examine age-related differences in the structure and flexibility of semantic memory networks. Understanding the factors that contribute to successful retention of semantic functions, and flexible behaviors such as communication abilities, across the lifespan is critical to successful aging.

We estimated the semantic memory networks of younger and older participants from three different samples by analyzing their verbal fluency responses (Kenett et al., 2013). For each dataset, we grouped the data based on age (e.g., younger vs. older adults), estimated and compared the properties of the semantic networks of these groups, and applied percolation analyses to assess age-related differences. Aligning with previous research assessing semantic networks and aging (Wulff et al., 2019), we expected that older adults would have a more segregated memory structure compared to younger adults. Aligning with previous research indicating loss of flexibility with aging (Salthouse, 2010), we expected that older adults would have a semantic network that breaks apart faster than that of younger adults, i.e., less flexible.

4. Methods

4.1. Participants

All participants across all three datasets were healthy, native English speakers. Demographic information from the datasets reflected the populations from which they were drawn (e.g., Dataset 1 (75% Caucasian (non-Hispanic), 13% Black or African American, 5% American Indian/ Native Alaskan, 3% Asian, and 3% prefer not to answer) who were recruited from Greensboro, North Carolina and a less diverse sample of mainly non-Hispanic Caucasians (>90%) for Datasets 2 & 3 who were recruited from central Pennsylvania). None reported history of neurological or physiological disorders, or major medical conditions (e.g., cancer, diabetes, heart disease). The first dataset, Dataset 1, was collected as part of a larger study on aging and creative thinking at the University of North Carolina at Greensboro (UNCG) and was approved by the Institutional Review Board (IRB) of UNCG. This dataset consisted of 56 participants, 28 younger (mean age = 21, SD = 2.79, males = 8, females = 20) and 28 older adults (mean age = 69.79, SD = 3.44, males = 13, females = 15). Datasets 2 and 3 were collected as part of two larger research studies at the Pennsylvania State University (Diaz, Karimi, et al., 2021; Diaz, Zhang, et al., 2020). All participants who chose to take part in these studies provided written informed consent and all experimental procedures were approved by the Pennsylvania State University IRB. The participant group of the second dataset, Dataset 2, included 50 participants, 25 younger (mean age = 28.84, SD = 5.83, males = 10, females = 15) and 25 older adults (mean age = 63.52, SD = 6.53, males = 9, females = 16). The participant group of the third dataset, Dataset 3, also comprised 50 adults, 25 younger (mean age = 24.4, SD = 3.7, males = 11, females = 14) and 25 older (mean age = 67.92, SD = 3.93, males = 11, females = 14).

4.2. Materials

4.2.1. Semantic fluency task

Participants completed a categorical verbal fluency task (listing animals). This task provides an efficient means to investigate people's ability to retrieve semantic information from long-term memory (Ardila, Ostrosky-Solís, & Bernal, 2006; Bousfield, Cohen, & Whitmarsh, 1958; Goñi et al., 2011; Patterson, 2011), and it is widely used to model group-based semantic networks (Siew et al., 2019). Although this one category represents a small sampling of the participants' overall semantic space, recent research examining a wide array of categories (>70) suggests that there is age and cohort stability in the exemplars that healthy adult participants produce, particularly among more basic categories like 'animals' (Castro, Curley, & Hertzog, 2020). According to standard procedures (Ardila et al., 2006) participants were given 60 s to speak aloud (Datasets 2 and 3) or type (Dataset 1) as many different animal category members as they could (Table 1 displays the average number of items produced per age group for each dataset). We also assessed vocabulary knowledge of the older and younger adults in Datasets 2 and 3 using the WAIS vocabulary test (Wechsler, 2008). There were no significant age-related differences in vocabulary knowledge in these two datasets (all p's > 0.1).

5. Network analysis

The semantic fluency data of all age groups were analyzed using a semantic network approach (Borodkin et al., 2016; Kenett et al., 2013). In this approach, each node represents a category exemplar (e.g., frog) and edges represent associations between two exemplars. These associations are the tendency of the sample to generate exemplar *b* (e.g., toad) when they have also generated exemplar *a* (e.g., frog). All network analyses were conducted in R using a publicly-available pipeline to analyze semantic fluency data as networks (Christensen & Kenett, 2019), with the following steps:

5.1. Network estimation

First, the *SemNetDictionaries* (Christensen, 2019b) and *SemNetCleaner* (Christensen, 2019a) R packages were used to preprocess participants' verbal fluency data. Participant repetitions (responses given by a participant more than once) and non-category members (e.g., alien, unicorn, beehive) were removed. Very few repetitions were produced (Dataset 1 = 0.53%, Dataset 2 = 1.95%, Dataset 3 = 1.13%) and these were produced by both younger and older adults. Other potential errors were corrected, including spelling errors, compound responses (i.e., responses where a space is missing between responses), variation on the same root word (e.g., cats to cat), and continuous strings (i.e., multiple responses entered as a single response). Next, the data were transferred into a binary response matrix, where columns represent the unique exemplars given by the sample and rows represent participants; the response matrix is filled out by 1 (if an exemplar was generated by that participant) and 0 (if that exemplar was not). The *SemNetCleaner* package (Christensen, 2019a) was used to further process the binary response matrix into a finalized format for network estimation. To control for confounding factors (such as different nodes or edges in both groups), as in previous studies (Borodkin et al., 2016; Christensen, Kenett, Cotter, Beaty, & Silvia, 2018) the binary response matrices only included responses that were given by at least two participants in each group. Then, to avoid the two groups including a different number of nodes, which may bias comparisons of network parameters (van Wijk, Stam, & Daffertshofer, 2010), responses in the binary matrices were equated, so that the networks of both groups in each sample were compared using the same nodes. After equating the networks across the two age groups, Dataset 1 had 45 nodes per network, Dataset 2 had 53 nodes per network, and Dataset 3 had 66 nodes per network.

