Remotely Close Associations: Openness to Experience and Semantic Memory Structure

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This is the peer reviewed version of the following article:

Christensen, A. P., Kenett, Y. N., Cotter, K. N., Beaty, R. E., & Silvia, P. J. (2018). Remotely Close Associations: Openness to Experience and Semantic Memory Structure. *European Journal of Personality, 32*(4), 480-492.

which has been published in final form at https://doi.org/10.1002/per.2157. This article may be used for non-commercial purposes in accordance with Wiley Terms and Conditions for Use of Self-Archived Versions.

Abstract:

Openness to experience—the enjoyment of novel experiences and ideas—has many connections to cognitive processes. People high in openness to experience, for example, tend to be more creative and have broader general knowledge than people low in openness to experience. In the current study, we use a network science approach to examine if the organization of semantic memory differs between high and low groups of openness to experience. A sample of 516 adults completed measures of openness to experience (from the NEO Five-Factor Inventory-3 and Big Five Aspect Scales) and a semantic verbal fluency task. Next, the sample was split into half to form high (n = 258) and low (n = 258) openness to experience groups. Semantic networks were then constructed on the basis of their verbal fluency responses. Our results revealed that the high openness to experience group's network was more interconnected, flexible, and had better local organization of associations than the low openness to experience group. We also found that the high openness to experience group generated more responses on average and provided more unique responses than the low openness to experience group. Taken together, our results indicate that openness to experience is related to semantic memory structure.

Keywords: openness to experience | semantic memory | network analysis | semantic networks

Article:

All R code, materials, and raw data files are openly available for reproduction and replication of analyses via the Open Science Framework: osf.io/craky/. The authors did not preregister the study.
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In the Big Five personality model, openness to experience is commonly found to be related to cognitive processes. In an examination of behavioural, affective, and cognitive processes related to Big Five personality traits, openness to experience was chiefly characterized by cognition (Zillig, Hemenover, & Dienstbier, 2002). Many studies link openness to experience to cognitive abilities such as intelligence, working memory, and creativity (DeYoung, Grazioplene, & Peterson, 2012; Kaufman et al., 2010; Kaufman et al., 2016). Few studies, however, have examined other cognitive factors, such as semantic memory—our knowledge about the word, such as word meanings, concepts, and categorizations of facts (McRae & Jones, 2013)—that might contribute to these relationships (Jauk, Benedek, & Neubauer, 2014; Kwantes, Derbentseva, Lam, Vartanian, & Marmurek, 2016; Prabhakaran, Green, & Gray, 2014).

Recent computational research suggests that the structure of semantic memory could be a cognitive factor that underlies more general cognitive differences associated with openness to experience. Highly creative people, for example, exhibit more flexible, interconnected relations between concepts than less creative people (Kenett et al., 2018; Kenett, Anaki, & Faust, 2014). Likewise, people higher in fluid intelligence show greater structure (i.e. more order) in their semantic memory (Kenett, Beaty, Silvia, Anaki, & Faust, 2016). Given the links between openness to experience, creativity, and intelligence, the structure of semantic memory might be related to openness to experience. The present study thus examined the structure of semantic memory between groups of high and low openness to experience using a computational network science approach.

Openness to Experience, Cognition, and Semantic Memory

Openness to experience has many links to basic cognition. Perhaps the most established one is creative thought (Oleynick et al., 2017), to the point that 'creativity' has been considered as an alternative label (Johnson, 1994). People high in openness to experience are described as *original*, *unconventional*, *imaginative*, *intellectual*, *curious*, and *creative* (Johnson, 1994; McCrae & Costa, 1997). Open people tend to seek out new experiences and to be more sensitive to novelty in experiences of interest and pleasure (Fayn, MacCann, Tiliopoulos, & Silvia, 2015; McCrae & Costa, 1997). Diverse experiences have been shown to enhance cognitive flexibility—the ability to break old cognitive patterns, overcome functional fixedness, and make novel associations between concepts (Guilford, 1967; Ritter et al., 2012)—which is a core component of creativity (Hennessey & Amabile, 2010). Indeed, openness to experience is the most consistent predictor of creative achievement in the arts and sciences (Feist, 1998; Kaufman et al., 2016).

In addition to creative output, open people's engagement in a variety of experiences leads to the acquisition of broad general knowledge. The breadth and depth of this knowledge is acquired by formal and informal education as well as life experiences (McGrew, 2009). People higher in openness to experience are consistently found to have higher crystallized intelligence—the accumulation of knowledge over time, including language, information, and concepts of a specific culture (Ackerman & Heggestad, 1997; DeYoung et al., 2012; McGrew, 2009). They are also more likely to spend their time doing activities that encourage the accumulation of information such as reading all genres of literature for pleasure (Finn, 1997; McManus & Furnham, 2006). In general, open people tend to be curious and have a motivation to learn, which makes them more likely to explore and invest in many knowledge domains (Kashdan, Rose, & Fincham, 2004; Silvia & Sanders, 2010; von Stumm, 2018). Thus, people high in openness to experience actively attain information that contributes to general knowledge and semantic knowledge, more specifically.

To date, a handful of studies have implied a link between openness to experience and semantic memory. In one study, people high in openness to experience came up with more semantically distant verbs—determined via latent semantic analysis (LSA; Landauer & Dumais, 1997)—when cued to generate a creative verb for a noun (Prabhakaran et al., 2014). Interestingly, intelligence, working memory, and facets related to the openness aspect of openness to experience—defined by perceptual and aesthetic engagement—were related to semantic distance, but facets related to the intellect aspect of openness to experience were not (DeYoung et al., 2012). In another study, Kwantes et al. (2016) applied LSA to assess the semantic content of people's responses to scenarios that were associated with different Big Five personality traits—for openness to experience, the scenario was, 'Where would you travel if you had an all-inclusive trip and why?' The authors found that people higher in openness to experience used more words in their response that were related to the descriptors of openness to experience (Kwantes et al., 2016). Finally, openness to experience is a consistent predictor of performance on semantic verbal fluency tasks—generating as many responses as possible for a single category—which taps the ability to recall semantic information stored in long-term memory (e.g. animals; Sutin et al., 2011). Given the aforementioned evidence, people high in openness to experience might differ from people low in openness to experience in how they recall and use semantic information. Thus, investigating the structure of their semantic memory via semantic networks may offer a way to investigate these differences.

