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Structure and Flexibility: Investigating the Relation Between the Structure of the Mental Lexicon, Fluid Intelligence, and Creative Achievement

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Creativity is mainly viewed by current theories as either a bottom-up or top-down cognitive process. However, a growing body of research indicates that both processes contribute to creative ability. Furthermore, in both accounts the structure of the mental lexicon plays a key component, either as directly related to creative ability (bottom-up) or as the basis upon which top-down processes operate (top-down). Thus, the examination of the mental lexicon structure as related to both types of processes can shed further light on the nature of creative ability. In this study, we use network science methodology to examine how fluid intelligence and creative achievement are related to the structure of the mental lexicon. A large sample of participants completed a semantic verbal fluency task and was divided into 4 groups, based on their performance on intelligence and creative achievement measures. A network science methodology was then used to extract and compare the lexical network structure of the semantic category between the 4 groups. The results of this analysis revealed that while fluid intelligence was more related to structural properties of the lexical network, creative achievement was more related to flexible properties of the lexical network. Furthermore, we found that the lexical network of the high-fluid-intelligence and high-creative-achievement group exhibited a combination of both effects. These findings provide insight into structural and functional properties of semantic networks, and they demonstrate the utility of network science in examining high-level cognitive phenomena, such as creativity and intelligence.

Keywords: creativity, network science, mental lexicon, executive functions

Recent theories of creativity propose two seemingly competing accounts. One account is the bottom-up, associative theory of creativity (Mednick, 1962). This account argues for differences in the structure of the mental lexicon, which influences creative thought (Gruszka & Necka, 2002; Kenett, Anaki, & Faust, 2014; Mednick, 1962; Rossmann & Fink, 2010; Schilling, 2005; Zhong, Dijksterhuis, & Galinsky, 2008). The second account is the top-down executive functions theory of creativity (Beaty, Benedek, Silvia, & Schacter, 2016; Benedek, Jauk, Sommer, Arendasy, & Neubauer, 2014; Beaty & Silvia, 2012). This account argues for the importance of executive functions in the creative process, such as fluid intelligence, retrieval abilities, and cognitive control (Beaty & Silvia, 2012; Benedek et al., 2014; Benedek & Neubauer, 2013; Jauk, Benedek, & Neubauer, 2014; Lee & Therriault, 2013; Nusbaum & Silvia, 2011; Silvia, Beaty, & Nusbaum, 2013). Recently, Beaty, Silvia, Nusbaum, Jauk, and Benedek (2014) examined the claims of these accounts regarding creative ability. This examination revealed the contribution of both associative structure and executive functions to the creative process. However, the specific role of both bottom-up and top-down processes remain an open question.

In the present study we attempt to address this issue from a different perspective, namely, by examining the structure of the mental lexicon, known also as semantic memory. Semantic memory refers to the storage of word meanings, natural and artificial concepts, and general world knowledge (Jones, Willits, & Dennis, 2015; McRae & Jones, 2013). In both accounts of creativity, semantic memory is a key component. Yet, according to the

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bottom-up account semantic memory is directly related to creative ability (Mednick, 1962), while according to the top-down account semantic memory is the basis upon which top-down processes operate (Benedek & Neubauer, 2013). Thus, examining the structure of the mental lexicon in relation to measures of executive functions and creative ability may shed further light on the roles of bottom-up and top-down processes in creativity.

The bottom-up account of creativity proposes that creativity results from individual differences in the structure of their semantic memory. Thus, creative individuals have a richer and more flexible associative network than less creative individuals (Mednick, 1962). According to this theory, creative individuals are characterized by "flat" (more and broader associations to a given stimulus) instead of "steep" (few and common associations to a given stimulus) associational hierarchies (but see Benedek & Neubauer, 2013). Thus, creative individuals may have more associative links in their network and can connect associative relations faster than less creative individuals (Rossmann & Fink, 2010). Gruszka and Necka (2002) examined the priming of close and remote associations by low- and high-creative individuals. They showed that high-creative individuals have a more complex lexicon network structure and activate a wider range of associations across their lexicon network (Gruszka & Necka, 2002). Recently, Kenett et al. (2014) conducted an empirical network study that directly investigated Mednick's notion of the difference between low- and high-creative individuals. This study revealed how the semantic network of high-creative individuals is less rigid than that of low-creative individuals. Therefore, these findings provide empirical network evidence for Mednick's theory (Mednick, 1962). High-creative individuals seem to have a more flexible semantic memory network structure, which may allow for more efficient retrieval strategies when generating weaker associations.

The top-down account of creativity proposes that creative thought is a top-down process that taps individual differences in the ability to control attention and cognition (Beaty et al., 2016, 2014). Several recent studies have examined a range of controlled processes in creativity and specifically fluid intelligence (Beaty & Silvia, 2012; Benedek, Franz, Heene, & Neubauer, 2012; Jauk et al., 2014; Silvia & Beaty, 2012). Fluid intelligence (*Gf*) is the ability to apply a variety of mental operations to solve novel problems (Avitia & Kaufman, 2014; Carroll, 1993; Horn & Cattell, 1966; McGrew, 2005). In a series of studies, Silvia et al. (Nusbaum & Silvia, 2011; Silvia, 2008; Silvia & Beaty, 2012) examined the relation between *Gf* and creativity via structural equation modeling (Ullman & Bentler, 2003). These studies revealed that (a) *Gf* strongly predicted creativity responses of participants in a divergent thinking task, (b) the effect of *Gf* on creativity was mediated by markers of executive switching (the ability to shift idea categories during the task), and (c) that people with higher *Gf* were better at using an effective creativity strategy when given one (see Silvia, 2015 for a review).