Next, the *SemNeT* package (Christensen, 2019a) was used to compute the association profiles of verbal fluency responses. We used the cosine similarity function in this package to estimate the edges between nodes. The cosine similarity function is commonly used in latent semantic

Table 1
Number of verbal fluency responses for younger and older adult groups across the three datasets (standard deviation in parentheses).

	Dataset 1	Dataset 2	Dataset 3
Younger	20.79 (3.58)	22.52 (5.07)	24.92 (5.16)
Older	12.57 (3.04)	19.2 (4.76)	21.28 (5.9)

analysis of textual-corpora (Landauer & Dumais, 1997) and is related to Pearson's correlation, which can be considered as the cosine between two normalized vectors. Unlike Pearson's correlation, the cosine similarity ranges from 0 to 1 because it is based on the co-occurrence of responses. If two responses do not co-occur, then the cosine similarity is 0; if they always co-occur, then the cosine similarity is 1. Therefore, the associations were all positive, which has the advantage of not assuming that the lack of co-occurrence suggests a negative association between two responses (whereas Pearson's correlation carries that potential). The word similarity matrix was then examined as an n x n adjacency matrix of a weighted, undirected network, where each word represented a node in the network and the edges between two nodes represented the similarity between them.

To minimize possible spurious associations, we applied the Triangulated Maximally Filtered Graph (TMFG; Christensen, Kenett, Aste, Silvia, & Kwapil, 2018; Massara, Di Matteo, & Aste, 2016). The TMFG captures the most relevant information (i.e., minimizing spurious relations and retaining high correlations) within the original network. This approach retains the same number of edges between the groups, which avoids the confound of different network structures being due to a different number of edges (Christensen, Kenett, Aste, et al., 2018). Thus, the networks constructed by this approach can be directly compared because they have an equivalent number of nodes and edges. The TMFG method was applied using the *NetworkToolbox* package (Christensen, 2018) in R. In examining the structure of the networks, the edge weighting was retained as this information was required for the percolation analysis. Although it is possible to binarize the edge weights, weighted and unweighted semantic networks often correlate with one another (Abbott, Austerweil, & Griffiths, 2015).

5.2. Network analysis

The *NetworkToolbox* package was used to analyze the network properties. We incorporated three commonly used graph theory measures: *(a)* clustering coefficient, *(b)* average shortest path length, and *(c)* modularity index. *Clustering coefficient* refers to the extent that neighbors of a node will themselves be neighbors (i.e., a neighbor is a node *i* that is connected through an edge to node *j*). A higher clustering coefficient indicates a more interconnected semantic network (Siew et al., 2019). *Average shortest path length* refers to the average shortest number of steps (i.e., edges) needed to traverse between any pair of nodes; the higher the average shortest path length, the more spread out a network is. Previous research on semantics has shown that the shortest path length in semantic networks corresponds to participants' judgments as to whether two concepts are related to each other (Kenett et al., 2017; Kumar, Balota, & Steyvers, 2019). *Modularity* estimates how a network breaks apart (or partitions) into smaller sub-networks or communities (Fortunato, 2010). It measures the extent to which the network has dense connections between nodes within a community and sparse (or few) connections between nodes in different communities. Thus, the higher the modularity, the more the network breaks apart to subcommunities. Such subcommunities can be thought of as subcategories in a semantic network (e.g., farm animals in the 'animals' category). Previous research has shown that modularity in semantic networks is inversely related to a network's flexibility (Kenett, Gold, et al., 2016; Kenett et al., 2018).

5.3. Statistical analysis

We used two complementary approaches to statistically examine the validity of the results. First, we simulated random networks for each age group (separately, for each dataset) to statistically test whether the network parameters were different from a sampling of random networks with the same nodes and edges (Steyvers & Tenenbaum, 2005). To this end, we generated a large sample of Erdös-Rényi random networks with a fixed edge probability (Erdös & Rényi, 1960) and compared the empirical network measures of both groups to this random distribution. Significant differences in tests against random networks show that there is a purposeful, non-random structure in a semantic network. For each simulated random network, we computed its clustering coefficient, average shortest path length, and modularity. This procedure was simulated 1,000 times to achieve a random reference distribution for each measure. The empirical network measures were then compared to their reference distribution to evaluate their statistical significance. This was achieved via a one-sample *Z*-test for each network parameter.

Second, for each dataset, we used a bootstrapping approach (Efron, 1979) to simulate and compare partial younger adult and older adult semantic networks using the *SemNetCleaner* package in R (Christensen, 2019a). Based on previous studies (Borodkin et al., 2016; Christensen, Kenett, Cotter, et al., 2018; Kenett, Beaty, et al., 2016), the bootstrapping procedure involves a random selection of half of a network's nodes. The bootstrapping approach examines the consistency of the effect within the network under the rationale that if the full networks differ from each other, then any partial networks containing the same nodes should also be different. This method also tests whether any age differences are simply due to chance. Partial networks were constructed for each semantic network separately for these selected nodes. This method is known as the without-replacement bootstrap method (Bertail, 1997). Finally, for each partial network, the clustering coefficient, average shortest path length, and the modularity measures were computed. This procedure was simulated 1,000 times. The difference between the bootstrapped partial networks on each network measure for each dataset was then tested with independent samples *t*-test comparisons.