Semantic Network Analysis and Measurement

Recent research has applied network science tools to investigate cognitive phenomena such as the structure of language and memory (Baronchelli, Ferrer-i-Cancho, Pastor-Satorras, Chater, & Christiansen, 2013; Borge-Holthoefer & Arenas, 2010; De Deyne, Kenett, Anaki, Faust, & Navarro, 2016; Karuza, Thompson-Schill, & Bassett, 2016). In semantic networks, nodes represent concepts or words in memory and edges signify the relations between them (e.g. semantic similarity). By structuring language and memory as a network, network science can directly and quantitatively examine classic cognitive theory and the operations of cognitive processes that take place in memory retrieval and associative thought (Anderson, 1983; Baronchelli et al., 2013; Collins & Loftus, 1975). Cognitive networks, for example, have identified mechanisms of language development (Hills, Maouene, Maouene, Sheya, & Smith, 2009; Steyvers & Tenenbaum, 2005), shown how specific network parameters influence memory retrieval (Vitevitch, Chan, & Goldstein, 2014; Vitevitch, Chan, & Roodenrys, 2012; Vitevitch, Goldstein, & Johnson, 2016), and provided new insight into the semantic structure of second languages in bilinguals (Borodkin, Kenett, Faust, & Mashal, 2016).

A popular way of constructing semantic memory networks is based on verbal fluency tasks (Goñi et al., 2011; Kenett et al., 2013). Verbal fluency tasks present the participant with a single category for which they generate as many category exemplars as they can (Borodkin et al., 2016; Kenett et al., 2013). In both methods, participants are given a limited amount of time to generate their associations (usually 60 seconds). For this study, we constructed our semantic networks using a verbal fluency task (i.e. the *animals* category). While different semantic categories have been used for this task, the animal category is the most widely used, as it has a universal taxonomy (i.e. the animal kingdom) and has shown only minor differences across different languages and cultures (Ardila, Ostrosky-Solís, & Bernal, 2006).

Semantic Network Terminology

Of the network models that have been developed in network science theory, the small world network model (Watts & Strogatz, 1998) has been one of the most widely used to examine complex systems. Small world networks are defined by two main characteristics: the network's clustering coefficient (CC) and its average shortest path length (ASPL). The CC of a node refers to the extent that two neighbours of a node will themselves be neighbours (i.e. a neighbour is a node *i* that is connected through an edge to node *j*). In this way, the average clustering of the nodes in the network (referred to hereafter as CC) indicates how semantic information is organized at a local level (e.g. marine animals). A network with a higher CC suggests that exemplars that are near-neighbours to each other (e.g. fish–dolphin–whale–shark) tend to co-occur. For example, Borodkin et al. (2016) have shown how the CC of the second language in bilinguals is higher, attributed to less organized semantic networks compared with the organization of the semantic network of their first language.

The ASPL refers to the average shortest number of steps (i.e. edges) needed to traverse between any pair of nodes. In semantic networks, short path lengths indicate increased interconnectivity and smaller distances between concepts, which may relate to a greater ability to switch from one sub-category to another, with fewer mediating associations (e.g. cat–fish–dolphin compared with cat–dog–fish–whale–dolphin). According to the Adaptive Control of Thought (ACT) model, lower ASPL might affect *spreading activation*—the activation of associations between concepts—and facilitate the search and retrieval of associations in memory (Anderson, 1983; Collins & Loftus, 1975). In this regard, Kenett, Levi, Anaki, and Faust (2017) have shown how shorter distances in a semantic network predict behavioural performance in a relatedness judgement task. Furthermore, higher creative ability has been related to lower ASPL (Benedek et al., 2017; Kenett et al., 2014). These studies have argued that the lower ASPL in the semantic network of high creative individuals may have contributed to their ability to generate more unique responses to target words than the less creative group (Kenett et al., 2014).

The final network measure, commonly used to quantify semantic networks, is modularity. Modularity identifies how a network breaks apart (or partitions) into smaller sub-networks or *communities* (Fortunato, 2010; Newman, 2006). The modularity statistic (Q) 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, a network with a large Q would have more neatly compartmentalized (or more rigidly defined) communities in the network compared with a network with a small Q. In a semantic network, these communities might represent sub-categories of a larger category. The animal category, for example, might have sub-categories of pets, reptiles, insects, and marine animals (Goñi et al., 2011). Recent studies have highlighted the significance of modularity in cognitive networks in typical and clinical populations (Kenett, Gold, & Faust, 2016; Siew, 2013). For example, the semantic network of individuals with high functioning autism (Asperger's syndrome) exhibits a higher modularity value than matched controls, which is attributed to their rigidity in processing creative language (Kenett, Gold, et al., 2016).

The Present Study

Given the evidence presented previously, it seems that openness to experience might be related to semantic memory, which may facilitate the relationship between the trait and cognitive abilities. Our study is the first network analysis on the relation of openness to experience and semantic memory structure. We assessed openness to experience using two different inventories, the NEO Five-Factor Inventory-3 (NEO-FFI-3; McCrae & Costa, 2007) and Big Five Aspect Scales (BFAS; DeYoung, Quilty, & Peterson, 2007), to capture a broad, comprehensive measurement of the trait. We then divided the sample in half to form groups of high and low openness to experience. Previous studies, using a similar semantic network approach, have found that highly creative people tend to have semantic network structures that are more interconnected (low ASPL) and flexible (low Q; Benedek et al., 2017; Kenett et al., 2014; Kenett, Beaty, et al., 2016) than less creative people. Because of openness to experience's relationship with creativity, we predicted that the high openness to experience group's semantic network would exhibit similar network properties, namely, a lower ASPL and Q. Finally, because more efficient search and retrieval processes are supported by the structure of a small world network (i.e. a large CC and a small ASPL; Marupaka & Minai, 2011), we anticipated that the CC would be higher for the high openness to experience group than the low openness to experience.

