Convergent Thinking and Insight Problem Solving Relate to Semantic Memory Network Structure

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Abstract

The associative theory of creativity has long held that creative thinking involves connecting remote concepts in semantic memory. Network science tools have recently been applied to map the organization of concepts in semantic memory, and to study the link between semantic memory and creativity. Yet such work has largely overlooked the domain of convergent thinking, despite the theoretical importance of semantic memory networks for facilitating associative processes relevant for convergent problem solving (e.g., spreading activation). Convergent thinking problems, such as the Compound Remote Associates (CRA) test, can be solved with insight (the sudden "aha" experience) or analysis (deliberately and incrementally working towards the solution). In a sample of 477 participants, we adopted network science methods to compare semantic memory structure across two grouping variables: 1) convergent thinking ability (i.e., CRA accuracy), and 2) the self-reported tendency to solve problems with insight or analysis. Semantic memory networks were constructed from a semantic fluency task, and problem solving style (insight or analysis) was determined from judgments provided during solving of CRAs. We found that, compared to the low-convergent thinking group, the high-convergent thinking group exhibited a more flexible and interconnected semantic network—with short paths and many connections between concepts. Moreover, participants who primarily solved problems with insight (compared to analysis) showed shorter average path distances between concepts, even after controlling for accuracy. Our results extend the literature on semantic memory and creativity, and suggest that the organization of semantic memory plays a key role in convergent thinking, including insight problem solving.

Keywords: convergent thinking; insight; problem solving; remote associates test; semantic networks

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The associative theory of creativity posits that creative thinking ability relates to differences in how people organize and combine concepts in memory (Mednick, 1962; but see Benedek & Neubauer, 2013). This theory has received recent support from research adopting computational network science methodologies, exposing differences in semantic memory structure—the organization of facts and concepts in human memory (McRae & Jones, 2013; Kumar, 2021)—between individuals varying in real-life creative achievement (Kenett et al., 2016; Ovando-Tellez et al., 2022) and divergent thinking (DT; Benedek et al., 2017; He et al., 2020; Kenett et al., 2014; Kenett & Faust, 2019). DT is the ability to generate multiple novel and appropriate ideas; it is generally considered an expansive creative process, and is broadly measured via tasks which allow several appropriate solutions (Guilford, 1967; Reiter-Palmon et al., 2019). On the other hand, convergent thinking (CT) is the ability to produce the correct solution to a problem; it is a creative process characterized by a narrowing of possibilities, measured by tasks which require homing into a single correct solution (Cortes et al., 2019; Guilford, 1967).

To date, however, it remains unclear how semantic memory network structure relates to performance on creative tasks requiring CT. Furthermore, it is unknown whether semantic memory network structure relates specifically to the phenomenon of insight—a common problem solving strategy characterized by the spontaneous awareness of an idea, also known as the "aha" experience (DeYoung et al., 2008). As some people are more prone to solving CT problems with insight, instead of deliberate, analytical thinking, it is possible that specific structural properties of semantic memory, such as stronger connections between concepts, may facilitate insight problem solving (Schilling, 2005). Specifically, individuals with more interconnected and flexible semantic memory structures may benefit from atypically short distances between semantically distant concepts (i.e., words that are largely unrelated in meaning) and increased randomness in the relations between concepts, leading to the retrieval of correct solutions to insight problems.

In the present research, we adopt network science methods to model semantic memory structures (1) related to performance on a convergent thinking task, and (2) related to the strategy (either insight or analysis) used to solve CT problems. Analysis is a stepwise and logical problem solving strategy that stands in opposition to the suddenness of insight (Metcalfe & Wiebe, 1987; Newell & Simon, 1972), allowing us to examine whether insight problem solving is specifically linked to semantic memory structure. Altogether, our goal was to extend research on the role of memory in creative problem solving (Gerver et al., 2022) by exploring how semantic memory structure relates to CT ability and insight problem solving.