5.4. Percolation analysis

The percolation analysis was conducted using the *CliquePercolation* package in R (https://CRAN.R-project.org/package=CliquePercolation), which applied the percolation algorithm to the semantic networks of the younger and older participants across all datasets (as described in Farkas et al., 2007; Palla et al., 2005). The clique percolation method identifies overlapping communities, or subgraphs, of an entire weighted network (Farkas et al., 2007). For this analysis, we used the weighted semantic networks of the younger and older adult groups. Based on these network structures, we defined the number of *k-cliques*, or the fully connected networks of 'k' nodes. A community of k nodes are k-cliques that share at least one overlapping node. We used the `estimateNetwork` function from the *bootnet* package in R (Epskamp, Borsboom, & Fried, 2018) and then we used these estimated networks to calculate the optimal number of k-clique communities for the younger and older adult networks. Applying $k = 3$, the smallest possible size of k-cliques, to our analyses allowed for sensitivity to the smallest possible communities. These k-cliques were considered further only if their Intensity (*I*, strength) surpassed a specific *I* threshold, indicating the weighted connection between words is stronger than the threshold (Farkas et al., 2007).[1] Based on the varied edge connections between nodes in weighted networks, the optimal *I* range for our analyses was (0.01, 1), reflecting the minimum and maximum values of semantic relatedness, respectively. We then removed any overlapping connections between communities of semantically related words that fell below an increasing threshold until the networks became maximally fragmented.

Next, we calculated the Area Under the Curve (AUC) by calculating the number of connected nodes in the semantic networks across a range of thresholding values between when the *I* threshold equaled 0.01 (i.e.,

[1] In unweighted networks, there is a fixed weight threshold, *W*, and all links in the module must have weights higher than the link weight threshold *W* (Palla et al., 2005). Weighted networks, on the other hand, use intensity thresholds, *I*, and the links in these networks often contain links with weaker connections than the intensity threshold I (Farkas et al., 2007).

the minimum threshold, all connections will exceed this and be included) to when the I threshold equaled 1 (i.e., the maximum threshold, all nodes will not exceed this and will be excluded). This allowed us to compute the *percolation integral*, or how fast components in the network broke apart from the 'giant component' – the maximal number of nodes that are connected to each other in the network (Kenett et al., 2018). For example, a network that breaks apart quickly (at lower thresholds) will have a steeper percolation slope and a lower integral value. To test the significance of the clique percolation analysis between younger and older adults, we conducted 500 realizations of the percolation test, comparing the structure of semantic connections between the nodes from the younger and older adult semantic networks. In each iteration, we calculated the percolation integral for each network and then ran independent-sample t-test analyses to determine if the integral means of the two age groups were significantly different (Kenett et al., 2018).

6. Results

6.1. Verbal fluency performance

Before analyzing the semantic networks of younger and older adults, we assessed their performance on the verbal fluency task. We thus computed independent-samples t-test analyses on the number of items produced on the categorical verbal fluency task between the two age group across the three datasets (Table 1). For all datasets, we found that the younger adults produced significantly more items than the older adults – in Dataset 1 $t(54) = 9.25$, $p < 0.001$, Dataset 2 $t(48) = 2.39$, $p = 0.02$, and Dataset 3 $t(48) = 2.32$, $p < 0.001$ – replicating previous work on verbal fluency and aging (Clark et al., 2009; Park et al., 2002). Importantly, these age-group differences were controlled for by equating the responses across groups for each dataset's network (see *Network Estimation* section for additional details).

6.2. Older adults have more segregated and less efficient semantic networks than younger adults

Next, we estimated the semantic networks of the younger and older participants across the three datasets. To visualize the networks (Fig. 1), we applied the force-directed layout (Fruchterman & Reingold, 1991) of the Cytoscape software (Shannon et al., 2003). In these 2D visualizations, nodes are represented by the respective circles and edges between them are represented by lines. Since these networks are undirected and weighted, the edges convey symmetrical (i.e., bidirectional) similarities between two nodes.

To statistically validate our results, we incorporated two complimentary statistical significance testing methods. First, we compared our modeled semantic networks to randomly generated graphs. Across all three datasets, the simulated random network analysis revealed that the graph theory metrics (average shortest path length, clustering coefficient, and modularity) for the younger and older adult groups were statistically different from random networks (all p's < 0.001).

The group-based network analysis computes a single value for each network measure for the different age groups. To statistically examine the differences between the younger and older adults' networks, we applied a bootstrapped partial networks analysis (Bertail, 1997; Kenett et al., 2014) to generate a distribution of values for each of the network measures that were derived from a subset of the empirical data (see Methods for more details). This resulted in a sample distribution of 1,000 samples for all measures (clustering coefficient, average shortest path length, and modularity) for each network (Fig. 3). An independent samples t-test was conducted on each network measure to analyze the differences between the bootstrapped partial networks of the younger and older adults (Fig. 2):

6.3. Clustering coefficient

For Dataset 1, our analysis revealed that younger adults had a higher clustering coefficient compared with older adults, $t(1998) = -22.59$, $p < 0.001$. Aligning with Dataset 1, our analysis of Dataset 2 revealed that