Crystalized intelligence (*Gc*), on the other hand, refers to the breadth of knowledge a person has and the ability to use that knowledge to solve problems (Avitia & Kaufman, 2014; Carroll, 1993; Horn & Cattell, 1966; McGrew, 2005). Several studies have examined the relationships between *Gf, Gc,* and creativity (Batey, Chamorro-Premuzic, & Furnham, 2009; Furnham & Chamorro-Premuzic, 2006; Nusbaum & Silvia, 2011). For example, Sligh, Conners, and Roskos-Ewoldsen (2005) examined the relation between *Gf* and *Gc* and creativity in average- and high-IQ students. Specifically, the authors examined how *Gf* and *Gc* are related to the two key components of the creative process—novelty/generation and appropriateness/interpretation (Runco & Jaeger, 2012). The authors found that while *Gc* was significantly correlated with creativity in average IQ students, *Gf* was significantly correlated with creativity only in high-IQ students. Importantly, the authors showed significant correlations between *Gf* and *Gc* only with the interpretation component, and not the generation component (Sligh et al., 2005). These findings demonstrate the interdependence of the two stages of creativity—generation/novelty and interpretation/appropriateness—indicating that they may tap different cognitive processes (Kaufman, Kaufman, & Lichtenberger, 2011; Lee & Therriault, 2013).

Beaty et al. (2014) examined the contribution of both bottom-up and top-down processes in creative ability. The authors used Latent Semantic Analysis (LSA; Landauer & Dumais, 1997; Landauer, Foltz, & Laham, 1998) to explore individual differences in associative abilities. LSA quantifies the semantic similarity between words in a given semantic space by determining the probability of a given word co-occurring in a specific context (e.g., a paragraph of a document; see M. N. Jones, et al., 2015). LSA has been empirically applied to examine semantic priming, memory, and creativity (Chwilla & Kolk, 2002; Coane & Balota, 2011; Griffiths, Steyvers, & Firl, 2007; Howard & Kahana, 2002; L. L. Jones & Golonka, 2012; Prabhakaran, Green, & Gray, 2014; Steyvers, Shiffrin, & Nelson, 2004). Beaty et al. (2014) calculated semantic distance values of responses generated by participants during verbal fluency tasks to specific target words (e.g., *hot*). These responses were compared for semantic similarity to the target word, and a semantic distance value was derived by computing the inverse of the semantic similarity coefficients (Prabhakaran et al., 2014). This provided an assessment of associative ability—an individual difference reflecting variation in the organization of their mental lexicon. This measure of associative ability, along with several other measures of cognitive ability (such as *Gf*), was used to examine the contribution of both bottom-up and top-down processes in creative cognitive ability (i.e., divergent thinking). This was achieved via structural equation modeling (SEM; Ullman & Bentler, 2003). The authors found joint effects of both semantic distance and executive abilities, namely broad retrieval ability and fluid intelligence, on the quantity and quality of divergent thinking responses. Thus, the authors conclude that both bottom-up mental lexicon structure and top-down executive functions contribute to the creative process. However, the use of SEM can only reveal the contribution, or mediating effect of latent variables (i.e., *Gf* or associative ability) on the dependent variable (i.e., divergent thinking ability). SEM cannot determine the exact nature of this mediating effect, as it only indicates the weight of the relation linking the latent variable and the dependent variable (MacCallum & Austin, 2000; MacKinnon, Fairchild, & Fritz, 2007; Tomarken & Waller, 2005).

In the present study, we use network science methodology to conduct a more sensitive examination of the role of bottom-up and top-down processes in creativity. This is achieved by applying network science methodology to examine the relation between fluid intelligence, creative achievement, and the structure of the mental lexicon, a key component in both accounts of creativity. Network science is based on mathematical graph theory, providing quantitative methods to investigate complex systems as networks (Baronchelli, Ferrer-i-Cancho, Pastor-Satorras, Chater, & Christiansen, 2013; Boccaletti, Latora, Moreno, Chavez, & Hwang, 2006; Borge-Holthoefer & Arenas, 2010). A network is comprised of nodes, which represent the basic unit of the system (e.g., mental lexicon), and links or edges that signify the relations between them (e.g., semantic similarity). At the cognitive level, this approach is mainly applied to investigate complex systems of language and memory structure (Baronchelli et al., 2013; Borge-Holthoefer & Arenas, 2010; Chan & Vitevitch, 2010; De Deyne, Kenett, Anaki, Faust, & Navarro, in press; De Deyne & Storms, 2008; Kenett et al., 2014; Kenett, Kenett, Ben-Jacob, & Faust, 2011; Steyvers & Tenenbaum, 2005; Vitevitch, 2008; Vitevitch, Chan, & Goldstein, 2014; Vitevitch, Chan, & Roodenrys, 2012).

Of the various network models developed in network science theory, the network model that has been widely used to examine complex systems is the Small World Network model (SWN; Milgram, 1967; Watts & Strogatz, 1998). Two main characteristics of a SWN are the network's clustering coefficient (CC) and its average shortest path length (ASPL). The CC refers to the probability that two 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*). The ASPL refers to the average shortest number of steps needed to be taken between any two pair of nodes. A SWN is characterized by having a high CC and a short ASPL. To examine whether a specific network is a SWN, the statistical properties of empirical data are compared to those of a random null network with the same number of nodes and edges (Boccaletti et al., 2006).

Two main network measures that have been examined in neurocognitive network studies are the modularity and the small-world-ness measures. A network's modularity (Q) examines how a complex system, comprised of many nodes and edges, breaks apart (or partitions) into smaller subnetworks (Fortunato, 2010; Newman, 2006). The larger the modularity measure, the more the network is comprised from subnetworks (Newman, 2006). Extensive research indicates the importance of modular network structure in neurocognitive networks and how neurodegenerative diseases disrupt modularity (Bullmore & Sporns, 2012; Meunier, Lambiotte, & Bullmore, 2010; van Straaten & Stam, 2013). Current research has begun to highlight the role of modularity in typical and atypical cognitive networks (Kenett, Gold, & Faust, 2015; Siew, 2013). The small-world-ness measure (S) quantifies the "small-world-ness" of a specific network (Humphries & Gurney, 2008) by computing the ratio between the CC and the ASPL, and it reflects the extent to which a network is "small-worlded" (a value greater than 1 indicates that the network is small-worlded). Neurocognitive research indicates that as neural and cognitive networks develop, they become more structured and less small-worlded (Kenett et al., 2013; Smit et al., 2012; Yap et al., 2011). Thus, the S measure can be considered as a measure of a network's "chaotic" state.