The Associative Theory and Semantic Memory Networks

In the associative theory of creativity (Mednick, 1962), creative thinking involves the ability to connect semantically distant concepts stored in long-term memory (cf. Kenett & Faust, 2019). Mednick further proposed that the memory structures of highly creative individuals are characterized by "flatter" associative hierarchies (i.e., equally strong associations between similar and dissimilar concepts), as opposed to "steeper" associative hierarchies (i.e., stronger associations between more similar concepts, such as *table-chair*; Mednick, 1962). Following Mednick, researchers have posited that the semantic memory structure of highly creative individuals should be characterized by relatively few clusters of tightly interconnected concepts (Rossman & Fink, 2010). However, empirical tests of the associative theory have been historically limited, due to the challenges of modeling the structure of semantic memory (Benedek & Neubauer, 2013).

Recently, the application of quantitative network science methods has allowed researchers to directly examine the relationship between semantic memory structure and creativity. Network science is based on mathematical graph theory, which represents complex systems as graphs, or networks (e.g., Börner et al., 2008; Newman et al., 2006). A network is composed of nodes (e.g., semantic concepts) connected via edges (e.g., semantic similarity between two concepts). Network science tools have received increasing attention in the cognitive sciences (Baronchelli et al., 2013; Hills & Kenett, 2021; Siew et al., 2019), having been adopted as a valuable tool in the studies of semantic memory (Castro & Siew, 2020; Faust & Kenett, 2019; Hills & Kenett, 2021; Kenett & Thompson-Schill, 2020; Morais et al., 2012; Siew et al., 2019), language (Beckage et al., 2011; Solé et al., 2010; Hudson, 2007), and human learning (Karuza et al., 2016, 2019), among other constructs (for a review, see Siew et al., 2019).

Commonly assessed measures of network properties include the clustering coefficient (CC), average shortest path length (ASPL), and modularity (Q). In semantic networks, edges denote the semantic similarity between concepts (nodes). CC measures the network's local connectivity—it refers to the probability that two neighbors of a node will themselves be neighbors (a neighbor is a node *i* that is connected through an edge to node *j*). A higher CC reflects higher overall local connectivity in the network (Siew et al., 2019). ASPL is a measure of the average shortest number of steps needed to be taken between any pair of nodes, so higher ASPL is reflected in a more spread out network. Research on semantic networks has shown that ASPL predicts participants' judgments regarding whether two concepts are related to each other, with lower ASPL for more closely related concepts—indicating that semantically related concepts are stored closer together in semantic networks (Kenett et al., 2017). Q measures how a network breaks apart (or partitions) into smaller sub-networks (or "communities"), such that larger Q reflects communities that are more distinct and separate from each other within a network (Newman, 2006). Such communities may reflect semantic categories in a semantic network (e.g., animals, vehicles, foods).

In the context of creativity, numerous studies have shown that individuals with stronger DT abilities—people who generate more original ideas on open-ended tasks—exhibit a "small-world" semantic memory structure marked by a shorter ASPL, smaller Q, and larger CC (Benedek et al., 2017; Denervaud et al., 2021; He et al., 2020; Kenett et al., 2014; Watts & Strogatz, 1998), which relates to higher flexibility (Kenett, Levy et al., 2018) and higher efficiency (He et al., 2021) of the semantic networks. This more flexible and efficient semantic memory structure has also been linked to higher-order linguistic expressions, such as creative metaphor production (Li et al., 2021) and comprehension (Kenett, Gold et al., 2018). A study simulating search processes over semantic memory networks—via a "random walk" initiated within the semantic memory network of highly creative individuals, compared to that of less creative individuals—showed that the random walk over the high-creative semantic memory network accessed more novel concepts and exhibited more long-distance travel (Kenett & Austerweil, 2016). Recently, it has been also found that such a richer, more flexible semantic memory structure also relates to higher real-world creative achievement (Ovando-Tellez et al., 2022). Altogether, network science investigations of creative thinking have exposed a more flexible semantic memory network structure—marked by higher connectivity, shorter paths between concepts, and less modularity—potentially facilitating the ability to connect distant concepts when thinking creatively.

