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Flexible Semantic Network Structure Supports the Production of Creative Metaphor

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ABSTRACT

Metaphors are a common way to express creative language, yet the cognitive basis of figurative language production remains poorly understood. Previous studies found that higher creative individuals can better comprehend novel metaphors, potentially due to a more flexible semantic memory network structure conducive to remote conceptual combination. The present study extends this domain to creative metaphor production and examined whether the ability to produce creative metaphors is related to variation in the structure of semantic memory. Participants completed a creative metaphor production task and two verbal fluency tasks. They were divided into two equal groups based on their creative metaphor production score. The semantic networks of these two groups were estimated and analyzed based on their verbal fluency responses using a computational network science approach. Results revealed that the semantic networks of high-metaphor producing individuals were more flexible, clustered, and less rigid than that of the low-metaphor producing individuals. Importantly, these results replicated across both semantic categories. The findings provide the first evidence that a flexible, clustered, and less rigid semantic memory structure relates to people's ability to produce figurative language, extending the growing literature on the role of semantic networks in creativity to the domain of metaphor production.

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Introduction

Metaphor is a form of higher-order linguistic expression that conveys an abstract idea using nonliteral language (Faust, 2012; Mirous & Beeman, 2012). Producing a metaphor involves combining seemingly unrelated concepts from memory (i.e., making a mental "leap") to create a meaningful or comprehensible linguistic expression (Bowdle & Gentner, 2005; Mednick, 1962). Metaphor is considered a creative expression of language in conversational dialogue (Lakoff & Johnson, 1999), such as when people express emotions and experiences in nonliteral terms (Beaty & Silvia, 2013). Ample studies have investigated the cognitive basis of metaphor comprehension – how people passively process metaphorical expressions (Chiappe & Chiappe, 2007; Gold, Faust, & Ben-Artzi, 2012; Kenett, Gold, & Faust, 2018; Samur, Lai, Hagoort, & Willems, 2015; Shibata et al., 2012) – but few have focused on metaphor production (Chiappe & Chiappe, 2007), especially *creative metaphors* – the self-generation of a novel figurative expression (Beaty & Silvia, 2013; Silvia & Beaty, 2012). In the present research, we explore one possible cognitive mechanism that has been linked to metaphor comprehension and creative thinking – semantic memory structure – testing whether variation in people's ability to produce creative metaphors relates to variation in the organization of concepts in semantic memory networks.

The cognitive basis of metaphor production

Despite the paucity of work on metaphor production, theories of metaphor comprehension and semantic processing may provide insight into how people produce such nonliteral language (Collins & Loftus, 1975; Glucksberg, McGlone, & Manfredi, 1997; Kintsch, 2000; Quillian, 1967). The property attribution model of metaphor comprehension provides a useful framework for conceptualizing metaphor production, which holds that, to compose a metaphor, people need to make an abstract link (or attributive category) between two concepts – a "topic" and a "vehicle" – with the attributive category reflecting a common feature between the two concepts (Glucksberg et al., 1997). Thus, when people process (or produce) a metaphor, they need to search for and extract the similar features, establishing new connections (or temporarily strengthening weaker

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connections) between the topic (e.g., music) and vehicle (e.g., medicine) via the attributive category (e.g., “healing”).

The prediction model (Kintsch, 2000) is another model of metaphor comprehension that can be recast to conceptualize metaphor production. According to this model, once the common features of a topic and vehicle are identified, they may be used to further search semantic memory for an apt vehicle. Semantic memory is the cognitive system that stores facts and knowledge, irrespective of time or context (Kumar, 2020). Of relevance for creative metaphor production, semantic memory plays a central role in creative thinking (Abraham, 2014; Kenett & Faust, 2019; Mednick, 1962). Amabile, Barsade, Mueller, and Staw (2005) noted that, the more potentially relevant elements that can be retrieved from memory, the higher the possibility that novel links between these elements will be established. This claim was supported by computational work that highlights the role of retrieving remote associations in creative problem-solving (Helie & Sun, 2010), consistent with the view that creative thinking is mediated by a memory search-based mechanism (Friedman & Förster, 2002; Gruszka & Necka, 2002; Neçka, 1999). Past work suggests a relationship between semantic ability and individual differences in metaphor production ability. Chiappe and Chiappe (2007) examined conventional metaphor production – the ability to produce common figurative expressions based on stem-completion tasks (e.g., “Life is (fragile); “glass”) – and showed a unique contribution of verbal knowledge to metaphor production ability, suggesting that people with a broader knowledge base can more effectively produce common metaphors.

In subsequent research, Beaty and Silvia (2013) reported a dissociation between cognitive abilities that support conventional vs. *creative metaphors* (i.e., producing novel figurative expressions based on open-ended prompts), finding that, while conventional metaphor benefited more from crystallized intelligence (i.e., vocabulary knowledge), creative metaphor benefited more from broad retrieval abilities (i.e., verbal fluency). These findings for conventional metaphor were consistent with Chiappe and Chiappe (2007), indicating that a broader knowledge base is conducive to recalling established figurative expressions. On the other hand, the findings for creative metaphor indicate that the *process* of strategically retrieving items from semantic memory is conducive to creating new metaphoric expressions. It remains unclear, however, whether the underlying *structure* of semantic memory influences how people produce creative metaphors. While studying the structure of semantic memory is challenging (Jones, Willits, & Dennis, 2015), advances in the application of network science have made it possible to quantify and investigate it (Siew, Wulff, Beckage, & Kenett, 2019).

Mapping semantic memory using computational network methods

Network science tools have recently been used 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; Siew et al., 2019). Network science is based on graph theory, providing quantitative methods to represent complex systems, such a semantic memory, as networks (Siew et al., 2019). In semantic memory 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 quantitatively examine classic cognitive theory and the operations of cognitive processes that take place in memory retrieval and associative thought (Baronchelli et al., 2013; Siew et al., 2019). 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 (Kenett, Levi, Anaki, & Faust, 2017; Kumar, Balota, & Steyvers, 2020), and provided new insight into the semantic structure of second languages in bilinguals (Borodkin, Kenett, Faust, & Mashal, 2016).