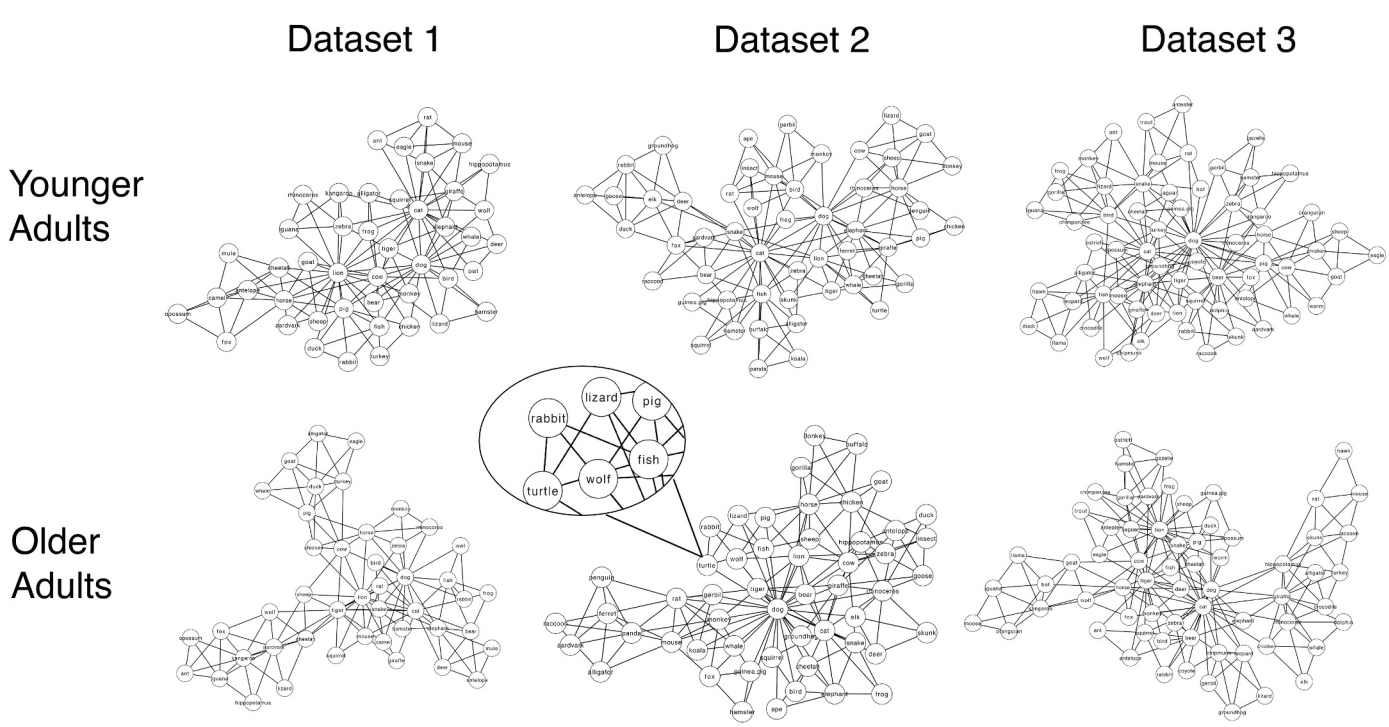

Fig. 1. A 2D Visualization of the semantic networks of younger and older adult groups across the three datasets. Here, each circle represents a word (node), and lines represent connections between word nodes. A section of the graph has been highlighted to illustrate the connections among words in this section of the network.

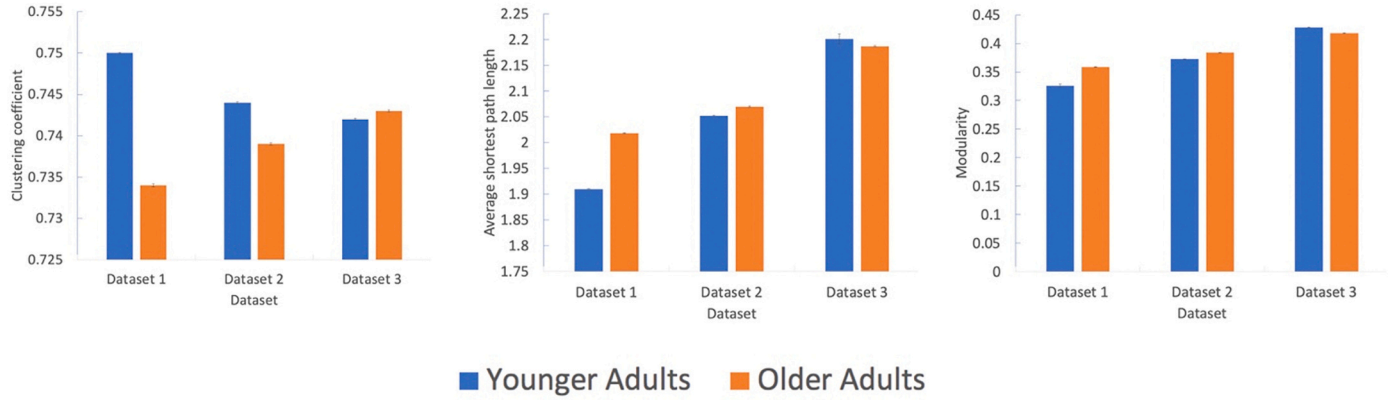

Fig. 2. The results from the partial network analysis for clustering coefficient (left), average shortest path length (center), and modularity (right) for the younger and older adult groups across the three datasets. X-axis – age groups across the three datasets. Y-axis – dependent variables (clustering coefficient, average shortest path length, and modularity; Error bars denote standard error).

younger adults had a higher clustering coefficient compared with older adults, $t(1998) = -8.34$, $p < 0.001$. In contrast to the first two datasets, there were no group differences for clustering coefficient between younger and older adults in Dataset 3, $t(1998) = -6.81$, $p = 0.31$.