Convergent Thinking and Insight Problem Solving

To date, the study of semantic memory structure and creativity has predominantly focused on DT, providing empirical support for the associative theory of creativity (Mednick, 1962). Much less is known, however, about the role of semantic memory structure in CT. To test his associative theory of creativity, Mednick developed the Remote Associates Test (RAT), which presents three words (e.g., *cream-skate-water*) and requires participants to think of a fourth word that conceptually unites them (i.e., *ice*). The RAT is now primarily thought to engage CT because it requires "converging" on the single correct solution (Lee et al., 2014). The RAT, and CT more broadly, involves the retrieval and combination of remote semantic associations relevant to the problem context (Mednick, 1962). RAT problem difficulty depends on the remoteness of the associations between its items, with harder problems having more semantically distant items (Marko et al., 2019). Thus, the ability to solve CT problems like the RAT may depend in part on an individual's semantic memory structure: if remote concepts have more connections and are represented "closer" to each other in semantic networks, it should be easier to solve RAT problems (He et al., 2020). This point is particularly relevant when considering recent views that creative cognition engages both an initial divergent (i.e., generative) process, wherein the representational space is expanded during broad memory search, and a later convergent (i.e., evaluative) process, involving the narrowing down of alternatives to a single response (Smith et al., 2013). Taken together, we may expect similar relationships to exist between CT and semantic memory network structure as those that have been demonstrated for typical DT tasks (Benedek et al., 2017; Denervaud et al., 2021; He et al., 2020; Kenett et al., 2014).

CT tasks such as the RAT are thought to be undertaken via two different mental strategies: analysis and insight (Bowden, 1997). *Analysis* is considered a deliberative process, involving a logical, stepwise progression, where people systematically search memory for potential solutions (Metcalfe & Wiebe, 1987; Newell & Simon, 1972). *Insight*, in contrast, is considered a phenomenological experience of suddenness with which the correct solution spontaneously pops into mind, termed an “aha” moment (Lehrer, 2008; Mayer, 1992, 1995). Insight problems frequently elicit the self-reported “aha” experience, including the RAT (Bowden et al., 2005; Chein & Weisberg, 2014; Mayer, 1995; Pols, 2002) and other classic insight problems (e.g., the nine-dot problem; Ansburg, 2000; Cunningham et al., 2009). The compound remote associates (CRA) test is a modern variation of the RAT, designed to illicit both insightful and analytical problem solving strategies (Bowden & Jung-Beeman, 2003a; Bowden et al., 2005; Jung-Beeman et al., 2004). Notably, people who more often use insight to solve CRA problems generally solve more problems than people who tend to use analysis (Ellis et al., 2021; Salvi et al., 2016).

Individual differences research has revealed several cognitive factors that may support CT performance (Sawyer, 2011). For example, CRA accuracy is strongly predicted by crystallized intelligence—the ability to employ general knowledge (e.g., vocabulary) to solve problems (Cattell, 1963)—over and above other cognitive abilities (Ellis et al., 2021). More broadly, CT has been associated with working memory capacity and executive control (Chein & Weisberg, 2014; Ellis & Brewer, 2018), raising questions about the extent to which CT tasks (e.g., the RAT) measure intelligence or creativity (Lee & Therriault, 2013; see also Beaty, Nusbaum et al., 2014). Working memory capacity has been shown to explain over half of the variance in insight problem solving performance (Chuderski & Jastrzębski, 2018), although the predictive nature of working memory has been noted to be lower for insight compared to non-insight problems (Gilhooly & Webb, 2018). The link between working memory and insight may nevertheless be driven by fluid intelligence—the ability to flexibly utilize strategies to solve problems (DeYoung et al., 2008)—which holds a strong predictive value over both insight problem solving (Davidson, 2003; Schooler & Melcher, 1995) and working memory capacity (Kane et al., 2005).

Despite links between intelligence and insight, the relationship between knowledge and insight remains unclear, although the question may be addressed by using network science to measure the structure of semantic memory. It has previously been suggested that the generation of novel semantic associations, and specifically those required for insight problem solving, are reliant on a “small-world” semantic memory network structure (Schilling, 2005)—characterized by high interconnectedness and flexible relations between concepts (i.e., high CC and low ASPL). Additionally, task difficulty on the CRA has linked to knowledge constraints defined by the task items, as well as to the size of the semantic search space, wherein an overly large search space has been shown to hinder insight problem solving (Becker et al., 2020; Bowers et al., 1990). Insight problem solving has also been associated with knowledge restructuring, with proposals that overcoming fixation (i.e., the influence of prior information) or an impasse on a problem is dependent on a reorganization between semantic items (Ohlsson, 1984), and that any such ability to “break out of frame” is central to individual differences in insight (DeYoung et al., 2008). Indeed, it was demonstrated that individuals who performed better on CT problems (riddles which required overcoming a usual representation to solve) showed a dynamic restructuring of semantic networks only in parts of the network which were relevant to solving the problem (Bieth et al., 2021). These results provide empirical support for the model of insight proposed by Schilling (2005)—that insight problem solving is supported by a flexible restructuring of semantic memory networks, which creates a “shortcut” that decreases the distance (e.g., ASPL) and increases the connections (e.g., CC) between concepts.