A growing body of work has applied semantic network analysis to examine the role of knowledge in creative thinking (Kenett & Faust, 2019). Kenett, Anaki, and Faust (2014) compared the semantic memory structure in low and high creative individuals – people who scored low and high on creative thinking tasks and scales assessing creative achievements – finding that higher creative individuals presented a more flexible, clustered, and condensed semantic network compared to lower creative individuals. These results support the associative theory of creativity (Mednick, 1962), which posits that high creative individuals have a more condensed and flexible associative network than that of less creative individuals; these results were partially replicated by the within-subject design studies, thus extending research on individual differences in creativity with individual-based semantic networks (Benedek et al., 2017; Bernard, Kenett, Ovando-Tellez, & Benedek, 2019; He et al., 2020). In a similar vein, Kenett and Austerweil (2016) compared the difference in cognitive search between low and high creative individuals using a random walk mode, showing that a random walk over the semantic network of high creative individuals "finds" more novel words and moves further through the network for a given number of steps.

Regarding metaphors, in a recent study, Kenett et al. (2018) investigated how low and high creative individuals performed on a novel metaphor comprehension task. Importantly, these groups were the same groups analyzed by Kenett et al. (2014), that found differences in the semantic memory structure between these two groups. The authors found that the high creative group comprehended novel metaphors better than the low creative group, potentially due to their more flexible semantic memory structure (Kenett et al., 2018). Although these findings indicate that semantic memory structure supports metaphor comprehension, it remains unclear whether memory structure contributes to the production of creative metaphors. To examine this issue, comparing the semantic networks of people that are low and high in their ability to produce such creative metaphors is needed.

A popular way of estimating semantic memory networks is based on verbal fluency tasks (Ardila, Ostrosky-Solís, & Bernal, 2006; Goni 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) within 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 has a universal taxonomy (i.e., the animal kingdom) and has shown only minor differences across different languages and cultures (Ardila et al., 2006).

Of the network models that have been developed in network science theory, the Small World Network model (SWN; Watts & Strogatz, 1998) has been one of the most widely used to examine complex systems. SWNs are defined by two main characteristics: the network's average shortest path length (ASPL) and its clustering coefficient (CC) measures. 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 the faster diffusion of information and smaller distances between concepts with fewer mediating associations (e.g., cat-fish-dolphin compared to cat-dog-fish-whale-dolphin), the shorter ASPL is suggested to be effective for searching apt concepts in creative activity (He et al., 2020; Kenett et al., 2014; Latora & Marchiori, 2001). CC refers to the extent that two neighbors of a node will themselves be neighbors (i.e., a neighbor is a node that is connected through an edge to node), which indicates how semantic information is organized at a local level (e.g. birds). A network with a higher CC suggests that there is high possibility for exemplars that are near-neighbors to each other (e.g. sparrow–hummingbird–eagle–pigeon) to co-occur. (cf. Christensen et al., 2018). Also, higher CC indicates a broader search process through semantic space, thereby increasing the possibility to find unique ideas in divergent thinking (Kenett et al., 2014; Marupaka, Iyer, & Minai, 2012). A third 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). Higher modularity indicates that there are more sub-communities, more dense connections between the nodes within these sub-communities, and fewer connections between nodes across different sub-communities (Newman, 2006). Higher Q has been related to rigidity of thought by blunting spreading activation within sub-communities, evidenced by studies in phonological processing (Siew, 2013) and in clinical populations, such as Asperger syndrome (Kenett, Gold, & Faust, 2016). Taken together, the shorter the ASPL, the larger the CC, and the smaller the Q, the more flexible and efficient the semantic network association is (Kenett et al., 2014; Kenett & Faust, 2019).

The present research

Computational network science methods have been used to study the role of semantic memory structure in supporting complex cognitive processes such as creative thinking (Kenett, 2019; Kenett & Faust, 2019). Relatedly, network science research has revealed how a more flexible network structure – characterized by high connectivity and short path lengths between semantic concepts – contributes to people's ability to comprehend metaphors (Kenett et al., 2018). To date, however, whether and how semantic memory structure impacts people's ability to produce entirely new figurative language remains unclear. Thus, the main aim of the current study is to use computational network science tools to capture, quantify, and compare the semantic memory structures of people with low and high creative metaphor production abilities.

To measure creative metaphor production ability, participants completed two creative metaphor tasks (Beaty & Silvia, 2013; Silvia & Beaty, 2012). They also completed two verbal fluency tasks (animals and fruits/vegetables), which allowed us to construct group-based semantic networks of low- and high-creative metaphor groups using computational network tools. Given previous work finding that higher creative individuals tend to have a more flexible, clustered, and less rigid semantic memory structure (low ASPL and Q, high CC) – a network structure conducive to efficient combination of weakly connected concepts (Kenett & Faust, 2019) – we predicted that high-metaphor ability individuals will show a similar semantic network profile (low ASPL and Q, high CC). Additionally, previous studies typically use a single category to access the semantic network of a group (Christensen et al., 2018; Kenett, Beaty, Silvia, Anaki, & Faust, 2016), which limits the ability to examine the robustness and generality of results beyond a single category. Here, we address this issue by examining two semantic categories (e.g., fruits/vegetables), hypothesizing that results would replicate across both categories.

Methods

Participants

Participants were recruited from the University of North Carolina at Greensboro (UNCG) and surrounding community from a larger study on the psychology and neuroscience of creativity (see Beaty et al., 2018). The total sample included 186 participants; only participants who completed both verbal fluency tasks (animals and fruits/vegetables) were included in the semantic network analysis (n = 142; Table 1). All participants were English speakers with normal or corrected to normal vision; they were paid for their participation. The study was approved by the UNCG Institutional Review Board and participants completed informed consent prior to completing the study.