6.4. Average shortest path length

In Dataset 1, younger adults had a lower average shortest path length when compared with older adults, $t(1998) = 26.59$, $p < 0.001$. In Dataset 2, younger adults also had a lower average shortest path length compared with older adults, $t(1998) = 2.85$, $p = 0.004$. However, the

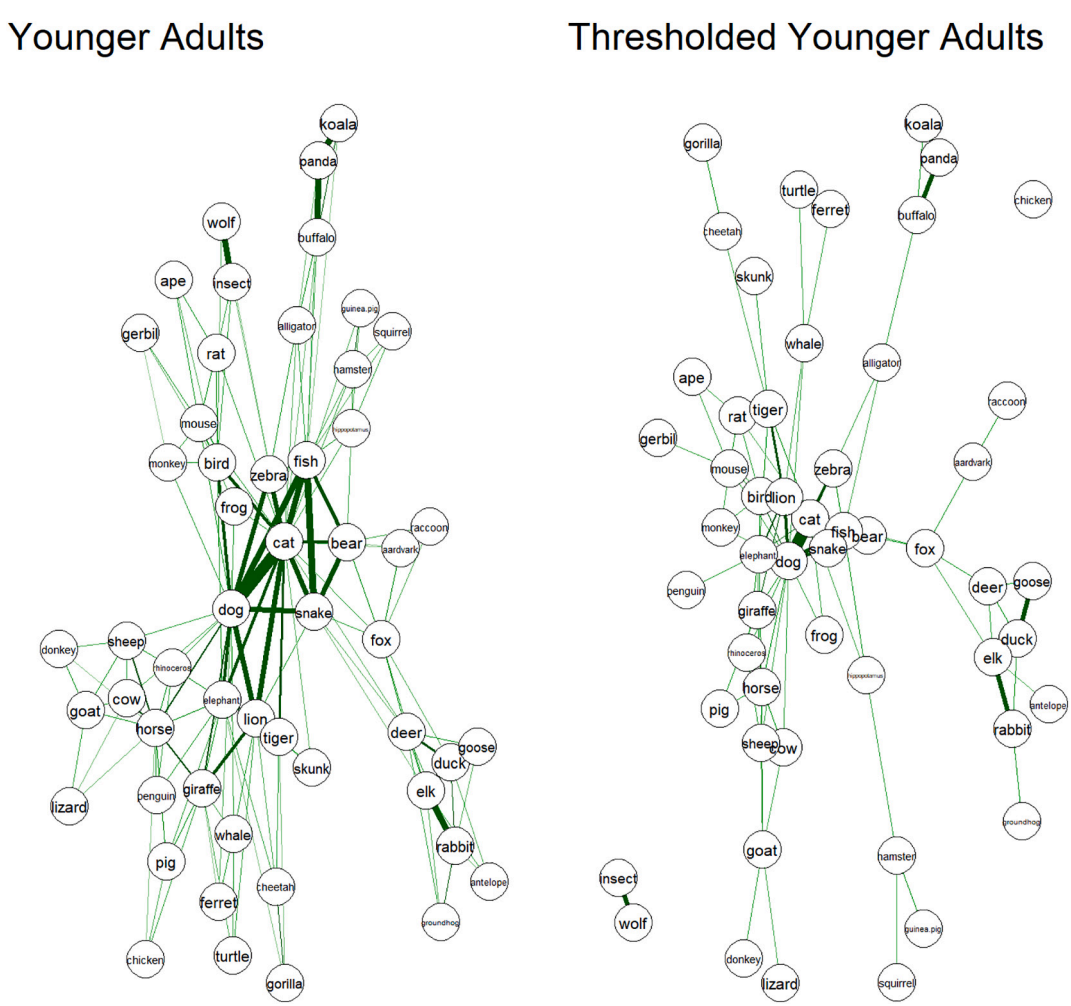

Fig. 3. A comparison between a fully connected semantic network of the younger adult group in Dataset 2 (left) and the same semantic network after increasing the intensity threshold to 50% (right). Edge thickness denotes connectivity weight strength between two nodes (words) in the semantic network (i.e., the thicker the edges, the stronger the connection).

younger adults in Dataset 3 showed a higher average shortest path length when compared with older adults, $t(1998) = -3.90$, $p < 0.001$.

6.5. Modularity

In both Datasets 1 and 2, younger adults had lower modularity values compared to older adults, $t(1998) = 22.42$, $p < 0.001$; $t(1998) = 5.59$, $p < 0.001$, respectively. Dataset 3 showed that younger adults had higher modularity values compared to older adults, $t(1998) = 1.01$, $p < 0.001$.