Considering the strong links between executive abilities and CT performance, and the limited empirical support that semantic memory plays a role in CT, individual differences accounts of CT remain incomplete. Moreover, the RAT—the most common assessment of CT—was initially developed by Mednick (1962) to investigate associative semantic hierarchies. Yet it remains unclear whether RAT performance actually relates to such associative memory structures, given the lack of empirical work directly examining semantic memory structure and CT. Likewise, how the organization of concepts in semantic memory relates to insight problem solving remains unclear.

The Present Research

The associative theory of creativity (Mednick, 1962) posits that creative thinking involves the combination of semantically distant concepts stored in long-term memory. With regards to semantic memory, the associative theory predicts that highly creative individuals are characterized by many connections between semantically distant concepts, suggesting that the organization of concepts in semantic memory supports the ability to think creatively and solve problems. Although semantic memory structure has been linked to performance on DT tasks (Benedek et al., 2017; He et al., 2020; Kenett et al., 2014; Kenett & Faust, 2019), to date, its role in CT and insight is unclear. In the present study, we aimed to address this question by modeling semantic memory network organization in a large sample of participants who completed the CRA ($N = 412$). Participants also indicated if they solved each CRA problem with insight or analysis, allowing us to specifically test whether semantic memory network structure differs in people who tend to solve problems using insight instead of an analytical strategy. Given prior theorizing on the links between insight and semantic memory network structure (Schilling, 2005), and empirical work reporting associations between memory structure and DT (Benedek et al., 2017; He et al., 2020; Kenett et al., 2014), we expect the semantic memory networks of individuals with high CT ability—including those reporting higher proportion of insight solutions—to show a more flexible and interconnected semantic memory network structure (i.e., higher CC and lower ASPL and Q).

Methods

Participants

A total of 491 participants were recruited as part of a larger study at Arizona-State University (see Ellis et al., 2021). Participants were tested on a large battery of cognitive tasks over two separate 2-hour sessions in a laboratory setting. 477 participants who completed either the semantic fluency or the CRA task were retained in the final sample. Several participants were further removed: Those who scored below 2 standard deviations on the animal fluency task ($N = 11$) or on the CRA ($N = 20$), and others who did not complete both the animal fluency task and the CRA ($N = 34$), A total of 412 participants were retained for further analysis ($M = 19.21$, $SD = 1.90$; 49.0% male; 50.0% female; 1.0% NA).

Materials

Compound Remote Association Test. A total of 30 items were presented to participants for the CRA, selected from a larger scaled item list developed by Bowden and Jung-Beeman (2003b). The CRA presents three cue words (*cream, skate, water*); participants are instructed to find the target solution, i.e., a single word that produces a real compound word with each of the three cues independently (*ice*). For each trial, participants were given 30s to generate a solution, with responses allowed after 5s from the start of the trial. All items were selected so that every cue and response appeared only once within the entire item set, as either cue or correct solution. Following each trial on the CRA, participants reported the mental strategy they used during that problem by answering a single question asking them to rate on a 4-point Likert scale whether they used a primarily insight or analysis strategy (1 = *full analysis*; 2 = *partial analysis*; 3 = *partial insight*; 4 = *full insight*; see Chein & Weisberg, 2014). For our statistical analyses, we collapsed across the first two levels (1 = *full analysis*; 2 = *partial analysis*) of the strategy scale to generate a single level defining high analysis strategy, and the last two levels (3 = *partial insight*; 4 = *full insight*) to generate a single level defining high insight strategy.