Participants were divided into two groups by the median of the Z-value of their creative metaphor production score (cf. Christensen et al., 2018; Kenett et al., 2016). We conducted an independent samples t test on the Z-score of low and high-metaphor production groups. Results showed that the creative metaphor score of the high-metaphor production group was significantly larger than that of the low-metaphor production group, $t_{(140)} = 16.6$, $p < .001$, which indicates that the grouping was appropriate.

Table 1. Descriptive statistics for demographics and creative metaphor scores.

	Age		Gender (n)		Metaphor Score
Sample	M (SD)	Range	Male	Female	Z-value: M (SD)
Full (N = 142)	21.91 (4.34)	18– 47	37	105	.04 (1.0)
Low (N = 71)	21.56 (4.46)	18– 47	18	53	−.79 (.50)
High (N = 71)	22.25 (4.22)	18– 34	19	52	.87 (.68)

Behavioral tasks

Creative metaphor production task

A creative metaphor production task was used to assess participants' ability to produce novel metaphors (Beaty & Silvia, 2013; Silvia & Beaty, 2012). In this task, participants were asked to describe two past experiences with a metaphor, which was self-paced (no time limit) (cf. Beaty & Silvia, 2013; Silvia & Beaty, 2012). Instructions included definitions and examples of different types of metaphors. Two prompts were presented to participants, which were taken from prior work on creative metaphors (Beaty & Silvia, 2013; Silvia & Beaty, 2012). The first metaphor prompt was "Think of the most boring high school or college class that you've ever had. What was it like to sit through?" Examples of metaphoric stems were provided to help them get started (e.g., "Being in that class was … "). The second prompt stated "Think about the most disgusting thing you ever ate or drank. What was it like to eat or drink?" Potential response stems were also provided for this prompt (e.g., "Eating that _____ was … "). Participants were instructed to "be creative" to emphasize the importance of originality; past work has shown that this "be creative" instruction typically yields more unique responses on creativity tasks (Acar, Runco, & Park, 2020; Christensen, Guilford, & Wilson, 1957; Harrington, 1975; Said-Metwaly, Fernández-Castilla, Kyndt, & Van den Noortgate, 2020). The task was administered on a desktop computer running MediaLab.

Four trained raters scored the creative metaphor responses using the subjective scoring method (Amabile, 1982; Silvia, 2011). This method was used in previous studies of metaphor (Beaty & Silvia, 2013; Silvia & Beaty, 2012) and it has been shown to be a reliable assessment of creative thinking (Silvia, 2011). Raters were trained to give a single score to each response, from 1 (*not at all creative*) to 5 (*very creative*), on the basis of three criteria: remoteness (the conceptual distance of the metaphor), novelty (the degree to which the response is original), and cleverness (how funny, witty, or interesting the response is). An example of a metaphor response for the "gross food/drink" prompt from a participant in the low-metaphor group is "That drink was dirt." An example metaphor from a participant in the high-metaphor group is "That broccoli was mushier than The Notebook."

To derive a variable for analysis, we used structural equation modeling in Mplus 8 using creativity ratings from all participants who completed the metaphor tasks (n = 165). The four raters were modeled as indicators of two lower-order metaphor variables ("gross food" and "boring class" prompts), which were in turn modeled as

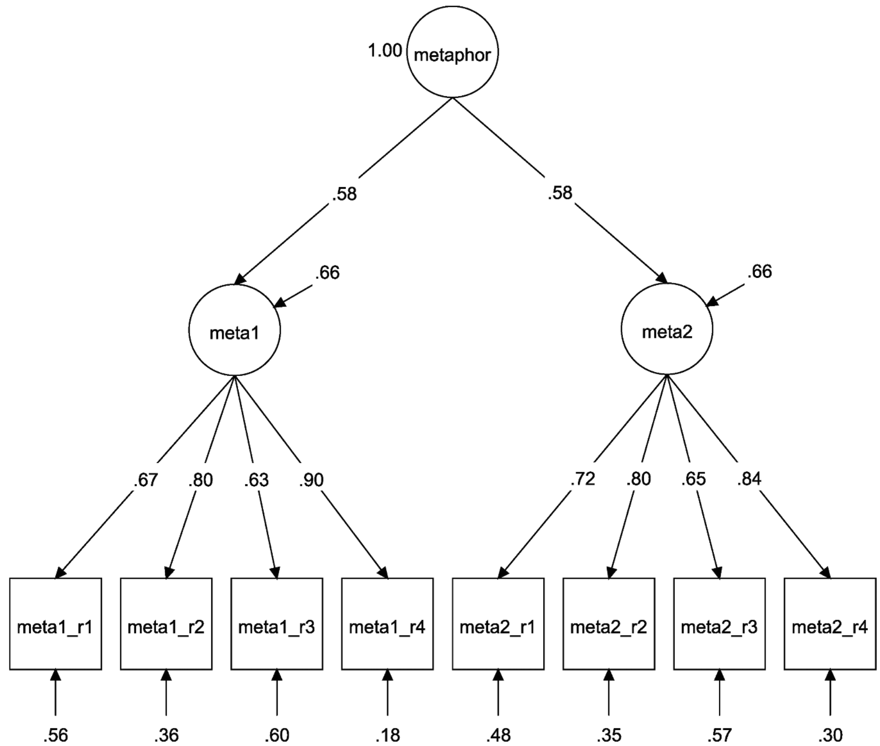

Figure 1. Confirmatory factor analysis of creative metaphor. Factor scores were extracted to form high and low-metaphor groups for group-based semantic network analysis. meta1 = boring class metaphor; meta2 = gross food metaphor; r1-r4 = rater1-rater4.

indicators of higher order variable metaphors (Figure 1, Beaty & Silvia, 2013; Silvia & Beaty, 2012). This measurement model fit the data well: χ^2 (19) = 25.836, $p < .135$; CFI .988; RMSEA .047; SRMR .039. We formed high- and low-metaphor groups via median split of the extracted latent factor, which was standardized via Z score ($M = 0$, $SD = 1$; see *Participants*).