Methods

Participants

There were 516 participants in the current study who were included across three samples. The first sample was collected during the Fall 2015 semester through the University of North Carolina at Greensboro's (UNCG) psychology research pool as part of a broader research project. The total sample included 311 participants and was based on a power analysis on a desired sample size of 300, given that project's primary aims. A total of 56 participants were excluded because of missing verbal fluency data, 41 because of inattentive responding, and 8 because of being non-native English speakers. The remaining sample consisted of 206 participants (54.9% Caucasian, 36.8% African American) who were primarily young adults (M = 19.16, SD = 3.33, 78.6% female, 15% male) enrolled in psychology courses. Participants were compensated with research credits for their participation in the study.

The second sample was collected during the Fall 2016 semester and the Spring 2017 semester at UNCG. Sample size was predetermined for the first author's thesis, which required at least 200 people. Data collection ended after the Spring 2017 semester concluded. A total of 262 participants were recruited using the university's psychology research pool, of which 60 participants were excluded because of missing fluency data, 21 because of inattentive responding, and 8 because of being non-native English speakers. The remaining sample consisted of 173 participants (53.2% Caucasian, 45.1% African American) who were primarily young adults (M = 18.61, SD = 1.10, 78.6% female, 20.2% male) and were enrolled in psychology courses. Participants were compensated with research credits for their participation in the study.

The third sample (*N* = 168) was obtained from a functional magnetic resonance imaging (fMRI) study (Beaty et al., 2018). Sample size was predetermined on the basis of a grant proposal, with recruitment ending after 2 years upon project start (Summer 2015–Summer 2017). Participants were recruited from UNCG and its surrounding community using fliers around campus and local ads describing an fMRI study on creativity. This study had several common exclusion and inclusion criteria for neuroimaging research: participants must be right handed, have no past psychiatric disorder, and cannot currently be taking any medication. Participants were excluded if any of these restrictions were met or if they were unable to complete the neuroimaging procedures (e.g. unremovable piercings and claustrophobia). Five participants were excluded because of inattentive responding, 8 because of missing data, and 18 because of being non-native English speakers. The final sample consisted of 137 participants (71.5% Caucasian, 27% African American) who were primarily young adults (*M* = 22.73, *SD* = 6.42, 73% female). This sample specifically oversampled art, music, and science majors to increase the sample's population of creative domains. Participants were compensated with $100 for completion of the study.

Materials

Openness to experience

NEO personality inventory. For one sample, NEO Personality Inventory-3 (NEO-PI-3) was completed, and for the other samples, the NEO-FFI-3 was competed. The NEO-PI-3 is a 240-item Big Five personality inventory that has been widely used around the world (McCrae, Costa, & Martin, 2005). The NEO-FFI-3 is a shortened version of the NEO-PI-3 and has good internal reliability (self-report $\alpha = 0.78$, informant $\alpha = 0.78$) when compared with the NEO-PI-3 (McCrae & Costa, 2007). The NEO-PI-3 has six items per facet—*ideas*, *values*, *fantasy*, *actions*, *feelings*, and *aesthetics*—for a total of 48 items, and the NEO-FFI-3 has total of 12 items, with one to three items per facet. Participants responded using a 5-point Likert scale ranging from 1 (*Strongly Disagree*) to 5 (*Strongly Agree*). Since all the questions used in the NEO-FFI-3 are used in the NEO-PI-3, only the 12 items that are included in both were used in the openness to experience score. The reliability for the NEO-FFI-3 measured in the sample was good ($\alpha = 0.75$).

Big Five Aspect Scales. Participants also completed the BFAS (DeYoung et al., 2007) openness to experience inventory, which splits personality traits into two aspects: openness (i.e. experiencing), reflecting perceptual and aesthetic engagement (10 items), and intellect, reflecting engagement in intellectual interests (10 items). Participants responded using a 5-point Likert scale ranging from 1 (*Strongly Disagree*) to 5 (*Strongly Agree*). The reliability values for openness and intellect in this sample were acceptable ($\alpha = 0.70$ and $\alpha = 0.78$, respectively). For all inventories, items that were in administered in a reverse response format (e.g. 'I do not like poetry') were coded to correspond to values higher in the trait.

Group construction. Because openness to experience is highly related to cognitive abilities and many items in the NEO-FFI-3 and BFAS inventories inquire about intellectual engagement (Christensen, Cotter, & Silvia, 2018), we followed Mõttus's (2016) suggestion to remove the items that had obvious overlap with the confounding factor of cognitive abilities and our outcome measure of semantic memory. We removed 11 items from the BFAS (including all 10 of the intellect items) and 4 items from the NEO-FFI-3 (including all three of the ideas items) on the basis of the network analysis of four different openness to experience inventories of Christensen, Cotter, et al. (2018). This left us with 17 items in total.

To create groups, we computed three mean facet scores on the basis of the 10 network-identified facets of Christensen, Cotter, et al. (2018). These facets were aesthetic appreciation (six items), fantasy (six items), and openness to emotions (five items). One item pertaining to the non-traditionalism facet was placed into the fantasy facet on the basis of the high correlation ($r = 0.54$) between the two facets (Christensen, Cotter, et al., 2018). The mean scores of these facets were used as indicators in a one-factor confirmatory factor analysis model, computed in Mplus (Muthén & Muthén, 2012), which resulted in a just-identified model. Then, the sample was sorted on the basis of the latent variable score of openness to experience and split into equal halves: 258 low and 258 high. The current study treats openness to experience as groups rather than as a continuous variable because methods for representing semantic networks at the individual level are currently not well developed (Benedek et al., 2017; Zemla & Austerweil, 2018; Zemla, Kenett, Jun, & Austerweil, 2016).