At the cognitive level, application of network science tools is mainly being used to investigate complex systems of language and memory structure (Baronchelli et al., 2013; Borge-Holthoefer & Arenas, 2010; Chan & Vitevitch, 2010; De Deyne et al., in press; Vitevitch, 2008, 2014, 2012). In the linguistic domain, lexicons of different languages display SWN characteristics, considered to be a fundamental principle in lexical organization (Borge-Holthoefer & Arenas, 2010; De Deyne & Storms, 2008; Kenett et al., 2011; Steyvers & Tenenbaum, 2005). Network science tools are also used to examine language acquisition and new word learning mechanisms (Hills, Maouene, Maouene, Sheya, & Smith, 2009a, 2009b; Steyvers & Tenenbaum, 2005). Hills et al. (2009b) applied network tools to investigate the developmental growth of early noun networks and examine the learning principles applied in such noun networks. With regard to creativity (other than the study of Kenett et al., 2014, described above), Schilling (2005) has presented a theory that suggests that insight problem solving is a result of a successful search throughout semantic memory, enabled by either finding "shortcuts" or by the creation of new links between previously unconnected nodes in the network. Finally, clinical research using network science tools to examine deficits at the cognitive level in clinical populations is beginning to emerge. Such research examines the mental lexicon organization of clinical populations suffering from speech, language, and thought disorders and provides novel insights to the nature of their deficiencies (i.e., Beckage, Smith, & Hills, 2011; Cabana, Valle-Lisboa, Elvevåg, & Mizraji, 2011; Holshausen, Harvey, Elvevåg, Foltz, & Bowie, 2014; Kenett et al., 2013; Lerner, Ogrocki, & Thomas, 2009; Mota et al., 2012; Voorspoels et al., 2014).

To examine how fluid intelligence and creative achievement are related to the structure of the mental lexicon, we use a computational method that analyzes participants' responses in a semantic verbal fluency task (Kenett et al., 2013). The verbal fluency task is widely used in neuropsychological and cognitive research (Ardila, Ostrosky-Solís, & Bernal, 2006). In semantic verbal fluency tasks, subjects are required to generate words from a certain category, such as *fruits* or *animals*, in a limited amount of time (usually 60 seconds). While different semantic categories have been used for this task, the animal category is the most widely used, as it is more universal and has shown only minor differences across different languages and cultures (Ardila et al., 2006). Although this task is easy to explain and conduct, it conveys a complex cognitive process. According to the main cognitive theory of the verbal fluency task, this cognitive process is comprised of two different processes—clustering and switching (Troyer, 2000; Troyer, Moscovitch, & Winocur, 1997; Troyer, Moscovitch, Winocur, Alexander, & Stuss, 1998). Clustering refers to retrieving words within a subcategory; switching refers to the process of switching from one subcategory, when the retrieval from this subcategory is exhausted, to a new subcategory. For example, in the animal category, clustering produces semantically related words (e.g., *dog–cat*) and switching allows jumping to a new animal subcategory (e.g., *cat–dolphin*; Troyer, 2000). Research on verbal fluency tasks, which are related to creative divergent thinking tasks (Carroll, 1993), suggests that participants with higher intelligence switch between categories more often (Troyer et al., 1997; Unsworth, Spillers, & Brewer, 2011). Switching ability is also related to higher performance on creative divergent thinking tasks (Nusbaum & Silvia, 2011). Thus, higher switching in the semantic verbal fluency task may indicate a more structured, modular lexical network, with smaller modules. Such a lexicon structure would support the top-down account of creativity. In regard to high creative achievement, however, we would expect a less modular, more flexible, structured lexical network (Faust & Kenett, 2014; Kenett et al., 2014). Such a lexicon structure would support the bottom-up account of creativity. Thus, in accordance with the bottom-up account of creativity, we predict that the high-creativity groups networks will be less structured (shorter ASPL and Q) and more chaotic (higher S) than the low-creative groups. Such prediction is supported by the findings of Kenett et al. (2014). In accordance with the top-down account, we predict that the high-*Gf* groups networks will be more structured (longer ASPL and higher Q). Such prediction is supported by the findings of Unsworth et al. (2011) and the theory proposed by Faust and Kenett (2014). Finally, in accordance with the findings of Beaty et al. (2014), we predict an interaction between *Gf* and creative achievement. We predict that the high-*Gf*, high-creative achievement group network would exhibit increased levels of both structure and chaos (longer ASPL, higher Q, higher S).

Method

Participants

The data was collected as part of a larger individual differences study on executive functions and creative achievement. The original sample consisted of 223 undergraduate students from the University of North Carolina at Greensboro. Participants received credit toward a research option in their course for completing the study. Due to the language-intensive nature of the tasks, we excluded non-native English speakers from the analysis (n = 26); we also excluded participants who failed to comply with study instructions (e.g., text messaging or leaving the room in the middle of the study; n = 15). The final sample therefore included 182 participants (153 female, 29 male; mean age = 19, *SD* = 2.65). All participants provided written informed consent. The study was performed in accordance with the guidelines and regulations of the University of North Carolina at Greensboro's Institutional Review Board, who approved the study.

Materials and Method

Behavioral tasks.

Fluid intelligence tasks. Participants completed four fluid intelligence tests: (a) an abbreviated version of the Ravens Advanced Progressive Matrices (18 items, 12 min; see Carroll, 1993); (b) a paper-folding task, which asks people to determine the final state of a piece of paper that has been folded, punched with holes, and unfolded (10 items, 3 min, Ekstrom, French, Harman, & Dermen, 1976); (c) a letter-sets task, which presents a series of four-letter combinations and requires people to determine which set does not follow a rule governing the other four (16 items, 4 min; Ekstrom et al., 1976); (d) a number-series task, in which participants complete a sequence of numbers by discovering a guiding rule (15 items, 4.5 min; Thurstone, 1938). To compute a general *Gf* score, we used principal component analysis (Abdi & Williams, 2010). This composite *Gf* score was constructed as the sum of the multiplication of each independent *Gf* score by its weight of the first unrotated principal component. The composite *Gf* score was computed with PCA, rather than a simple average, since the first unrotated principal component of each of these tasks is a more precise estimate of *Gf*. This is because this approach corrects for the unique variance in each of the *Gf* measuring tasks that are not due to *Gf* (see Benedek, Fink, & Neubauer, 2006, for a similar approach).