Semantic fluency tasks

Participants completed two category verbal fluency tasks: animals and fruits/vegetables. This task provides an efficient means to investigate people's ability to retrieve semantic information from long-term memory (Ardila et al., 2006; Bousfield, Whitmarsh, & Berkowitz, 1960; Goni et al., 2011), and it is widely used to model group-based semantic networks (Siew et al., 2019). According to standard procedure (Ardila et al., 2006), for each category, participants were given 60 seconds to write down (type) as many different examples as they could. Note that we included two categories (animals and fruits/vegetables) to test whether results are robust to semantic category.

Analyses

Total and unique responses. We conducted a series of analyses to determine whether the high- and low-metaphor groups differed in the total number of fluency responses and the number of unique responses per category. T-tests assessed potential group differences in the total number of responses. To assess potential differences in unique responses, McNemar's chi-squared test was used, which compares differences in proportions of paired nominal dichotomous data (Agresti, 2003)."

Network analysis

Network estimation

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

First, *SemNetDictionaries* (Christensen, 2019b) and *SemNetCleaner* (Christensen, 2019a) R packages were used to preprocess participants' verbal fluency data. Participant repetitions (responses given by a participant more than once) and non-category members (e.g., animals: sugar, small tree, and fictional character) were removed. Other potential errors were corrected, including spelling errors, compound responses (i.e., responses where a space is missing between responses), variation on roots (e.g. cats to cat), and continuous strings (i.e., multiple responses entered as a single response). Next, the data were transferred into a binary response matrix, where the columns represent the different unique exemplars given by the sample, rows represent participants, and the response matrix is filled out by 1 (if an exemplar was generated by that participant) and 0 (if that exemplar was not).

The *SemNetCleaner* package (Christensen, 2019a) was used to further process the binary response matrix into a finalized format for network estimation. To control for confounding factors (such as different nodes or edges in both groups), as in previous studies, the binary response matrices only include responses that are given by at least two participants in each group (Christensen et al., 2018; Kenett et al., 2016, 2013). Then, to avoid the two groups including different nodes (and different numbers of nodes), which may bias comparison of network parameters (van Wijk, Stam, & Daffertshofer, 2010), responses in the binary response matrices were equated, so that the networks of both groups are compared using the same nodes. This matching allows us to examine differences in network properties that are due to differences in the groups themselves (e.g., differences in metaphor production abilities). During this process, 23 and 7 nodes were excluded from the low and high-metaphor groups, respectively, leaving 106 nodes in each group for the animals category and 62 nodes in each group for the fruits/vegetables category for subsequent network analysis.

Next, the *SemNeT* package (Christensen, 2019b) was used to compute the association profiles of verbal fluency responses. We used the function of cosine similarity in this package to estimate the edges between nodes. 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:

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

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 word similarity matrix is examined as an n x 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 et al., 2018; Massara, Di Matteo, & Aste, 2016). The TMFG captures 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 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 analyzed 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 analyzed as unweighted (all weights are treated as equal) and undirected (bidirectional relations between nodes) networks.

Network analysis

The *NetworkToolbox* package was used to analyze the network properties (CC, ASPL, and Q). We used two complementary approaches to statistically examine the validity of the results. First, we simulated one set of random networks for both metaphor groups to statistically test whether the network parameters did not result from a null hypothesis of a random network with the same nodes and edges (Beckage, Smith, & Hills, 2011; Steyvers & Tenenbaum, 2005). To this end, for each semantic category, we generated a large sample of Erdös-Rényi random networks with a fixed edge probability (Erdös & Rényi, 1960) and compared the empirical network measures of both groups to this random distribution. For each simulated random network, we computed its CC, ASPL, and Q. This procedure was simulated with 1,000 realizations and resulted in a random reference distribution for each measure. The empirical network measures were then compared to the 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. Based on previous studies (Borodkin et al., 2016; Kenett et al., 2016), the bootstrapping procedure involves random selection of a subset of the nodes of the semantic network. Partial semantic networks were constructed for each group separately for these random nodes. This approach makes it possible to generate many simulated partial semantic networks, allowing for statistical examination of the difference between any two networks. Following the procedure of Epskamp, Borsboom, and Fried (2018), we generated graded partial semantic networks for both groups that involved 50%, 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 1,000 realizations for each of the graded partial bootstrapping analyses and an independent t test analysis were conducted to compare the difference in the measures across the two groups. This bootstrapped approach was computed, and its corresponding figures were generated using the *SemNetCleaner* package (Christensen, 2019a).

Results

We compared the average and the unique responses of low and high creative metaphor groups in both categories. The results showed no significant difference in the average response between the two groups in both categories (ps > .05, see Table 2). For the unique responses, across the sample, there were 287 and 147 unique responses in total for the animals and fruit/vegetables categories, respectively. The high creative metaphor producers generated 231 and 128 unique responses for animals and fruit/vegetables categories, respectively (68 and 41 of which were not given by the low group), and the low creative metaphor producers generated 219 and 106 unique responses for animals and fruit/vegetables, respectively (56 and 19 of which were not given by the high group). McNemar's chi-square tests showed that the proportion of unique responses in the high creative metaphor-producing group (231/287 = .805 for animals and 128/147 = .871 for fruit/vegetables categories) was significantly larger than that in the low creative metaphor-producing group (219/287 = .763 for animals and 106/147 = .721 for fruit/vegetables categories), [χ^2_{AN} (1) = .98, p = .323, φ = .274; χ^2_{VG} (1) = 7.35, p = .007, φ = .240] (Table 2). Thus, the high creative metaphor producers reported more unique responses than low creative metaphor producers, but only in the fruit/vegetables category.