Verbal fluency

Participants completed the *animal* category verbal fluency task. According to standard procedure (Ardila et al., 2006), participants had 60 seconds to 'write down as many different ANIMALS as you can'. For each participant, repetitions, variation on roots, and non-category members were converged (e.g. *cats* to *cat*) or excluded, using the *SemNetToolbox*[1] package in R (R Core Team, 2018), from the final analysis. Responses for each participant were then binarized using 1 for a response that was generated and 0 for a response that was not generated.

Inattentive responding. Inattentive responding was captured with two checks in the NEO inventory (NEO-FFI-3 or NEO-PI-3; participants were instructed to select '*Strongly Disagree*' and '*Strongly Agree*') and the inconsistency subscale (six item pairs) of the Attentive Responding Scale (Maniaci & Rogge, 2014; McKibben & Silvia, 2016, 2017). Participants were excluded if they scored 2 on the NEO inventory check or above 6 on the Attentive Responding Scale.

Procedure

A

cross all samples, participants completed all tasks and scales on computers using MediaLab. Participants provided informed consent to participate in the study and received research credit or were paid for their participation. All studies were approved by the university's Institutional Review Board.

Sample 1

[1] The most up-to-date version of the *SemNetToolbox* package can be retrieved from https://github.com/AlexChristensen/SemNetToolbox

This sample completed the openness to experience measures and verbal fluency task as a subset in a broader study, which investigated humour, intelligence, and personality (Christensen, Silvia, Nusbaum, & Beaty, 2018). First, the BFAS was completed (about 8 minutes), followed by the verbal fluency task, and then the NEO-FFI-3 was administered last (about 6 minutes).

Sample 2

The verbal fluency task was completed after participants provided demographic information. The BFAS was conducted next (about 8 minutes), and finally, the NEO-FFI-3 was administered (about 6 minutes).

Sample 3

The personality and fluency data were collected during the behavioural lab portion of an fMRI study. The BFAS inventory was collected first (about 8 minutes), followed by the NEO-PI-3 (about 20 minutes), and finally, the verbal fluency task was administered.

Statistical analyses

Behavioural analyses

Total number of responses. Pearson's correlation was used to examine the relation between the total number of responses given by each participant and the latent variable of openness to experience. For the groups, a *t*-test was used to determine whether one group produced more responses, on average, than the other. A greater number of total responses might suggest a greater depth of knowledge for the animal category.

Unique number of responses. To examine whether there was difference in the number of unique responses generated (i.e. responses generated by only one group), McNemar's chi-squared test was used (Agresti, 2003). The unique responses for the overall sample were used as the total number of unique responses. Responses reported by a group were given a 1, and responses not reported by a group were given a 0. A greater number of unique responses might suggest a greater breadth of knowledge for the animal category.

Network analysis

Semantic network construction. The semantic fluency data of the two openness to experience groups were analysed using a semantic network approach developed to analyse semantic fluency data (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*).

The networks were constructed in the following way. First, the cleaned responses were separated into their respective group of openness to experience. Then, as in previous studies, all unique animal responses were matched between the groups, and only responses generated by two or more participants in both groups were included (Kenett et al., 2013; Kenett, Beaty, et al., 2016). This criterion allows a direct comparison between the networks because they are constructed of the same nodes, thus controlling for confounding factors (e.g. differences in nodes or edges; Christensen, Kenett, Aste, Silvia, & Kwapil, 2018; van Wijk, Stam, & Daffertshofer, 2010). These data matrices were structured so that each row contained all responses generated by one participant and each column was a category exemplar (i.e. an animal).

Next, we calculated the word association matrix from the data matrices using the cosine similarity. The cosine similarity is commonly used in LSA (Landauer & Dumais, 1997) and is related to Pearson's correlation, which can be considered as the cosine between two normalized vectors. Below, we present the formula used to compute the cosine similarity:

$$\cos = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}, \quad (1)$$

where A_i represents the column vector of response *a* and B_i represents the column vector of response *b*. 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. Therefore, associations are all positively valued, 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 response of *dog*, for example, occurred the most in the sample, so any response that is infrequent and does not co-occur frequently is likely to have a negative association (e.g. dog–Siberian Husky, $r = -0.141$, $p = 0.001$; even though *Siberian Husky* is a breed of a *dog*).

The word similarity matrix is examined as an $n \times n$ adjacency matrix of a weighted, undirected network, where each word represents a node (n_i) in the network and the edges between two nodes represent the similarity between them. Most of the edges will have small values or weak associations, which represent noise in the network. To minimize the noise and possible spurious associations, we applied the triangulated maximally filtered graph (TMFG; Christensen, Kenett, et al., 2018; Massara, Di Matteo, & Aste, 2016). The TMFG constructs a sub-network, capturing the most relevant information (i.e. removal of spurious connections and retaining high correlations) within the original network (Kenett, Kenett, Ben-Jacob, & Faust, 2011). 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, et al., 2018; van Wijk et al., 2010). 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.

To examine the structure of the networks, the edges are binarized so that all edges are converted to a uniform weight (i.e. 1). Although the networks could be analysed using weighted edges (weights equivalent to the correlation strength), this potentially adds noise to the interpretation of the structure of the network. Moreover, Abbott, Austerweil, and Griffiths (2015) show that weighted and unweighted semantic networks produce similar results. Thus, the networks are analysed as unweighted (all weights are treated as equal) and undirected (bidirectional relations between nodes) networks.