Overall, the results from the three datasets indicated that the semantic network structures of younger and older adults were significantly different. Datasets 1 and 2 consistently showed that the networks of younger adults exhibited higher levels of efficiency as measured by shorter path lengths and greater interconnectedness as measured by higher clustering coefficient, compared to older adults (Dubossarsky et al., 2017; Latora & Marchiori, 2001). Alternatively, the semantic networks of older adults exhibited increased community structure, or higher modularity values. Dataset 3 results were somewhat unexpected such that younger adults showed longer average shortest path lengths, increased modularity, and there were no significant group differences in clustering coefficient. This unexpected finding from Dataset 3 remains somewhat surprising given that Datasets 2 and 3 were collected from the same overall community using the same laboratory setting and procedures. These results are discussed further in the Discussion section below.

6.6. Older adults' semantic networks break apart faster and are less flexible than younger adults

For each dataset, we conducted a clique percolation analysis on the weighted semantic networks of the two age groups to examine the flexibility of the semantic networks. Fig. 3 shows a comparison between a fully connected younger adult semantic network and the younger adult semantic network after thresholding to 50% (Dataset 2).

To assess age group differences, we examined the area under the curve and the percolation integral for the younger and older adults' semantic networks. To test for statistical significance, we ran 500 realizations of the percolation test. We conducted independent-samples *t*-test analyses on the distribution of percolation integrals between the semantic networks of the younger and older adult groups (Fig. 4).

Dataset 1: Our analysis revealed that the average percolation integral of the younger adult group ($M = 28.88$, SD = 0.98) was larger than that of the older adult group ($M = 28.29$, SD = 1.06), $t(998) = 9.07$, $p < 0.001$. The effect size for this analysis (d = 0.62) was found to exceed Cohen and Murphy's (1984) convention for a medium effect (d = 0.50).

Dataset 2: Our analysis revealed that the average percolation integral of the younger adult group ($M = 35.1$, SD = 1.02) was larger than that of the older adult group ($M = 33.95$, SD = 1.06), $t(998) = 18.70$, $p < 0.001$). The effect size for this analysis (d = 1.19) was found to exceed Cohen and Murphy's (1984) convention for a large effect (d = 0.80).

Dataset 3: Our analysis revealed that the average percolation integral of the younger adult group ($M = 43.61$, SD = 1.06) was larger than that of the older adult group ($M = 41.82$, SD = 1.13), $t(998) = 27.5$, $p < 0.001$. The effect size for this analysis (d = 1.58) was found to exceed Cohen and Murphy's (1984) convention for a large effect (d = 0.80).

These results provide consistent evidence that the semantic networks of older adults broke apart faster than the networks of younger adults, indicating less flexibility within the semantic networks of older adults. Notably, the percolation results replicated across all three datasets, despite the variability in network properties found in Dataset 3.

7. Discussion

In this study, we apply computational network science and percolation analyses to quantitatively examine the effects of semantic network structure on healthy aging, and specifically the connection between flexibility and the aging mental lexicon. We assessed the semantic networks of younger and older adults via network science methods and percolation analyses (Kenett et al., 2018; Siew et al., 2019). As hypothesized, we observed that younger adults had more interconnected and efficiently-organized semantic networks than older adults, as assessed by clustering coefficient, average shortest path length, and modularity in two of the three datasets analyzed. Furthermore, the percolation analysis provided a measurement of flexibility of the semantic networks. As predicted, the semantic networks of the younger adults were more flexible and resilient to the percolation process compared to the older adults' semantic networks—a finding that replicated across all three datasets. Taken together, our results provide insight into the structure of semantic networks in healthy aging, with implications for understanding the development of flexible thinking across the lifespan.

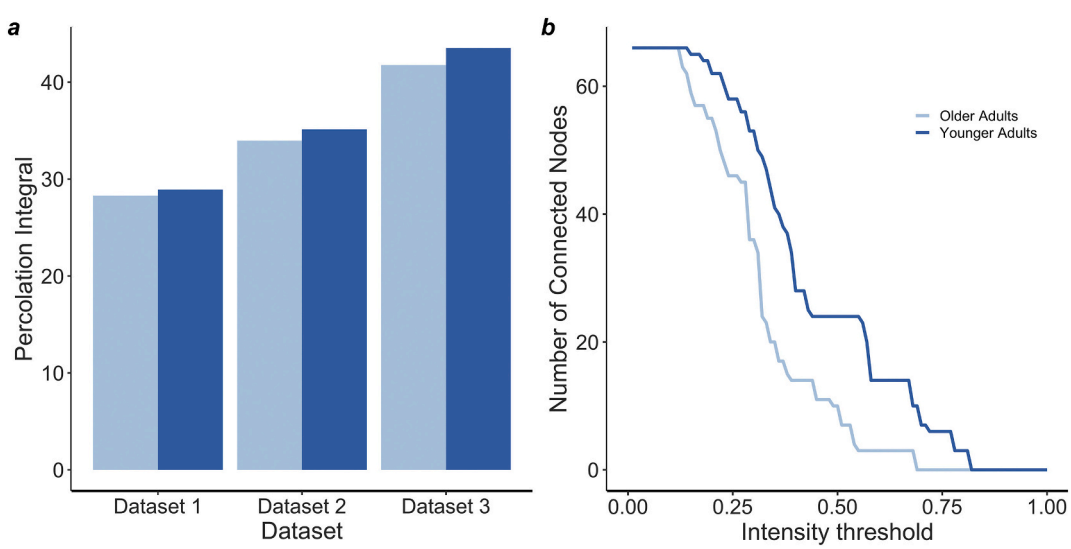

Fig. 4. a: Comparison of the percolation integrals between younger and older adults across the three datasets. The number of nodes in each dataset differs – Dataset 1 has 45 nodes, Dataset 2 has 53 nodes, and Dataset 3 has 66 nodes. b: An example of the number of connected nodes in the network at increasing intensity thresholds (I) for younger and older adults.