Animal Fluency Task. A total of 3 minutes was allowed for the completion of the animal fluency task (Ardila et al., 1996). During the task, participants were asked to generate as many animal names as possible, and to continue working until the time ran out. Responses were individually typed by the participant into a computer, and the Enter key was pressed to submit each response. The animal fluency task is the most widely used task to estimate group-based semantic networks (Christensen & Kenett, 2021).

Group Construction

Constructing semantic memory networks from fluency data is commonly analyzed over aggregated, group-based data (but see Benedek et al., 2017; Wulff et al., 2022; Zemla et al., 2020, for approaches to constructing individual-based networks). To model semantic networks associated with CRA performance, participants were first separated into 2 groups via a median split based on their accuracy on the CRA. We removed participants at the median amount of accuracy (N = 52) to construct well-defined groups and address "boundary" cases (i.e., participants at the median do not belong in either the "high" or "low" group; see Irwind & McClelland, 2003). This resulted in a high CT ability group (N = 176) and a low CT ability group (N = 186) for semantic network analysis based on overall CRA accuracy.

In a subsequent analysis of problem solving strategy, we separated participants across two dimensions of *insight* and *analysis* (i.e., low- and high- insight and analysis). We first removed trials on the CRA where an incorrect solution was provided (29% of all responses), as these trials were not informative of the problem solving strategy adopted for reaching a complete solution. Frequency of proportions of insight and analysis was then calculated by scoring the use of each problem solving strategy by participants. We then separated participants via a median split into low- and high- *insight* groups, as well as low- and high- *analysis* groups. Some participants were removed (N = 52) because they had a median level of problem solving strategy use for analysis (N = 20), insight (N = 29), or both (N = 3). Participants were assigned to one of four groups: high-insight/high-analysis (N = 57); high-insight/low-analysis (N = 132); low-insight/high-analysis (N = 133); and low-insight/low-analysis (N = 38). Importantly, we only retained the high-insight/low-analysis and low-insight/high-analysis groups for further analysis because 1) we only had hypotheses about these two groups and 2) we aimed to avoid confounds arising from having unequal sample sizes between the four groups.

All data used in this study as well as the preprocessing pipeline that was adopted is openly available on GitHub: https://anonymous.4open.science/r/dataandpreprocessing-D509/README.md

Semantic Network Estimation

The semantic fluency data was preprocessed and analyzed as semantic networks via the SemNA pipeline (Christensen & Kenett, 2021)—a recently developed, open-access pipeline for estimating and analyzing semantic network structure from semantic fluency data—using the following steps:

Preprocessing. Two R packages were used to automatically preprocess the semantic fluency data: *SemNetDictionaries* (version 0.2.0; Christensen, 2019a) and *SemNetCleaner* (version 1.3.4; Christensen, 2019b). First, within-participant repetitions (i.e., same responses provided more than once) and any non-category members (e.g., dragon, ant colony, moon) were removed from the data. Next, other potential errors in the responses were corrected, such as spelling errors, compound responses, root word variations, and continuous strings. Words that were not recognized by the software were then manually spell checked and corrected accordingly to standard English by a researcher. Next, the cleaned data was transformed into a binary response matrix, with columns representing each unique response given across participants, and rows representing individual participants. The response matrix included values of either 1 (i.e., participant *i* generated exemplar *j*) or 0 (i.e., participant *i* did not generate exemplar *j*). Response exemplars in the binary matrix included only those that were provided by at least two participants in the overall sample, a procedure that has been shown to allow for better control of confounding factors (e.g., differences in the number of nodes and edges between groups; Borodkin et al., 2016; Christensen et al., 2018). To further control for the confound of including a different number of nodes between the groups (van Wijk et al., 2010), responses across the binary matrices were equated, retaining for each group only those responses that were provided by the other groups. Thus, all the semantic network analyses in the present study only consider differences in the *organization of the same nodes* between semantic networks.