The Creative Achievement Questionnaire. The Creative Achievement Questionnaire (CAQ; Carson, Peterson, & Higgins, 2005) measures real-world creative accomplishments in 10 domains: visual arts, music, dance, architectural design, creative writing, humor, inventions, scientific discovery, theater/film, and culinary arts. Each domain is measured with seven items. The first item for each domain is a "no creativity" response: participants can indicate that they have no accomplishment in the area. The items then increase in steps toward greater accomplishment, with different score weighting for some of the items. Participant scores for each domain were recorded by adding all responses for that category based on the weight of each question. The scores can range from 0 (*having no training or talent in the area*) to 28 (*selecting all categories all the way up to "My work has been recognized nationally"*). Accordingly, most participants receive low CAQ scores, resulting in a skewed distribution of sample results (Silvia, Wigert, Reiter-Palmon, & Kaufman, 2012). To compute a general CAQ score, we used a log-transform on the sum of all CAQ subdomain scores.

Semantic verbal fluency. Participants completed the animal category semantic verbal fluency task. According to standard procedure (Ardila et al., 2006), participants had 60 seconds to generate as many animal category members they could think of. For each participant, repetitions and noncategory members were excluded from final analysis.

Construction of experimental groups. Participants were sorted according to their composite *Gf* score and divided into halves based on the median composite *Gf* score—participants in the low-*Gf* half were dummy coded with 1 and participants in the upper *Gf* half were dummy coded with 2. Next, all participants were sorted based on their general CAQ score and similarly divided into halves of low- and high-CAQ groups based on the median CAQ score. Participants were divided based on the median *Gf*/CAQ to include all participants in the sample. Furthermore, the median split was chosen in order to approach equal sample sized groups. As the network analysis method is sample based (see below), unequal sample size of the experimental groups might confound the results (see Kenett et al., 2015 for a similar discussion). Experimental subgroups were composed from the combination of these two classifications—low-*Gf*, low-CAQ (Group 1); low-*Gf*, high-CAQ (Group 2); high-*Gf*, low-CAQ (Group 3); and high-*Gf*, high-CAQ (Group 4). While the groups did not significantly differ in age and vocabulary knowledge (measured by the Advanced Vocabulary Test II; Ekstrom et al., 1976), they significantly differed in respect to the low/high classification of the two independent variables (*Gf*/CAQ; Table 1).

Lexical networks.

Semantic network construction. The semantic fluency data was analyzed using a recently developed network approach (Kenett et al., 2013). In this network, nodes represent the category members and edges represent word correlations, or the tendency of the sample to generate a word *b* given that a word *a* is generated. This approach controls for possible search strategy confounds (Abwender, Swan, Bowerman, & Connolly, 2001), where participants search throughout their lexicon and retrieve related nouns until their search process is exhausted (Kenett et al., 2013; Troyer et al., 1997).

First, data matrices were created for responses of the entire subsample for each of the four groups. These data matrices

Table 1
Descriptive Information of the Groups in the Present Study (SD in Parentheses)

Parameter	Low *Gf* Low CAQ (*N* = 47)	Low *Gf* High CAQ (*N* = 44)	High *Gf* Low CAQ (*N* = 44)	High *Gf* High CAQ (*N* = 47)
Age	19.09 (1.61)	18.45 (.79)	19.18 (2.54)	19.26 (4.25)
Gender M/F	8/39	3/41	7/37	10/37
Adv_Vocab	6.96 (2.77)	6.84 (1.89)	7.7 (2.36)	7.98 (2.73)
Gf	15.78 (2.68)	15.97 (2.71)	23.39 (3.13)	23.27 (3.36)
CAQ	.62 (.26)	1.32 (.24)	.49 (.33)	1.27 (.19)

Note. Adv_Vocab = mean Advanced Vocabulary Test score; *Gf* = mean composite *Gf* score; CAQ = mean general CAQ score.

were constructed such that each row contained all answers of a single participant, and each column was a unique word given by the entire sample. Each cell consisted of either 1, when a participant *i* generated word *j* or 0 when that participant did not generate the word. To compare between the lexical networks of all groups, we analyze only animal words generated by at least two participants in all groups (Kenett et al., 2013; van Wijk, Stam, & Daffertshofer, 2010). This resulted in lexical networks comprised of 76 common animal words generated by all of the four groups.

Next, we computed word correlations from the data matrices. The correlations between the words were calculated using Pearson's correlation. This correlation is based on the word-generation profile (the number of participants who generated that specific word). The more similar the word-generation profiles of two words is, the higher the word correlation between them (see Kenett et al., 2013). A word-correlation matrix is then created, which contains the word correlations between all pair of words generated in the sample.

The word-correlation matrix can be studied as an adjacency matrix of a weighted, undirected lexical network. An adjacency (also known as connectivity) matrix is a means of representing which nodes are adjacent to which other nodes in the network. That is, we created an $n \times n$ matrix in which n represents the number of nodes (words), and each cell represents the relation (word correlation) between all word pairs. Since most of the edges have small values (weak correlations), the relevant information about the network can be obscured. Several methods have been developed to overcome this obstacle by constructing a subgraph that captures the most relevant information embedded in the original network. Here we used the Planar Maximally Filtered Graph (PMFG) method (Kenett et al., 2011; Tumminello, Aste, Di Matteo, & Mantegna, 2005). To study the structure of the networks, the networks were binarized such that all edges were converted to a uniform weight = 1, and then analyzed as unweighted, undirected networks.

Network analysis. Analyses were performed with the Brain Connectivity Toolbox for Matlab (Rubinov & Sporns, 2010). The following parameters were calculated: the Clustering Coefficient (CC), the average shortest path length (ASPL), the network diameter (D), and the network modularity (Q; Boccaletti et al., 2006; Newman, 2006). To evaluate the network's clustering coefficient and average shortest path length, a random network was created with the same number of nodes and edges, and the CC and ASPL were calculated. Finally, the S measure (Humphries & Gurney, 2008) was computed to quantitatively evaluate the small-world nature of the network.