Network analysis. All network measures—CC, ASPL, and Q—were calculated with the *NetworkToolbox* package. To statistically examine the validity of our findings, we applied two complementary approaches. The first approach, simulation of random networks for each openness to experience group, statistically tested whether the network parameters did not result from a null hypothesis of a random network. To this end, we generated a large sample of Erdös–Rényi random networks with a fixed edge probability (Erdös & Rényi, 1960). Because all networks had the same number of nodes and edges, we simulated a distribution of random networks and compared the empirical network measures of both groups to this random distribution. For each simulated random network, we computed its CC, ASPL, and Q. This procedure was simulated with 1000 realizations and resulted in a random reference distribution for each measure. The empirical network measures were then compared with their reference distribution to evaluate its statistical significance. This was achieved via a one-sample *Z*-test for each network parameter.

Second, we used a bootstrapping approach (Efron, 1979) to simulate and compare partial semantic networks for both groups. On the basis of previous studies (Borodkin et al., 2016; Kenett, Beaty, et al., 2016), the bootstrapping procedure involved random selection of half of the nodes of the semantic network. Partial semantic networks were constructed for each group separately for these random nodes. This method is known as without replacement bootstrapping (Bertail, 1997; Politis & Romano, 1994; Shao, 2003). Therefore, any differences between the two networks should be due to differences in the groups rather than differences in nodes or edges. This approach makes it possible to generate many simulated partial semantic networks, allowing for statistical examination of the difference between any two networks. To better examine the reliability of this approach, following the procedure of Epskamp, Borsboom, and Fried (2018), we also generated graded partial semantic networks for both groups that involved 60%, 70%, 80%, and 90% of the nodes. For each partial network and for each group, the CC, ASPL, and Q measures were computed. This procedure was estimated with 1000 realizations for each of the graded partial bootstrapping analyses. This bootstrapped approach was computed, and its corresponding figures were generated using the *SemNetToolbox* package in R.

R code, data, and materials sharing. All R code, data, cleaning procedures, analytic methods, and study materials are available on the Open Science Framework for reproduction and replication purposes **osf.io/craky/**. We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study (Simmons, Nelson, & Simonsohn, 2011).

Results

Total and unique number of responses

Table 1 contains the descriptive statistics for age and number of verbal fluency responses for the full sample and the two openness to experience groups. In general, there was a significant correlation between the total number of responses and openness to experience

($r(514) = 0.17$, $p < 0.001$). With the total number of responses as the dependent variable, a t-test found that the high openness to experience group produced more responses on average ($M = 17.66$) than the low openness to experience group ($M = 16.57$), $t(514) = -3.53$, $p = 0.007$, $d = 0.24$.

Table 1. Descriptive statistics for age and total number of responses for the full sample and each openness to experience sample

Sample	**Age**		**Total number of responses**	
	***M* (*SD*)**	**Range**	***M* (*SD*)**	**Range**
Full ($N = 516$)	19.94 (4.33)	18–58	17.12 (4.61)	2–34
Low ($n = 258$)	19.74 (4.54)	18–58	16.41 (4.49)	4–34
High ($n = 258$)	20.14 (4.11)	18–58	17.83 (4.63)	2–27

Across the sample, there were 345 unique responses in total. Using McNemar's test, a test for differences in proportions of paired nominal dichotomous data, we evaluated the proportion of these responses given by each group to assess the number of unique responses. The high openness to experience group generated 299 of these responses (96 of which were not given by the other group), and the low openness to experience group generated 249 of these responses (46 of which were not given by the other group). The proportion of the number of unique responses in the high openness to experience group (0.867) was significantly larger than the proportion in the low openness to experience group (0.722), $\chi^2(1) = 16.91$, $p < 0.001$, $\varphi = 0.22$. Therefore, the high openness to experience group generated significantly more unique responses than the low openness to experience group.

Network analysis

Full networks

The semantic networks of both openness to experience groups were analysed, and the different network measures ASPL, CC, and Q were computed for each network (Table 2). To visualize the networks (Figure 1), we applied the force-directed layout of the cytoscape software (Shannon et al., 2003). In these 2D visualizations, nodes (i.e. animal exemplars) are represented as circles, and links between them are represented by lines. Since these networks are undirected and weighted, the links convey symmetrical (i.e. bidirectional) similarities between two nodes.

Table 2. Network measures for the two openness to experience groups

	Openness to experience group		
Network measure	**Low**	**High**	**Random**
ASPL	3.19	2.84	3.01 (0.017)
CC	1.03	1.05	0.038 (0.008)
Q	0.590	0.521	0.366 (0.018)

Note: The random networks display the mean and standard deviation (in parenthesis) of the simulated sampling distribution. ASPL, average shortest path length; CC, clustering coefficient; Q, modularity.

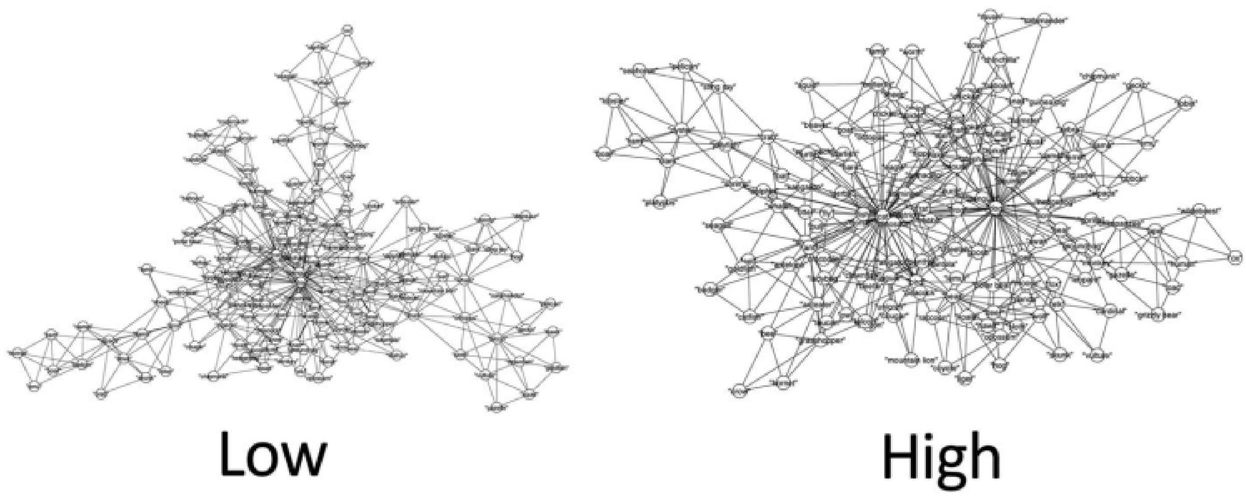

Figure 1. A 2D visualization of the semantic network of the openness to experience groups.