7.1. Older adults have more segregated and less efficient semantic networks than younger adults

Overall, the semantic network structures of younger adults were significantly more efficient, i.e., less segregated and more flexible than older adults. In our modeling of semantic networks, we assessed the organization of animal words in the mental lexicon of younger and older adults using verbal fluency data. We used a bootstrapping technique to estimate partial networks using half of the nodes for the older and younger adult networks. Datasets 1 and 2 results showed that younger adults had higher levels of network efficiency (lower average shortest path lengths), less segregation of sub-communities (lower modularity values), and greater connectivity (higher clustering coefficients) than older adults. These network property results generally reflect higher efficiency in network structure. Research in creativity has shown that a more efficient and flexible semantic memory structure is associated with higher levels of creativity (Kenett & Faust, 2019; Latora & Marchiori, 2001). While Dataset 3 was not consistent with the other two datasets, the verbal fluency responses of each dataset were fairly consistent, the age ranges were similar, and the community sample was from the same location as Dataset 2. Critically, despite this disparate observation in the network measures from one sample, the percolation analysis yielded consistent results across all three samples, indicating that age-related differences in network flexibility can be reliably uncovered, despite some variation in overall network structure.

The age-related differences for clustering coefficient, average shortest path length, and modularity reflect variance in network efficiency and interconnectedness (He et al., 2020; Latora & Marchiori, 2001). In sparsely connected networks (i.e., older adults), the shortest path between two nodes requires more steps than in a well-connected network, making the network less efficient (Latora & Marchiori, 2001). Modularity assesses the network's interconnectedness through sub-communities. These communities consist of densely connected clusters which share overlapping connections within the module (Fortunato, 2010). While segregation among communities can create smaller networks, higher levels of segregation (as was seen in the semantic networks of older adults) may make integrating information more difficult, which can be especially problematic in the case of semantic associations where words can share multiple, overlapping characteristics, leading to increased competition among similar concepts. In addition, clustering coefficient measures the extent to which nodes of a network cluster together and how they are organized in a network (Siew et al., 2019), and lower clustering coefficient in semantic networks has been related to poorer performance on recall tasks (Nelson, Bennett, Gee, Schreiber, & McKinney, 1993). Prior studies have also found that older adults' semantic networks are characterized by higher average shortest path length and lower clustering coefficient (Dubossarsky et al., 2017; Wulff et al., 2018; Wulff, Hills, & Hertwig, 2013)—indicating a less efficient and more segregated network—consistent with our findings for Datasets 1 and 2.

7.2. Older adults' semantic networks break apart faster and are less flexible than younger adults

Our study quantitatively assessed the flexibility of semantic memory as it relates to aging. The percolation analysis provides a quantitative measure of the flexibility of a network, and it can be used to examine flexibility of thought as well as the cognitive declines associated with aging (Kenett et al., 2018). Our analyses consistently found that across the three datasets, the younger adult semantic network percolation integral was larger than the older adult percolation integral. That is, the structure of the older adult groups' semantic networks broke down faster as intensity thresholds increased, indicating a less flexible network structure compared to the younger adult group.

While the percolation approach to measuring flexibility in thought remains an influential tool to study the cognitive differences associated with aging, only a handful of studies have utilized this technique. For example, Borge-Holthoefer et al. (2011) applied percolation analysis to examine the effects of Alzheimer's disease on semantic processing. Focusing on semantic deficits caused by disrupted search processes, the researchers simulated the degradation process of healthy semantic priming and hyperprimed networks typically exhibited by Alzheimer's patients. The researchers compared their simulated networks to empirical evidence from Alzheimer's patients and found qualitative agreement, concluding that network modeling is an appropriate approach.

In addition, percolation analysis has been applied to quantitatively operationalize the notion of flexibility inherent in creativity theory. Kenett et al. (2018) applied percolation analysis to the semantic networks of low- and high-creative individuals, previously investigated by Kenett et al. (2014). This previous investigation revealed that the high-creative semantic network had higher clustering coefficient and lower average shortest path length and modularity, which the authors inferred as indicating a more flexible semantic network. The percolation analysis applied by Kenett et al. (2018) revealed that the semantic network of the high-creative group broke apart slower than that of the less-creative group, thus directly supporting the high-creative group having a more flexible semantic memory structure (Kenett et al., 2018). In line with these results, our study reveals that younger adults' networks break apart slower than older adults, thus the semantic network of younger adults is more flexible. Stella (2020) used a similar percolation method to quantify the flexibility of the mental lexicon to concept failures, aphasic degradation, and aging. This study highlighted that across the lifespan, the mental lexicon is fragile against multiplex (combined semantic and phonological) attacks.

Networks that break apart faster, or at lower thresholds, have weaker connectivity between words. This notion of weakening connection strength relates to the transmission-deficit hypothesis (Burke, MacKay, Worthley, & Wade, 1991). The transmission-deficit hypothesis suggests that as connections between nodes weaken with increasing age, activation between semantic and lexical representations is affected. Although this hypothesis focuses on weaker links in phonological representations as being the key mechanism in age-related language production impairments, it does acknowledge that all links weaken over time. While age-related differences in semantic processes are not commonly observed, several recent studies have observed age-related semantic deficits in tasks that tap into executive aspects of semantics, such as semantic control or semantic selection (Hoffman, 2018; Hoffman, Loginova, and Russell, 2018).