Statistical analysis of empirical networks. Statistical hypothesis testing methods to compare between networks is currently lacking (Moreno & Neville, 2013). This lack of network comparison hypothesis testing is mainly due to difficulties in estimating or collecting a large sample of empirical networks and due to few statistical methods that compare between networks (see Moreno & Neville, 2013). To overcome this lack of statistical hypothesis testing methods for empirical network science, we use the bootstrap method (Efron, 1979). The bootstrap method was developed as a statistical sampling method to approximate the sampling distribution of a statistic from a sampled empirical dataset (Efron, 1979). This is done by resampling with replacement from the sampled data and creating a large number of random samples, known as bootstrap samples, that are iterated a large amount of iterations (usually a few thousand). A histogram of the set of these computed values is referred to as the bootstrap distribution of the statistic (Singh & Xie, 2010). While this method has certain drawbacks (Shalizi, 2010), its strength lies in the notion of resampling from the gathered empirical data. Another significant strength of this method is that unlike other sampling methods, the bootstrap method does not rely on any statistical assumptions, just on computational ability to simulate data (Shalizi, 2010). To statistically analyze our findings, we used the without replacement bootstrap method (Bertail, 1997; Efron, 1979; Politis & Romano, 1994; Shao, 2003) to simulate and compare random partial lexical networks (Kenett et al., 2014, 2015, 2013). We reasoned that if the lexical networks differed from each other, then any subnetwork consisting of the same nodes in all networks should also be different. Furthermore, the bootstrap method makes it possible to generate many partial lexical networks, allowing for statistical examination of the difference between the networks. To conduct the bootstrapping procedure, half of the nodes were randomly chosen. Partial lexical networks were constructed for each group separately for these random words. Finally, for each partial lexical network, the CC, ASPL, Q, and S measures were computed. This procedure was simulated with 1,000 realizations. A two-way between groups *Gf* × CAQ analysis of variance (ANOVA) was conducted on each network measure to examine the effect of *Gf* and CAQ on each of the partial network measures.

Procedure

The study was completed in groups of one to eight. Participants were given consent forms and briefed by an experimenter on the purpose of the study. Upon informed consent, the participants completed a series of intelligence tasks and questionnaires. All measures were administered on desktop computers using MediaLab v2010 software (Jarvis, 2010).

Results

We constructed the lexical networks based on the procedure described above. Next, the different SWN properties of the animal category lexical networks of all groups were calculated and compared (see Table 2). To visualize the networks, we used the force-directed layout of the Cytoscape software (Shannon et al., 2003) to plot the graphs (see Figure 1). In these 2D visualizations, nodes (words) are

Table 2
SWN Measures Calculated for the Lexical Networks of the Groups Analyzed in This Study

Parameter	Low *Gf* Low CAQ	Low *Gf* High CAQ	High *Gf* Low CAQ	High *Gf* High CAQ
CC	.64	.61	.65	.63
ASPL	3.43	3.20	3.94	3.32
CCrand	.08	.11	.09	.06
ASPLrand	2.59	2.61	2.58	2.54
Q	.61	.58	.62	.56
S	6.44	6.67	5.80	6.67

Note. CC = clustering coefficient; ASPL = average shortest path length; CCrand = Clustering coefficient of random graph; ASPLrand = average shortest path length of random graph; Q = modularity measure; S = small-world-ness measure.

represented as circles and links between them are represented by lines. Since these networks are unweighted and undirected, the links merely convey symmetrical relations between two nodes.

Both the quantitative analysis of the calculated network measures and the qualitative examination of the network visualization reveal differences between the animal lexical networks of the four groups. First, the low-CAQ groups showed larger ASPL and higher Q values, as indicated by their networks being more spread out and more compartmentalized than the high-CAQ groups' networks. Second, the high-CAQ groups showed higher S values than the low-CAQ groups, indicating higher flexibility of these networks. This is indicated by their networks being less structured than the low-CAQ groups' networks. Notably, the lexical network of Group 3 (high-*Gf*, low-CAQ) had the highest structural (ASPL and Q) and lowest flexibility (S) values. Finally, the lexical network of Group 4 (high-*Gf*, high-CAQ) had low structural (ASPL and Q) and high flexibility (S) values. Taken together, the results indicate that *Gf* has a "structuring" effect on the structure of the lexical network, while CAQ has a "chaotic" effect on the structure of the network, in line with our a priori hypotheses.

To examine the significance of the differences found between the networks, we applied the partial networks analysis (Bertail, 1997; Kenett et al., 2014). An in-house Matlab code was written for the partial networks procedure. This code randomly chose half of the nodes comprising the network. Next, partial lexical networks were constructed for all groups for this subset of nodes. Network measures were computed for each partial network and this procedure was reiterated 1,000 times. This resulted in a sample distribution of 1,000 samples for all measures (CC, ASPL, Q, and S) for all four groups (summarized in Figure 2).

A *Gf* (low, high) × CAQ (low, high) between Groups ANOVA was conducted to examine the effect of the two independent variables on the partial networks CC. This analysis revealed a significant main effect for CAQ, $F(1, 3996) = 20.866$, $p < .001$, $\eta^2 = .01$, resulting from higher CC values for the low-CAQ groups (Figure 2A).

A *Gf* (low, high) × CAQ (low, high) between Groups ANOVA was conducted to examine the effect of the two independent variables on the partial networks ASPL. This analysis revealed a significant main effect for *Gf*, $F(1, 3996) = 29.419$, $p < .001$, $\eta^2 = .01$. Furthermore, a significant interaction was found between *Gf* and CAQ, $F(1, 3996) = 60.97$, $p < .001$, $\eta^2 = .02$. This interaction stems from the differential effect *Gf* has on the mean ASPL of the partial networks of both CAQ groups. To investigate the nature of this interaction, we conducted a post hoc simple effects analysis. An independent samples *t* test analysis between the ASPL values of the low-*Gf*, low-CAQ group (Group 1) and low-*Gf*, high-CAQ group (Group 2) revealed a significant difference between the two groups, $t(1998) = -4.43$, $p < .001$. This effect stems from the low-*Gf*, high-CAQ having a significantly higher ASPL value than the low-*Gf*, low-CAQ group. An independent samples *t* test analysis between the ASPL values of the high-*Gf*, low-CAQ group (Group 3) and high-*Gf*, high-CAQ group (Group 4) revealed a significant difference between the two groups, $t(1998) = 6.54$, $p < .001$. This effect stems from the high-*Gf*, high-CAQ having a significantly lower ASPL values than the high-*Gf*, low-CAQ group (Figure 2B).