There were numerical (i.e. network measures) and qualitative (i.e. visualization) differences of each network structure between the groups (Table 2 and Figure 1, respectively). Large, individual figures of each group's network can be found in Figure S1 (low) and Figure S2 (high). The network of the low openness to experience group was visually more spread out and compartmentalized than the network of the high openness to experience group, which is apparent in the larger ASPL and modularity of the network, respectively. Conversely, the network of the high openness to experience was much more compact with decreased distance between associations, which is reflected in the lower ASPL, than the network of the low openness to experience group. To verify that the results of the full network analysis are not due to a null hypothesis, we conducted the simulated random networks analysis. This analysis revealed that all the empirical network measures for both openness to experience groups were significantly different from their simulated random measures (all p's < 0.001).

Table 3. Partial network bootstrapped approach results

	Network measures					
	ASPL		**CC**		**Q**	
Nodes remaining	***t***	***d***	***t***	***d***	***t***	***d***
90% (df = 1998)	−65.69	2.94	67.97	3.04	−65.26	2.92
80% (df = 1998)	−42.79	1.91	45.53	2.04	−41.33	1.85
70% (df = 1998)	−28.92	1.29	36.38	1.63	−30.86	1.38
60% (df = 1998)	−20.01	0.90	26.82	1.20	−25.98	1.16
50% (df = 1998)	−12.27	0.55	21.71	0.97	−19.16	0.86

Note: 1000 samples were generated for each percentage of nodes remaining. t-statistics and Cohen's d values are presented (Cohen, 1992). Negative t-statistics denote the high openness to experience group having *lower* values than the low openness to experience group. All p's < 0.001. Cohen's d effect sizes: 0.50, moderate; 0.80, large; 1.10, very large. ASPL, average shortest path length; CC, clustering coefficient; Q, modularity.

Partial boostrapped networks

Next, we applied bootstrap analyses to statistically examine the differences in network structure across the networks of the openness to experience groups (Table 3 and Figure 2). For each partial bootstrap analysis, *t*-tests were used to determine statistical differences in the bootstrapped partial networks.

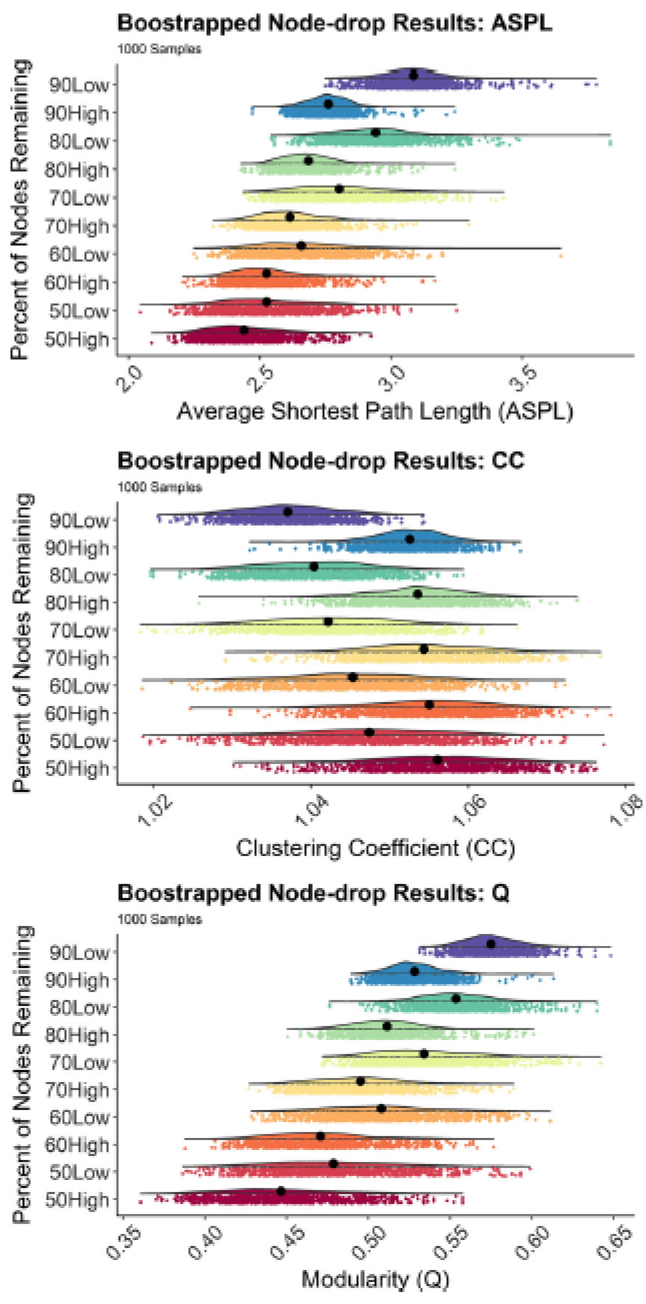

Figure 2. Plots of the bootstrapped partial network measures (1000 samples per nodes remaining percentage). Density plots are above the scatterplots (individual dots depict a single sample), with a black dot representing the mean. The *y*-axis denotes the openness to experience group (high and low) and the percentage of nodes remaining (e.g. 90Low = 90% nodes remaining bootstrapped sample for the low openness to experience group).