The controlled semantic cognition framework highlights the distinction between knowledge and selection processes (Hoffman, McClelland, & Lambon Ralph, 2018; Rogers et al., 2015). Robust organization of a semantic network can relate to both semantic knowledge (structure) and how one uses or traverses through that knowledge (process). In the current analyses, potential differences in process were controlled to some extent by using only nodes that were common across both younger and older participants. Since the same words were used to create the semantic networks in the percolation analysis, it is unlikely that the age difference that we observed reflects differences in knowledge. In fact, the WAIS vocabulary scores from our sample of older and younger adults in Datasets 2 and 3 did not show age-related differences in vocabulary knowledge. This suggests that the network differences that we found do not differ in the breadth of vocabulary, but point to age-related structural differences in the networks themselves. Moreover, our results indicate that there are age-related differences in how the communities of words in our semantic networks connect to each other.

While our analyses speak most directly to the structure of the network, our findings may also be related to search processes (i.e., how information traverses through the network). That is, our semantic network analyses were based on verbal fluency performance which requires each participant to utilize search processes within a specific category. It is possible that age-related differences in these search processes led to the differences we observed in the structure of semantic

memory (Jones, Hills, & Todd, 2015). Indeed, older adults have been found to switch between local and global contexts more often during a verbal fluency task and this age-related increase in switching was negatively correlated with performance on a digit span task, suggesting that these changes were due to working memory declines (Hills, Mata, Wilke, & Samanez-Larkin, 2013).

8. Limitations

Process and structure are both integral to semantic memory, yet it is possible to examine structure and process separately (Siew et al., 2019). Future investigations could examine the underlying search processes in semantic networks by measuring the order in which words are produced or the semantic distances between words (e.g., with a forward flow analysis, Gray et al., 2019). In addition to analysis techniques to assess search processing, future work should use tasks that rely less on controlled retrieval (i.e., verbal fluency), such as semantic judgement tasks.

Although our results consistently demonstrated age-related differences in the flexibility of younger and older adults semantic networks, there are a few limitations common to network science research (Wulff et al., 2019). We would have liked to make a direct comparison between individual differences and the percolation analysis results, however, one limitation of the clique percolation technique in this context is that it requires a group comparison, and therefore we were unable to examine individual differences. Future research should examine semantic network percolation analyses at the individual level to provide greater insight towards how semantic network flexibility relates to individual differences in aging. Additionally, future research should focus on connecting individual variation in other cognitive processes affected by aging, such as vocabulary knowledge, inhibitory control, executive functioning, and processing speed, to the flexibility measures that network science and percolation analyses provide.

Additionally, although our results suggest age-related differences in semantic networks, it's possible that these age group differences were driven by older adults' lower mental flexibility in general instead of a specific deficit in semantic flexibility. Indeed, the verbal fluency task, on which our analyses are based, is directly related to executive aspects of language such as semantic selection. To this end, a post-hoc analysis of executive control data from Datasets 2 and 3 revealed that older adults had longer response times on a Digit Symbol task and larger Stroop effect sizes compared to younger adults (see Appendix A). This suggests that our older adults had multiple cognitive differences. Although we control for this to some extent by examining only the words that both younger and older adults produced, age-related differences in executive function may have also contributed to the differences we observed here.

9. Conclusion

To summarize, the present study investigated the semantic network structure of older and younger adults. Using network science measures, we found differences in the semantic network structure: younger adults had higher levels of network efficiency, less segregation of subcommunities, and greater flexibility. Moreover, across the three datasets, the percolation analysis consistently found that older adults' semantic networks broke apart faster than younger adults'. Older adults' semantic networks were thus less flexible compared to younger adults', a finding with potential implications for age-related differences in language production. Specifically, this decreased efficiency and flexibility in semantic networks of older adults could be linked to behavioral performance in retrieval difficulty (Burke et al., 1991). Our findings provide quantitative evidence for diminished flexibility in older adults' semantic networks, despite the stability of other measures of semantic memory across the lifespan.

While our results most directly speak to semantic memory network structure, these findings very well may relate to the processes underlying semantic memory, as structural efficiency likely influences processing. To this point, the controlled semantic cognition model provides support for the idea that semantic cognition involves the interaction between several different aspects of semantics (Rogers et al., 2015), lending support to our idea that network structure constrains the search processes needed to effectively recall words for successful communication. While more research is needed to examine how structure and process interact, our results provide further insight to the aging mental lexicon. Our results demonstrate that although older adults demonstrate stability in the size and breadth of their lexicon, older adults have less flexible and less resilient semantic networks compared to younger individuals, which may play a role in age-related declines in flexible behaviors such as language production difficulties.

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Appendix A

Dataset 2	*YA Mean*	*OA Mean*	*t Stat*	*p Value*
Stroop Effect	−20.538	−81.504	4.129	<0.001
Digit Symbol	1268.823	1846.794	−8.183	<0.001
Dataset 3	***YA Mean***	***OA Mean***	***t Stat***	***p Value***
Stroop Effect	−31.505	−111.302	3.476	<0.001
Digit Symbol	1318.755	1971.391	−6.625	<0.001

We conducted post-hoc analyses on the executive control ability of younger and older adults for Datasets 2 and 3 – specifically, performance on the Digit Symbols and Stroop tasks. Independent-samples *t*-test analyses on the two datasets revealed that for both datasets, older adults had longer response times on the Digit symbol task and larger Stroop effects.

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