A *Gf* (low, high) × CAQ (low, high) between Groups ANOVA was conducted to examine the effect of the two independent variables on the partial networks Q. This analysis revealed a significant main effect for *Gf*, $F(1, 3996) = 7.764$, $p < .001$, $\eta^2 = .002$. Furthermore, a significant interaction was found between *Gf* and CAQ, $F(1, 3996) = 28.11$, $p < .001$, $\eta^2 = .01$. To investigate the nature of this interaction, we conducted a post hoc simple effects analysis. An independent samples *t* test analysis between the Q values of the low-*Gf*, low-CAQ group (Group 1) and low-*Gf*, high-CAQ group (Group 2) revealed a significant difference between the two groups, $t(1998) = -3.94$, $p < .001$. This effect stems from the low-*Gf*, high-CAQ having a significantly higher Q values than the low-*Gf*, low-CAQ group. An independent samples *t* test analysis between the Q values of the high-*Gf*, low-CAQ group (Group 3) and high-*Gf*, high-CAQ group (Group 4) revealed a significant difference between the two groups, $t(1998) = 3.56$, $p < .001$. This effect stems from the high-*Gf*, high-CAQ having a significantly lower Q values than the high-*Gf*, low-CAQ group (Figure 2C).

A *Gf* (low, high) × CAQ (low, high) between Groups ANOVA was conducted to examine the effect of the two independent variables on the partial networks S. This analysis revealed a significant main effect for *Gf*, $F(1, 3996) = 23.34$, $p < .001$, $\eta^2 = .01$. Furthermore, a significant interaction was found between *Gf* and CAQ, $F(1, 3996) = 63.55$, $p < .001$, $\eta^2 = .02$. To investigate the nature of this interaction, we conducted a post hoc simple effects analysis. An independent samples *t* test analysis between the S values of the low-*Gf*, low-CAQ group (Group 1) and low-*Gf*, high-CAQ group (Group 2) revealed a significant difference between the two groups, $t(1998) = 5{,}82$, $p < .001$. This effect stems from the low-*Gf*, high-CAQ having a significantly lower S values than the low-*Gf*, low-CAQ group. An independent samples *t* test analysis between the S values of the high-*Gf*, low-CAQ group (Group 3) and high-*Gf*, high-CAQ group (Group 4) revealed a significant difference between the two groups, $t(1998) = -5.47$, $p < .001$. This effect stems from the high-*Gf*, high-CAQ having a significantly higher S values than the high-*Gf*, low-CAQ group (Figure 2D). Taken together, the results of the partial network analysis replicate and verify the findings of the general network analysis.

Discussion

In this study, we examined how the structure of the mental lexicon is related to fluid intelligence and creative achievement. The structure of the mental lexicon is a key component in both bottom-up and top-down accounts of creativity (Beaty et al.,

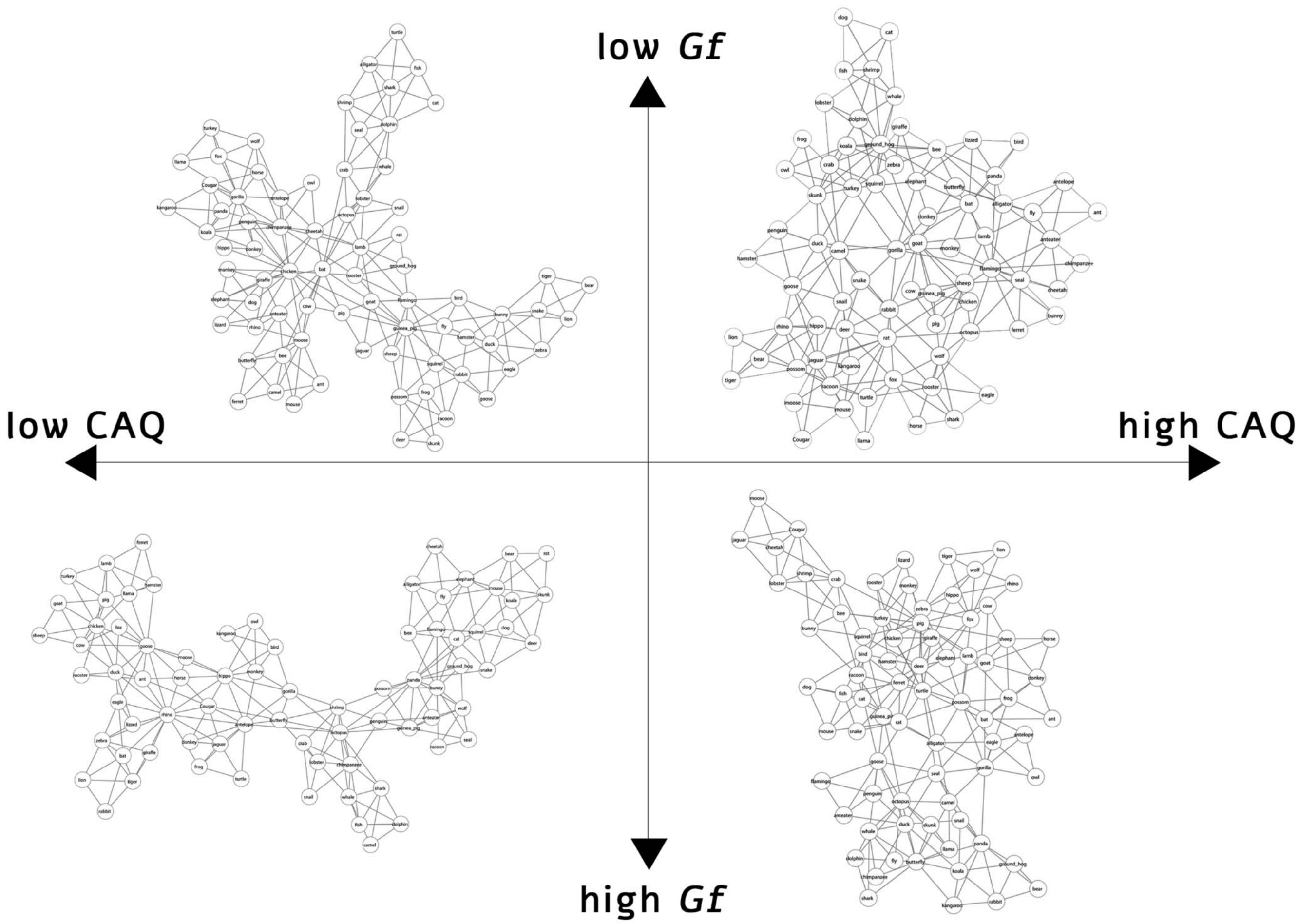

Figure 1. A 2D visualization of the lexical networks of all four groups. Nodes are the 76 common animal members generated by all four groups. The links between the nodes represent an unweighted, undirected connection between nodes. Networks are presented according to the two independent variables, *Gf* and CAQ.