The partial networks of the high openness to experience group had a significantly smaller ASPL across the bootstrapped samples compared with the partial networks of the low openness to experience group. The effect size ranged from moderate (*d* = 0.55; when 50% of the nodes were dropped) to very large (*d* = 2.94; Table 3). The CC was significantly larger for the partial networks of the high openness to experience group, and the effect sizes across the bootstrapped samples were large to very large (*d* = 0.97 to 3.04), compared with the partial networks of the low openness to experience group. Similar to the ASPL, the partial networks of the high openness to experience group had a significantly smaller Q value than the partial networks of the low openness to experience group. Across the bootstrapped samples, the effect size for Q ranged from large to very large (*d* = 0.86 to 2.92). Overall, the effect sizes ranged from moderate to very large, demonstrating substantial differences in semantic network structure between the groups (Figure 2).

Discussion

The present study is the first to examine the relationship between semantic network structure and openness to experience. People higher in openness to experience came up with a greater total number of responses on average and produced more unique responses. The semantic network analyses revealed that the semantic network of the high openness to experience group exhibited better local organization of associations (higher CC) and was more interconnected (lower ASPL) and flexible (lower Q) compared with the semantic network of the low openness to experience group. Our bootstrapped partial network analyses corroborated these results, suggesting the relationship between openness to experience and the structure of semantic knowledge appears to be robust. The findings suggest that semantic knowledge is represented differently in highly open people, which may facilitate their ability to reach more remote associations and in turn be more creative.

Semantic networks and openness to experience

The network analysis of the full networks revealed that the network of the high openness to experience group had smaller ASPL and Q values and a larger CC value. These results are in line with our predictions. In general, these findings suggest that the high openness to experience group's semantic network had more efficient retrieval of associations, meaning their ability to generate responses via clustering (high CC) and switching (low ASPL) processes was superior to the low openness to experience group. Moreover, the high openness to experience group's network structure had a smaller Q, suggesting their associations were less rigid than the low openness to experience group. These findings are similar to semantic networks related to creative ability (Benedek et al., 2017; Kenett et al., 2014; Kenett, Beaty, et al., 2016). The full network results, however, are mostly qualitative because they cannot be statistically tested directly.

Our quantitative assessment involved a partial bootstrapped network approach (Kenett et al., 2014). The partial bootstrapped networks revealed results that were in line with the full networks and consistent across the bootstrapped realizations. The partial networks of the high openness to experience group exhibited significantly smaller ASPL and Q and a larger CC than the partial networks of the low openness to experience group, supporting the findings for the full networks. In addition, the effect sizes ranged from moderate to very large, suggesting these differences are substantial. Notably, the more nodes that were retained, the larger the effect sizes were. This seems to suggest that, at the full network level, the network structures are very different.

Overall, these findings suggest that the high openness to experience group had a more flexible semantic organization—that is, a less rigid network structure (smaller Q). A growing body of research is demonstrating Q's role in flexibility of thought, by constraining the spread of activation over semantic and phonological networks (Faust & Kenett, 2014; Kenett, Gold, et al., 2016; Siew, 2013). On the one hand, these studies implicate *higher* modularity in more structured networks, related to intelligence and language development (Borodkin et al., 2016; Kenett, Beaty, et al., 2016), until an extreme state of rigidity as seen in the semantic network of people with high functioning autism (Kenett, Gold, et al., 2016). On the other hand, other studies reveal that *lower* modularity is related to higher creative ability (Kenett et al., 2014). Thus, our results extend and further support the negative relation between modularity and flexibility in cognition.

The high openness to experience group also had greater interconnectivity (smaller ASPL) between nodes in the semantic network, suggesting they could more easily reach more remote associations. This result also suggests that people high in openness to experience might be less likely to perceive disparate concepts as unrelated (Rossman & Fink, 2010). This quality could facilitate an enhanced ability to combine remote associations, which is thought to be a fundamental cognitive component of creative thinking (Finke, Ward, & Smith, 1992). In addition, the high openness to experience group had a larger CC, which suggests greater local organization. These two characteristics—small ASPL and large CC—are related to the structure of a small world network, which might support a more efficient search through semantic space (Marupaka & Minai, 2011). Indeed, Anderson's (1983) ACT model suggests that this interconnected, flexible structure facilitates the search and retrieval of associations in memory.

Total and unique number of responses

Our behavioural findings support this notion: the high openness to experience group reported more response on average and more unique responses in general than the low openness to experience group. This was demonstrated by a small correlation between openness to experience and number of responses and corroborated by the *t*-test performed between the two groups. Moreover, this result is consistent with previous work that suggests that people higher in openness to experience have greater general knowledge than people with lower openness to experience (Ackerman & Heggestad, 1997). Similarly, the high openness to experience group generated more unique responses than the low openness to experience group, which is likely because they have a flexible, interconnected semantic network structure that may have allowed better access to less common responses (Kenett & Austerweil, 2016). This finding is consistent with previous research, which demonstrated that people higher in openness to experience tend to provide more remote semantic responses (Prabhakaran et al., 2014). Overall, these results complement the network structure of the high openness to experience group, which had shorter paths and increased flexibility of relations between concepts.