Additionally, three t-test analyses were conducted to examine potential differences for the average number of responses between the animals and fruits/vegetables categories. The results showed that the average responses for the animals category were significantly high than that of the fruit/vegetables category [M (SD) $_{\mathrm{AN}}$ = 19.47 (4.12), M (SD) $_{\mathrm{VG}}$ = 16.02 (3.56), $t_{(141)}$ = 10.94, p < .001, d = .896]. When separated by group, the average number of responses of the animals category was higher than that of the fruit/vegetables category in both groups [$t_{low\ (141)}$ = 8.337, p < .001, d = 1.059; $t_{high\ (141)}$ = 7.154, p < .001, d = .737]. These results indicate that, regardless of metaphor creativity, people have a higher rate of associations with the animals category than the fruit/vegetables category.

Next, we estimated the animals and fruits/vegetables category semantic networks of the low and high creative metaphor-producing groups. We computed the network measures (CC, ASPL, and Q) for these four networks (Table 3) and visualized the networks (Figure 2). To visualize the networks (Figure 2), we applied the force-directed layout (Fruchterman & Reingold, 1991) of the Cytoscape software (Shannon et al., 2003). In these 2D visualizations, nodes are represented by the respective exemplars and edges between them are represented by

Table 2. Average and unique verbal fluency responses for the four metaphor groups.

Group	*n* (average) *M* (*SD*)	*n* (average) Range	*t*	*df*	*p*	*d*	*n* (total)	*n* (unique)	*n*	χ^2 *df* = 1	*p*	φ
Low_AN	19.56 (3.97)	12–34	.243	140	.809	.041	287	219	56	.98	.323	.274
High_AN	19.39 (4.32)	10–28						231	68			
Low_FV	15.63 (3.37)	9–25	−1.252	140	.213	−.210	147	106	19	7.35	.007	.240
High_FV	16.38 (3.72)	9–24						128	41			

n (average) = the average number of responses in each group; *n* (total) = the total number of unique responses in each category; *n* (unique) = the number of unique responses in each group; *n* = the number of unique responses not given by the other group. χ^2 was from the McNemar's chi-squared test; φ is the effect size of the McNemar's test. AN – animals; FV – fruit/vegetables.

Table 3. Network measures of low and high-metaphor networks for two semantic categories.

	AN-Low	AN-High	FV-Low	FV-High
ASPL	3.30	2.73	2.59	2.36
CC	.72	.75	.75	.76
Q	.61	.59	.52	.48

ASPL, average shortest path length; CC, clustering coefficient; Q, modularity. AN_Low, low creative metaphor-producing group in category animals; AN_High, high creative metaphor-producing group in category animals; FV_Low, low creative metaphor-producing group in category fruits/vegetables; FV_High, high creative metaphor-producing group in category fruits/vegetables.

lines. Since these networks are undirected and weighted, the edges convey symmetrical (i.e., bidirectional) similarities between two nodes. The network of the low-metaphor producing group is visually more spread out than the network of the high-metaphor producing group in both categories (Figure 2), consistent with the lower CC, higher ASPL, and higher Q of the low metaphor networks (Table 3).

To verify that the network analysis results are not due to a null hypothesis, we conducted a simulated random network analysis. This analysis revealed that all empirical network measures for the low- and high creative metaphor-producing groups were significantly different from their simulated random measures (all p's < .001). Notably, this result replicated across both semantic categories.

To examine potential differences in network structure across the low and high metaphor-producing groups, we conducted bootstrapped partial networks analyses for both categories (Bertail, 1997; Kenett et al., 2014). Here, five graded partial semantic networks were generated for both groups, constituting 50%, 60%, 70%, 80%, and 90% of the nodes.

Compared to the low metaphor-producing group, the partial networks of the high creative metaphor-producing group had a significantly lower ASPL and Q, and higher CC across the bootstrapped samples (Figure 3 and Table 4). The effect size ranged from moderate to very large (d = 0.72 to 1.66 for ASPL and d = 0.82 to 1.60 for Q), with effect size scaling with increasing number of nodes in the partial networks (i.e., d increased as nodes increased from 50% to 90%). In contrast, the CC was significantly larger for the partial networks of the high creative metaphor-producing group compared to the low metaphor-producing group; again, the effect size ranged from large to very large (d= 1.02 to 3.32). Importantly, these results replicated across the two categories (animals and fruits/vegetables). Thus, the semantic networks of participants who produced more creative metaphors were characterized by shorter paths between nodes (lower ASPL), more connectivity between nodes (higher CC), and lower modularity (lower Q).