2014). Thus, investigating any possible differences in the structure of the mental lexicon as related to fluid intelligence and creative achievement can shed further light on how both bottom-up and top-down processes interact and contribute to creativity. Such an examination is possible with the application of network science methodology, which is increasingly popular in cognitive research on complex systems of memory and language (Baronchelli et al., 2013; Borge-Holthoefer & Arenas, 2010; De Deyne et al., in press). Under the null hypothesis that the structure of the mental lexicon is similar across participants, examining differences in lexicon structure related to cognitive processes can be used in "reverse engineering" to study these processes.

A sample of participants ($N = 182$) was divided into four groups based on two independent variables: low/high fluid intelligence (*Gf*), as measured by a series of *Gf* tasks, and low/high creative achievement, as measured with the Creative Achievement Questionnaire (CAQ; Carson et al., 2005). All participants completed the animal category semantic fluency task. Finally, a recently developed network methodology was used to represent and compare the lexical network structure of the animal category for each of the four groups (Kenett et al., 2013).

The comparison between the networks of the four groups uncovered several differences that demonstrate the relation between *Gf* and CAQ and the lexical structure of the animal category. First, the low-CAQ groups' networks were more connected (higher CC) than the high-CAQ groups' networks. Second, both low-CAQ groups had more structured networks (longer ASPL and Q) compared to the high-CAQ groups' networks. Third, the high-CAQ groups' networks were more flexible (higher S) than the low-CAQ groups' networks. Notably, the lexical network of Group 3 (high *Gf*, low CAQ) had the highest structural (ASPL and Q) values and lowest flexibility, chaotic (S) value. Finally, the lexical network of Group 4 (high *Gf*, high CAQ) had low structural (ASPL and Q) values and high flexibility, chaotic (S) value. We statistically examined these differences by simulating a large sample of partial networks constructed from subsets of nodes comprising the full network for each group (Bertail, 1997; Kenett et al., 2014; Kenett et al., 2015). This partial network analysis generally replicated and verified the results found in the general network analysis, mainly emphasizing the relationship between the interaction of these two variables and the structure of the mental lexicon.

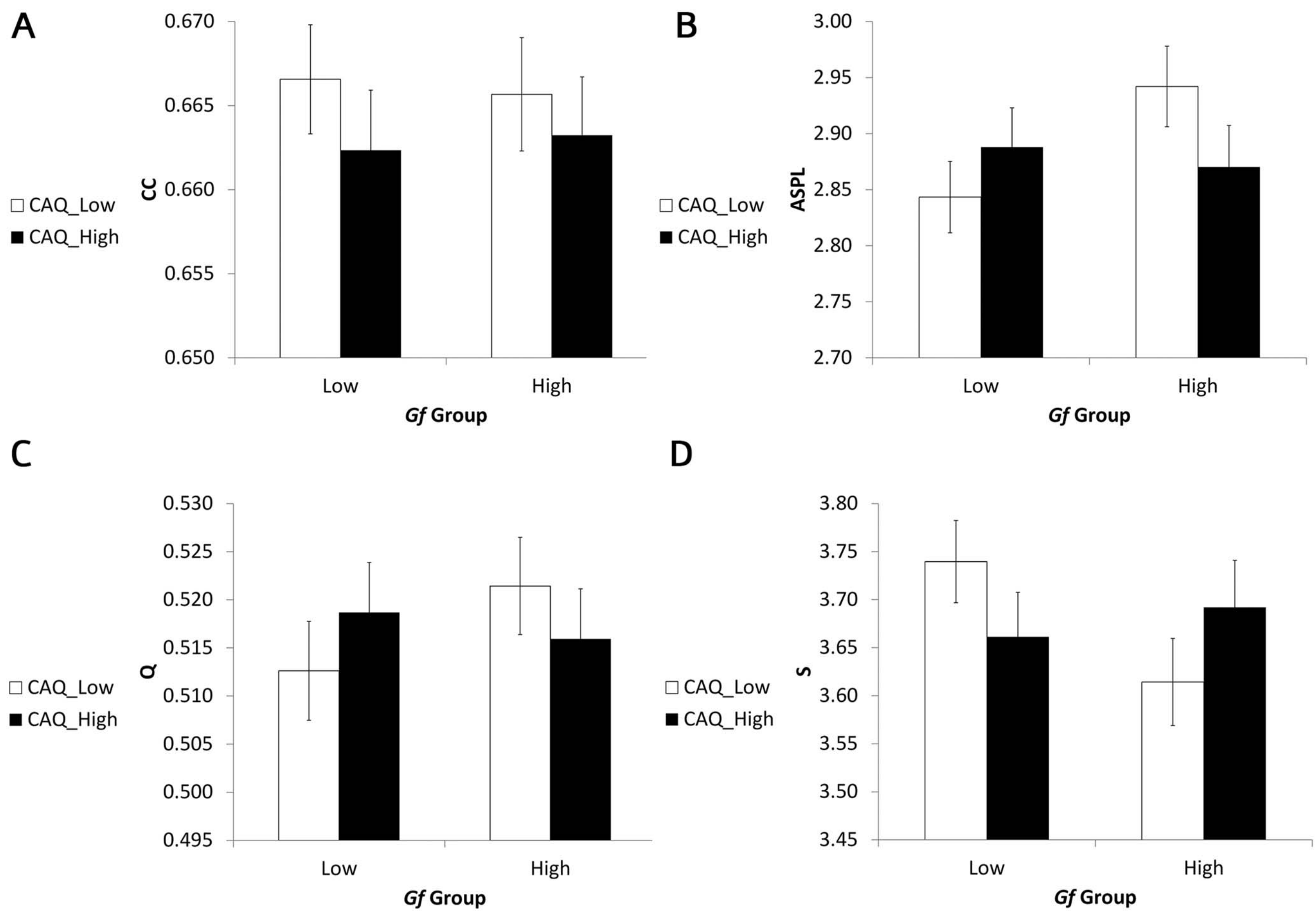

Figure 2. Partial network analysis of the four groups for CC (**A**), ASPL (**B**), Q (**C**), and S (**D**). X-Axis—the two *Gf* groups (low, high), white/black bars—the two CAQ groups (low, high). Y-Axis—dependent variables (CC, ASPL, Q, and S; error bars depict standard error).