Limitations

A few limitations exist in our study. Most prominently, although we removed items from the NEO-FFI-3 and BFAS that were related to intelligence and cognitive outcomes, these variables are only self-report and do not directly assess explicit cognitive ability. Therefore, future research should parse out the extent to which the relationship of openness to experience and semantic memory structure exists beyond cognitive abilities. A second limitation was that we examined how openness to experience is related to semantic memory structure at the aggregated, group level. Openness to experience varies across people (Oleynick et al., 2017); thus, our aggregated group-based semantic networks might minimize such important relations between openness to experience and semantic memory structure at the individual level. Approaches to represent individual semantic networks are currently being developed (Benedek et al., 2017; Zemla et al., 2016; Zemla & Austerweil, 2018). Thus, future work should use more sophisticated designs that are needed to examine the relation between openness to experience and semantic memory structure at the individual level. Finally, we applied bootstrapping methods as a way to statistically examine our network results, which is a common approach in cognitive and psychometric network analysis (Epskamp et al., 2018; Kenett, Gold, et al., 2016). In our approach, we removed a percentage of nodes from the full networks and compute partial networks. In psychometric networks, however, it is more common to remove participants (Epskamp et al., 2018). Removal of participants in semantic networks poses considerable difficulties, potentially leading to biasing the network measures and an over-representation of infrequent responses in the group's semantic network, which would also lead to biased results. Further statistical methodological development is needed to develop statistical tools that are better able to statistically examine the validity of the results of such empirical networks.

Conclusion

The present study applied network science methodology to examine the relation between the structure of semantic concepts and high and low openness to experience groups. We found that the high group of openness to experience was related to a semantic network structure that was more interconnected, flexible, and had better local organization of associations. Behavioural analyses complemented these network findings by revealing that the high openness to experience group generated a greater number of unique responses and more responses on average in a semantic verbal fluency task. These findings provide support for the relationship between the structure of semantic memory and openness to experience. This study also provides evidence that differences in personality may be directly related to the structure, recall, and application of semantic information (Kwantes et al., 2016).

Acknowledgement

R. E. B. and P. J. S. were supported by grant RFP-15-12 from the Imagination Institute (**www.imagination-institute.org**), funded by the John Templeton Foundation. The opinions expressed in this publication are those of the authors and do not necessarily reflect the view of the Imagination Institute or the John Templeton Foundation.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Data S1. SI 1. Semantic network structure of the low Openness to Experience group SI 2. Semantic network structure of the high Openness to Experience group

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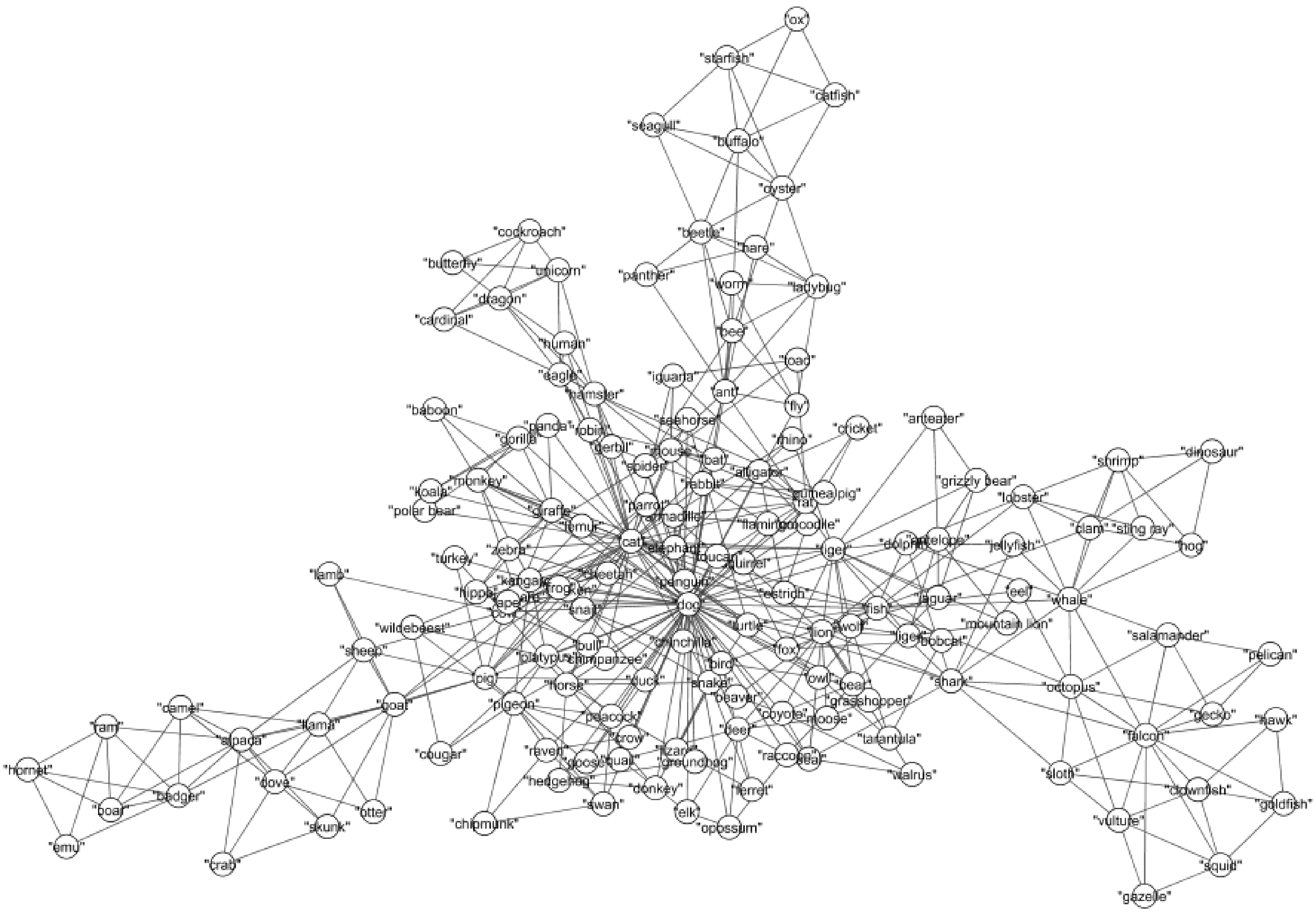
Remotely Close Associations: Openness to Experience and Semantic Memory Structure

Supplementary Information

SI 1. Semantic network structure of the low Openness to Experience group



SI 2. Semantic network structure of the high Openness to Experience group