Network Construction. We computed association profiles for the CRA groups between the fluency responses using the *SemNeT* (version 1.4.4) package (Christensen & Kenett, 2021) in R (version 4.2.0) using R studio (version 2022.02.3). We conducted two separate network analyses: 1) CRA accuracy based (low- vs. high- CRA accuracy), and 2) CRA problem solving strategy-based (high-insight/low-analysis vs. low-insight/high-analysis) while controlling for accuracy. To estimate edges in the networks, we employed the cosine similarity function in the *SemNeT* package to generate an n x n adjacency matrix (i.e., associations between each response) for each group (Christensen et al., 2018). Cosine similarity is an established method for calculating the angle of two vectors in an abstracted space and is commonly adopted in latent semantic analysis of text corpora (Landauer & Dumais, 1997) and related methods of semantic distance computation (Beaty & Johnson, 2021). Cosine similarity defines the co-occurrence probability of two words abstracted as normalized vectors. Ranging from 0 to 1, a cosine similarity of 1 represents two words that always co-occur, while a value of 0 represents two words that never co-occur.

Using the *SemNeT* package, we then applied the triangulated maximally filtered graph (TMFG; Christensen et al., 2018; Massara et al., 2016) to the adjacency matrix for each group. TMFG, which captures only the most reliable relations within the cosine-determined networks, excludes spurious associations from the final networks (Christensen et al., 2018). Specifically, TMFG applies a structural constraint on the association matrix, constraining the number of edges retained in the final networks.

Network Analysis. To analyze the networks, we first compared the network metrics CC, ASPL, and Q of all empirically generated networks against those of randomly generated networks, conducting the analysis separately for the CT accuracy-based and problem solving strategy-based groupings. We then implemented a case-wise bootstrap analysis (Efron, 1979) to analyze potential differences in the semantic memory network structure between-groups. The bootstrapping approach serves as a test of significance for the network comparisons, evaluating whether any differences are above-chance (as group-based calculations of network metrics only provide a single value per group). Bootstrapping was conducted via the *SemNeT* package in R (Christensen & Kenett, 2021), with 1000 iterations. Networks for resampled group were generated separately for each network, using with-replacement bootstrapping (Bertail, 1997). Network measures (CC, ASPL, and Q) were calculated for each resampled group's network. For the low- and high- CT accuracy-based network analysis, we compared the two networks by conducting an independent-samples *t*-test analyses for each network metric. We then used ANCOVAs, controlling for CRA accuracy, for the problem solving strategy-based network analysis, to examine differences in the network metrics between the high-insight/low-analysis and low-insight/high-analysis groups.

Results

Fluency and Accuracy

We began by testing for potential group differences in fluency (on the animal fluency task) and accuracy (on the CRA) across both analyses (**Figure 1** and **Table 1**). We found a significant

	CRA	Animal Fluency Task			
		n (average)		*n*	*n*
Group	*M (SD)*	*M (SD)*	Range	(within)	(between)
high CT	38.7 (10.2)	38.8 (10.3)	13-71	426	63
low CT	30.8 (9.91)	32.4 (8.09)	13-61	482	119
high-insight/low-analysis	12.7 (4.33)	33.4 (8.77)	14-71	438	66
low-insight/high-analysis	9.5 (3.99)	35.8 (10.30)	13-59	404	46

Table 1. *Descriptive statistics for the CRA and Animal Fluency Task*

Note. n (average) = the average number of responses in each group; n (within) = the total unique number of responses given by individuals within the group; n (between) = the total unique number of responses not given by the other groups.

effect of CT ability on fluency: people in the high CT group (M = 38.8) generated more responses in the animal fluency task than people in the low CT group (M = 32.4), $t(361) = -6.52$, $p < .001$, $\eta 2 = .10$, 95% CI [-8.21, -4.41]. For problem solving strategy, we found a significant effect on fluency, such that people in the high-insight/low-analysis group (M = 35.8) generated more responses on the animal fluency task than those in the low-insight/high-analysis group (M = 33.4), $t(264) = -2.07$, $p = .04$, $\eta 2 = .02$, 95% CI [-4.75, -0.12]. To avoid differences in fluency between the groups from influencing semantic network comparisons, all semantic networks were matched on number of nodes and edges in the network analyses (Kenett & Christensen, 2021).