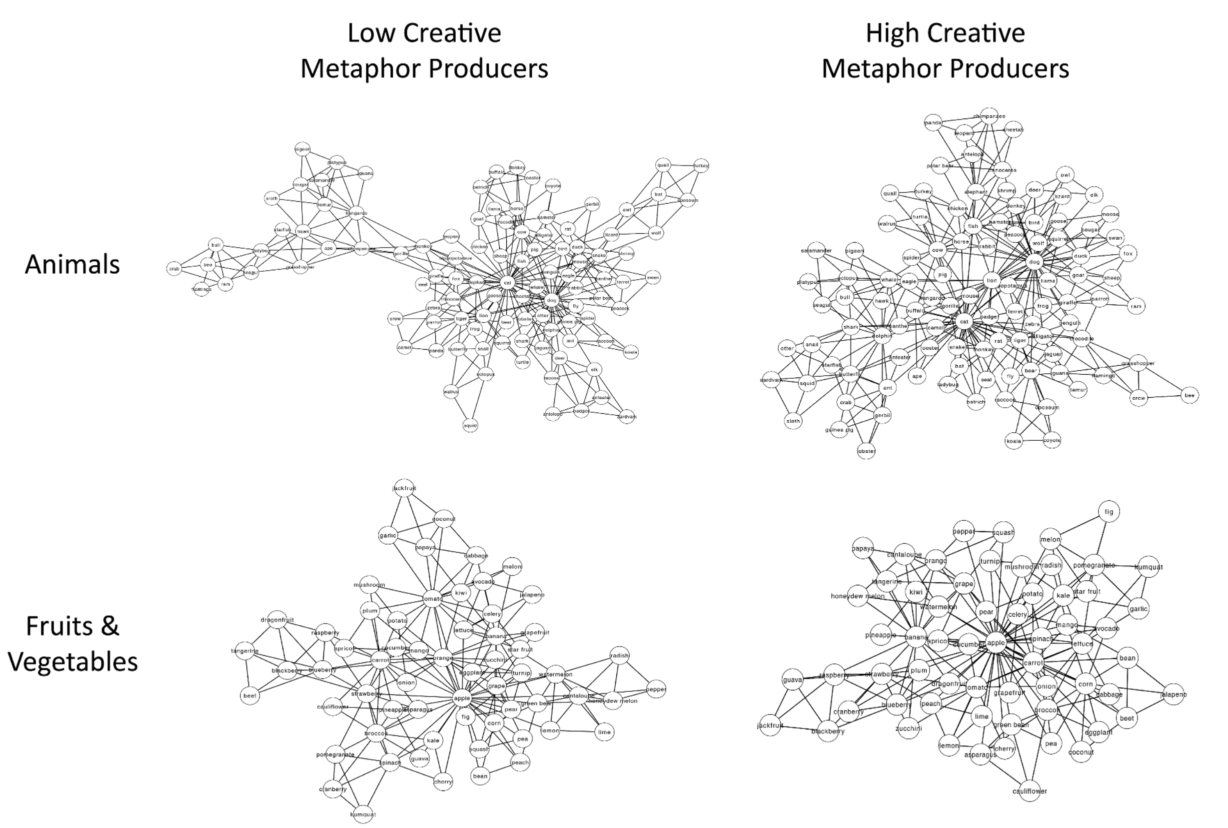

Figure 2. A 2D visualization of the semantic network of high and low creative metaphor-producing groups for two semantic categories.

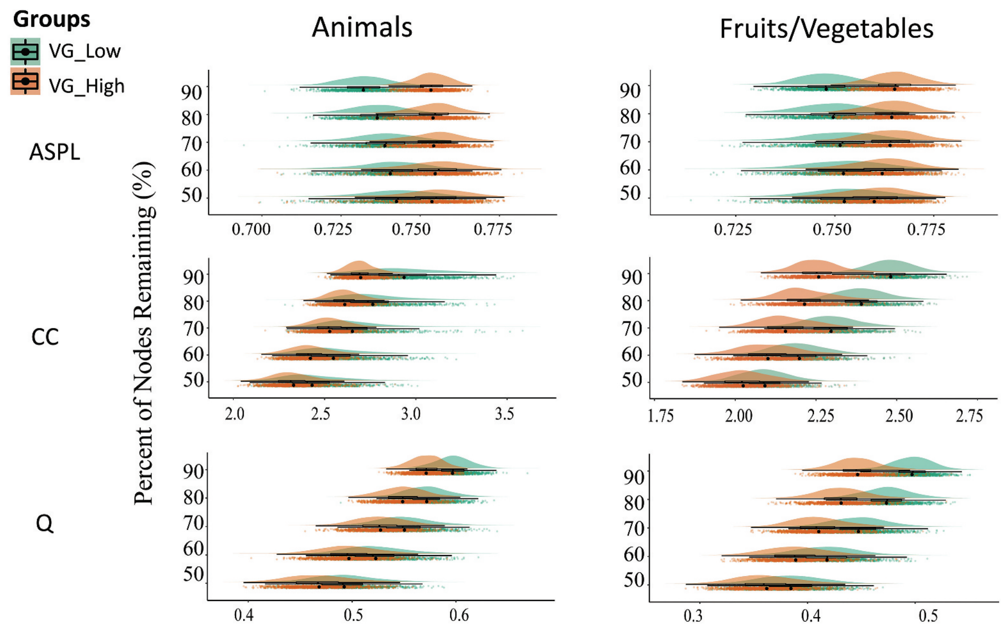

Figure 3. Plots of the bootstrapped partial network measures (1000 samples per nodes remaining percentage). Density plots are above the scatterplots (individual dots depict a single sample), with a black dot representing the mean. The y-axis denotes the percentage of nodes remaining (e.g., 90% = 90% nodes remaining in the bootstrapped sample). The x-axis denotes the network measure values.

Table 4. Partial bootstrapped network results for two semantic categories.

	Network Measures								
	ASPL			CC			Q		
Group and Notes Remaining	*t*	*d*	*p*	*t*	*d*	*p*	*t*	*d*	*p*
Animals									
90% (*df* = 1998)	37.00	1.66	< .001	−74.17	3.32	< .001	35.72	1.60	< .001
80% (*df* = 1998)	25.74	1.15	< .001	−52.48	2.35	< .001	26.13	1.17	< .001
70% (*df* = 1998)	19.72	.88	< .001	−39.78	1.78	< .001	21.44	.96	< .001
60% (*df* = 1998)	19.37	.87	< .001	−31.52	1.41	< .001	21.04	.94	< .001
50% (*df* = 1998)	16.18	.72	< .001	−22.69	1.02	< .001	18.34	.82	< .001
Fruits/vegetables									
90% (*df* = 1998)	71.39	3.19	< .001	−62.00	2.77	< .001	58.29	2.61	< .001
80% (*df* = 1998)	51.19	2.29	< .001	−45.44	2.03	< .001	42.28	1.89	< .001
70% (*df* = 1998)	40.03	1.79	< .001	−34.86	1.56	< .001	33.57	1.50	< .001
60% (*df* = 1998)	26.65	1.19	< .001	−25.38	1.14	< .001	23.80	1.06	< .001
50% (*df* = 1998)	20.18	.90	< .001	−19.37	.87	< .001	17.76	.79	< .001

1000 samples were bootstrapped for each percentage of nodes remaining. *t*-statistics and Cohen's *d* values are presented (Cohen, 1992). Negative *t*-statistics denote the high metaphor-producing group having *higher* values than the low metaphor-producing group. All *p*'s < .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.