Taken together, our results provide a more sensitive analysis of the relation between fluid intelligence, creative achievement, and the structure of the mental lexicon. Our results demonstrate how high *Gf*, as assessed with a battery of *Gf* tasks, is related to a more structured lexical structure of the animal category—exhibited by higher modularity and longer ASPL. On the other hand, our results demonstrate how high creative achievement, as assessed with the CAQ, is related to a more flexible lexical structure of the animal category—exhibited by lower modularity of the network, thus making it more condensed and raising its small-world nature.

The present findings shed further light on how both bottom-up and top-down accounts of creativity may interact and contribute to the generation of creativity: the more flexible lexicon structure of the mental lexicon related to high CAQ (also found in Kenett et al., 2014) may contribute to the ability of making novel connections. The more structured lexicon structure of the mental lexicon related to high *Gf*, on the other hand, may contribute to the ability to more easily switch between small modules, thus overcoming conventional solutions (Nusbaum & Silvia, 2011; Unsworth et al., 2011). The findings presented here are supported by previous studies that found that individuals with low latent inhibition and high IQ exhibited extraordinary creative achievements (Carson, Peterson, & Higgins, 2003; Kéri, 2011). Thus, while creativity encompasses a flexible, chaotic nature (novelty), it must also contain some degree of structure (appropriateness). Current theory on creativity views such opposing and controlling forces as “controlled chaos” (Bilder & Knudsen, 2014; Kaufman, 2014).

More generally, our results are situated within current cognitive theories that view typical and atypical cognitive processing as interplay between flexibility and rigidity of thought processes. Faust and Kenett (2014) have recently proposed a cognitive theory of the relation between the structure of the mental lexicon and typical and atypical thought processes. This theory proposes a cognitive continuum of lexicon structure. On one extreme of this continuum lies rigid, structured lexicon networks, such as those exhibited in individuals with Asperger syndrome (Kenett et al., 2015). On the other end of this continuum lies chaotic, unstructured lexicon networks, such as those exhibited in individuals with schizophrenia (Spitzer, 1997). According to this theory, efficient semantic processing is achieved via a balance between rigid and chaotic lexicon structure (Faust & Kenett, 2014). In regard to individual differences in creative ability, as the structure of the mental lexicon is more rigid, it is less creative, reaching in extreme cases the point of a pathological state. In contrast, as the structure of the mental lexicon is more chaotic, it is more creative, yet in extreme cases it may result a pathological state. This proposal is supported by research showing how persons with autism exhibit difficulty in creativity tasks (Craig & Baron-Cohen, 1999; Kenett et al., 2015; Turner, 1999). In regard to the other extreme of this continuum, research has found correlations between creativity and schizotypical personality traits (Kaufman & Paul, 2014) and also that persons with schizophrenia exhibit atypical processing of metaphoric expressions (Zeev-Wolf, Faust, Levkovitz, Harpaz, & Goldstein, 2015). Our results are further related to the shared vulnerabilities model of creativity and psychopathology (Carson, 2011, 2014). This model proposes that creativity and psychopathology share a genetic factor that is expressed as either creativity or psychopathology depending on an interaction between cognitive vulnerabilities (latent inhibition, novelty seeking, and neural hyperconnectivity) and protective factors (high IQ, cognitive, and flexibility). This model proposes that protective factors related to top-down control, in the form of high IQ, coupled with chaotic thought processes, exhibited with lowered latent inhibition, are related to higher level of creativity (Carson, 2014). This prediction can be quantified in network science terms of Q and ASPL, as indicators of structure, and S, as indicator of chaos.

A few limitations of this study exist. First, the network method used in this study is group based and cannot account for individual lexical networks. Future research is required to expand our network approach to the analysis of individual semantic networks (see Morais, Olsson, & Schooler, 2013 for such a recent novel approach). Second, in this study we focused on fluid intelligence in regard to its top-down effect on creative ability (Nusbaum & Silvia, 2011). However, other top-down functions have been related to creative ability, such as broad retrieval abilities and working-memory capacity (Avitia & Kaufman, 2014; Benedek et al., 2014; Silvia, 2015; Silvia et al., 2013). Future studies should also examine the effect of other top-down processes on the structure of the mental lexicon. Third, in this study we measured creative accomplishment via the subjective self-report CAQ (Carson et al., 2005). While widely used as a measure of creativity, the CAQ has also been criticized for its limitations (Silvia & Beaty, 2012). Specifically, concerns have been raised in regard to subjective score inflation by the participants and the skewness of the results, which make it difficult to analyze (Silvia & Beaty, 2012). Future research should replicate the results of the present study with other measures of creativity, such as divergent thinking tasks or the remote association test (Mednick, 1962; Runco & Acar, 2012). Finally, in this study we analyzed participant's responses on a semantic verbal fluency task to analyze the lexical network structure of the animal category. However, this task is strongly related to executive functions (Ardila et al., 2006; Troyer et al., 1997; Unsworth et al., 2011), which can confound the results. Future studies should use a less biased task which will allow extracting a more "natural" mental lexicon structure, such as free associations (De Deyne et al., in press).

In conclusion, the present study used network science methodology to examine the effect of both bottom-up (as assessed with a measurement of creative achievement) and top-down (as assessed with a battery of fluid intelligence tests) processes on the structure of the mental lexicon. This was done due to the mental lexicon being a key component of both competing theories of creativity. Thus, examining differences in lexicon structure related to these variables can advance the understanding of their contribution to creativity. We found that creative achievement has a more flexible, chaotic effect on the structure of the mental lexicon. Fluid intelligence, on the other hand, has a more structural effect on the structure of the mental lexicon. Finally, we found that the lexical network of the high-fluid-intelligence, high-creative-achievement group exhibits a combination of both effects. Our findings support and extend the findings of Beaty et al. (2014) and provide a more direct investigation of the contribution of both structural and functional processes in creative ability.

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