Discussion

In the current study, for the first time, we capture, quantify, and compare the semantic memory structures of people with low and high creative metaphor production abilities using a computational network science approach. Our main finding was that the semantic networks of the high creative metaphor-producing group are more flexible and less rigid (smaller ASPL and Q), and more clustered (larger CC) than that of the low creative metaphor-producing group. Critically, these results replicated across two different semantic categories (animals and fruits/vegetables). The findings thus indicate that semantic knowledge is represented differently in high creative metaphor producers, which may promote their ability to search more remote and apt associations for vehicles to topics and in turn produce more creative metaphors.

As predicted, the semantic network of people with higher creative metaphor production ability had a smaller ASPL and Q, and a larger CC value. This "small-world" network is flexibly and efficiently structured (Kenett & Faust, 2019; Latora & Marchiori, 2001), characterized by high global/local efficiency, higher clustering, and lower modularity. In the context of semantic networks, these network properties relate to higher connectivity between weakly related concepts and a more broadly connected network (He et al., 2020; Latora & Marchiori, 2001). Such an efficient network organization may facilitate establishing apt common properties for both "topics" and "vehicles," thereby forming more creative metaphors. The qualitative analysis of the networks was quantitatively confirmed by the partial bootstrapped network results (Christensen & Kenett, 2019). Indeed, results from the partial bootstrapped networks were consistent with that of full networks, which revealed that the partial networks of high creative metaphor producers exhibited significantly smaller ASPL and Q, and larger CC, relative to the partial networks of the low creative metaphor producers, supporting the findings for the full networks. Additionally, the effect sizes ranged from moderate to very large, with the percentage of nodes remaining increasing from 50% to 90%, suggesting these differences of semantic networks between low and high creative metaphor groups are substantial.

Our results also highlight global differences in semantic memory network properties, regardless of metaphor ability. We found no differences in the average responses of the low and high creative metaphor groups for both categories. However, the number of *unique responses* within group differed in the fruits/vegetables category (but not for the animal category), indicating that high creative metaphor producers are able to retrieve more uncommon responses from their semantic memory structure, especially in categories with less strong associations (e.g., fruits/vegetables). Notably, we did not replicate previous work reporting differences in fluency between low and high creative groups (Christensen et al., 2018; Kenett et al., 2014), but we did replicate past work showing more unique responses in more creative individuals. These findings speak to the ongoing debate regarding the relative roles of semantic network structure vs. semantic retrieval processes. Future work should continue to examine the extent to which creative metaphor production is driven by semantic structure or executive retrieval abilities (cf. Benedek et al., 2013; Menashe et al., 2020).

Metaphor production and semantic memory

How do such rich semantic networks facilitate the production of creative metaphors? Based on the property attribution model, metaphor processing involves making an abstract link between two concepts – a "topic" and a "vehicle" (Glucksberg et al., 1997). Extending this view, people whose semantic network does not contain (or cannot establish) the necessary links between the "topic" and "vehicle" are less able to produce a highly original metaphor. This contention is supported by previous studies showing that print exposure (Chiappe & Chiappe, 2007) and crystallized intelligence/vocabulary knowledge (Beaty & Silvia, 2013) are important predictors of metaphor quality, highlighting the importance of both richer semantic networks and richer stores of general knowledge in establishing abstract links to produce more creative metaphors.

In the context of the property attribution model, the spreading-activation theory of semantic processing (Collins & Loftus, 1975) could provide insight into the process of creative metaphor production. In this view, memory search is theorized as activation spreading from a concept in memory to its directly connected concepts (or nodes) in a semantic network until an intersection is found. Thus, people with a richer memory structure (smaller ASPL and Q, and bigger CC) are better at searching nodes that are semantically distant (i.e., even located in the distinct regions of the network) or low-frequency concepts (Gray et al., 2019; Gruszka & Necka, 2002; Kenett & Austerweil, 2016). Hence, they are more efficient at finding and establishing such abstract links (e.g., common features between "topic" and "vehicle"). This view was supported by previous studies: people with a broader knowledge base can more effectively produce conventional metaphors (Chiappe & Chiappe, 2007) and people with higher verbal fluency (i.e., efficient knowledge retrieval) tend to produce more creative metaphors (Beaty & Silvia, 2013).

Additionally, the computational prediction model of metaphor comprehension (Kintsch, 2000) has been adapted to explain metaphor production (Chiappe & Chiappe, 2007). According to this theory, once the potential common features of the topic and vehicle in the semantic neighborhoods of topic properties are identified, they may be used to further search for an apt vehicle. Thus, individuals with more "rigid" or less rich semantic networks likely have greater difficulties searching many features of topic properties in the semantic neighborhoods, or they may "get stuck" within strongly connected properties surrounding the topic (Kenett et al., 2016; Siew, 2013). This may increase the difficulty to further reach an apt vehicle and thereby decreasing the possibility to produce a creative metaphor. Thus, our results provide important empirical support for classical linguistic theories of metaphor processing and semantic memory.

Metaphor, creativity, and semantic networks

In similar research on creativity, the same flexible network pattern was found in higher creative individuals (Kenett et al., 2014; Kenett & Faust, 2019). Regarding

ASPL, short path lengths indicate smaller distances and increased interconnectivity between concepts. According to the associative theory of creativity, creative individuals tend to show a richer and more flexible associative network than less creative individuals (Mednick, 1962). Several studies have found that higher creative individuals have a smaller ASPL compared to lower creative individuals (Kenett et al., 2014; Kenett & Faust, 2019). Similarly, Gray et al. (2019) applied a computational corpus-based measure of semantic distance to compute the semantic distance between pairs of associative responses in a chained free association task, and related these distances to individual differences in creativity. The authors show that higher creative individuals are able to search farther away through their memory and retrieve more remote chained free associations (Gray et al., 2019). In the current study, the shorter ASPL of high-metaphor producers may similarly allow them to establish distant connections between topics and vehicles, which is important for producing creative metaphor.

Regarding CC, our results revealed that the semantic networks of high creative metaphor producers were more clustered and exhibited greater local organization. Theoretically, the possibility a particular concept can be retrieved from the semantic network depends on the extent to which it is activated (Collins & Loftus, 1975; Klimesch, 1987). Thus, our results suggest that high creative metaphor producers have a higher likelihood of activating the near-neighbors of each node, thereby facilitating a broader search process through semantic space (Kenett & Austerweil, 2016; Marupaka et al., 2012). They thus could reach more rich features of "topics" and find more apt "vehicles" for producing more creative metaphors. High CC is consistently found in the semantic networks of high creative individuals (Kenett & Faust, 2019) and people higher in the personality trait openness to experience (Christensen et al., 2018). Additionally, previous studies found that people who produced more original ideas also identified word pairs as more related, especially for pairs of words being theoretically more distant (Bernard et al., 2019; Rossmann & Fink, 2010). Thus, for highly creative metaphor producers, theoretically more distant concepts appear closer in their semantic networks. Therefore, people who have higher local clustering and condensed semantic networks tend to have wider range of associations – properties that tend to be conducive to creative thought (Gruszka & Necka, 2002) – thereby facilitating a broader search process through semantic space and increasing the possibility of finding weak abstract links between "topics" and "vehicles.

We also found that the high-metaphor producers had a less rigid network, corresponding to fewer sub-networks (i.e., smaller Q). In semantic networks, Q reflects the extent to which a complex system could break apart into smaller sub-networks (Fortunato, 2010; Newman, 2006). So, the high the Q is, the more sub-networks the structure has. For example, people with Asperger syndrome have shown hyper-modular semantic networks, which may hinder their ability to break apart from a specific module in the network and spread into other modules, thus resulting in rigidity of thought (Kenett, Gold, et al., 2016). Similarly, the community structure of the phonological network found that the densely connected phonological modules (high Q) could "trap" spreading activation of phonological processing (Siew, 2013). Thus, the more modular the structure of the semantic network is, the less flexible it is.

In the present study, higher creative metaphor producers' network structure had smaller Q. Therefore, when searing for a creative metaphor, they may be better able to break from a specific module in the network and spread into other modules. This flexibility may help high-metaphor producers to find more apt, novel, and interesting properties for both the "topics" and "vehicles," thus producing a more creative metaphor. MacCormac (1986) proposed that, when comprehending a metaphor, if the organization of concepts is fixed and rigid in long-term memory, the semantic change necessary for metaphor comprehension becomes difficult (if not impossible). It seems plausible that similar principles underlie metaphor production, but future work is needed to examine the relation between metaphor comprehension and metaphor production.

Additionally, several studies have documented the role of Q in flexible thinking, which relates to inhibiting the restriction of the activation spread over semantic and phonological networks (Kenett et al., 2016; Siew, 2013). However, these studies suggest that high and low Q are probably beneficial to different cognitive processes. On the one hand, generally, higher modularity (usually in more structured networks) relates to fluid intelligence and language (Borodkin et al., 2016; Kenett et al., 2016). On the other hand, lower modularity is related to higher creative performance (Benedek et al., 2017; Kenett et al., 2014). Our results extend this work to the domain of metaphor production, further illustrating the need for higher flexibility in semantic memory to generate creative ideas.

In sum, our findings are consistent with previous studies using computational network science methods to study creative thinking (Benedek et al., 2017; Kenett et al., 2014; Kenett & Faust, 2019), providing quantitative evidence of differences in semantic networks associated with figurative language production.

Summary, limitations, and future directions

The present study contributes to our understanding of the role of semantic memory structure in metaphor production. Notably, our findings replicated across two semantic categories – high-metaphor producers showed the same flexible network structure in two categories, which differed significantly from low-metaphor producers – pointing to the robustness and generalizability of the results. At the same time, some potential limitations should be mentioned.

First, we used dichotomization to separate the groups. Dichotomizing a continuous variable (e.g., metaphor creativity) might cause potential issues, such as loss of information about individual differences, overlooking nonlinear relationships, and decreasing the effect size and power (MacCallum et al., 2002). Regarding individual differences, recently, some studies have developed a network approach to investigate the relationship between semantic networks and individual cognitive abilities (Benedek et al., 2017; He et al., 2020; Morais, Olsson, & Schooler, 2013). Thus, future research is needed to expand our approach to the analysis of individual semantic networks. As individual semantic networks are assumed to be stable and consistent (Morais et al., 2013), we predict that extracting the semantic networks of individuals with low and high-metaphor production ability will replicate the group findings. Additionally, as the relationship of semantic network measures (e.g., ASPL and CC) and verbal creativity was shown to be linear (Benedek et al., 2017; He et al., 2020; Kenett et al., 2016), the potential nonlinear issue of dichotomization in the present study may be minimal. Meanwhile, the large effect size found in current study indicates that the dichotomization may not have exerted much influence.

Second, although we found group differences in the structure of semantic networks, the fluency tasks used to construct these networks require selective retrieval processes. To address the process vs. structure question, and to rule out the role of process in constructing semantic networks, future research should employ semantic tasks that do not place strong demands on controlled retrieval processes (e.g., semantic similarity tasks; Kenett et al., 2017). Another potential limitation concerns the quantification of metaphor quality via subjective human raters. Although this approach is common in creativity assessment, the findings may be strengthened by employing objective assessments of creative quality, such as computational measures of semantic distance (Beaty & Johnson, 2020).

In summary, the current study quantitatively examined the differences in semantic memory network organization between lower and higher creative metaphor producers. The findings provide the first evidence that a flexible, clustered, and less rigid semantic memory structure relates to people's ability to produce figurative language (such as creative metaphors), extending the growing literature on the role of semantic networks in creativity to the domain of metaphor production. Further, our results provide important support for classic linguistic theories on metaphor and semantic memory.

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