Regarding CRA accuracy, as expected, there was a significant effect of CT ability on accuracy: people in the high CT group (M = 38.7) scored more accurately on the CRA than people in the low CT group (M = 30.8), $t(361) = -31.02$, $p < .001$, $\eta 2 = .73$, 95% CI [-8.37, -7.38]. We also found an effect of problem solving strategy on CRA accuracy, such that individuals in the high-insight/low-analysis group (M = 12.7) scored more accurate responses on average than those in the low-insight/high-analysis group

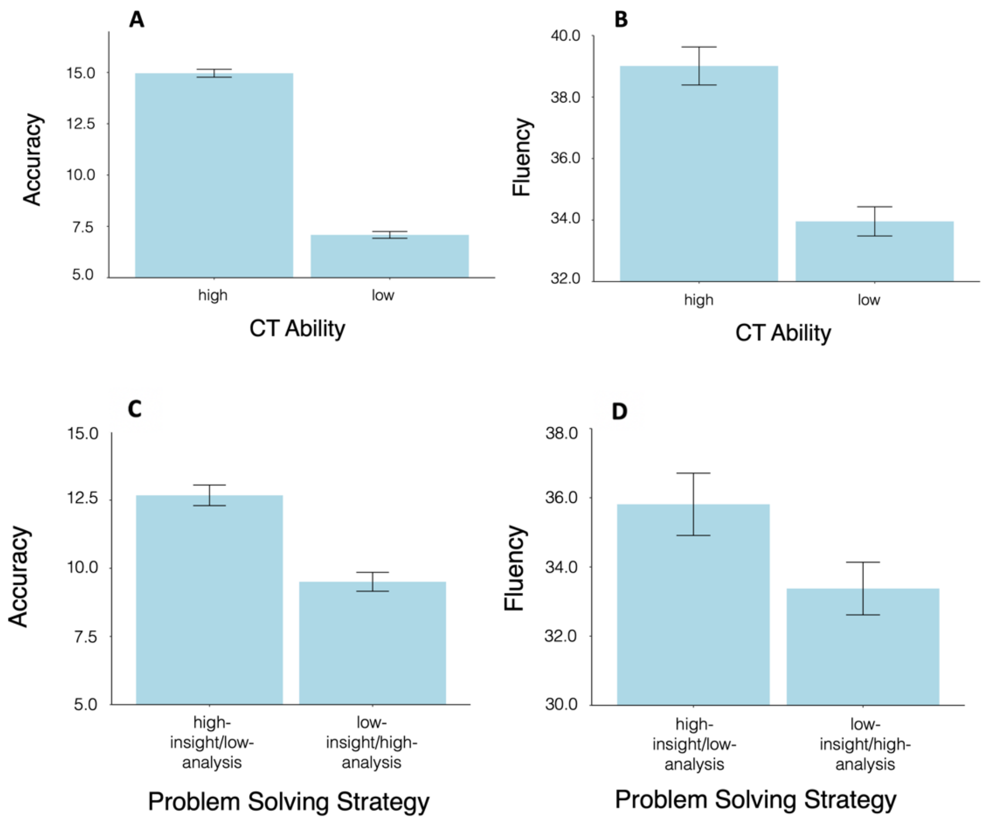

Figure 1. *Plot of Accuracy on the CRA and Fluency on the Animal Fluency Task.*

Note. Mean Accuracy on the CRA (A) and Fluency on the animal fluency task (B) for each of the 2 CT ability groups; Mean Accuracy on the CRA (C) and Fluency on the animal fluency task (D) for each of the 2 problem solving strategy groups.

($M = 9.5$), $t(264) = -6.20$, $p < .001$, $\eta 2 = .13$, 95% CI [-4.18, -2.16]. This pattern replicates past work showing higher CRA accuracy associated with insight (Ellis et al., 2021; Salvi et al., 2016).

CT Ability-based Semantic Network Analysis

Next, we examined semantic memory networks in the CT ability groups. We computed the semantic memory networks and the properties of these networks; this led to semantic networks with 283 nodes. The networks were visualized via Cytoscape 3.9.1 (Shannon et al., 2003; **Figure 2**), generating 2D representations of unweighted and undirected networks, where circles represent concepts and lines represent the links between concepts.

	M				
Parameter	high CT group	low CT group	*t*	*p*	*d*
ASPL	4.24	4.87	32.90	< .001	1.47
CC	0.73	0.72	-34.86	< .001	1.56
Q	0.72	0.74	41.22	<. 001	1.84

Table 2. *Results from a 1000 iteration bootstrapping and two-samples t-test.*

Note. Means of each group are presented for all network parameters. t-statistics and Cohen's d values are presented (Cohen, 1992). 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.

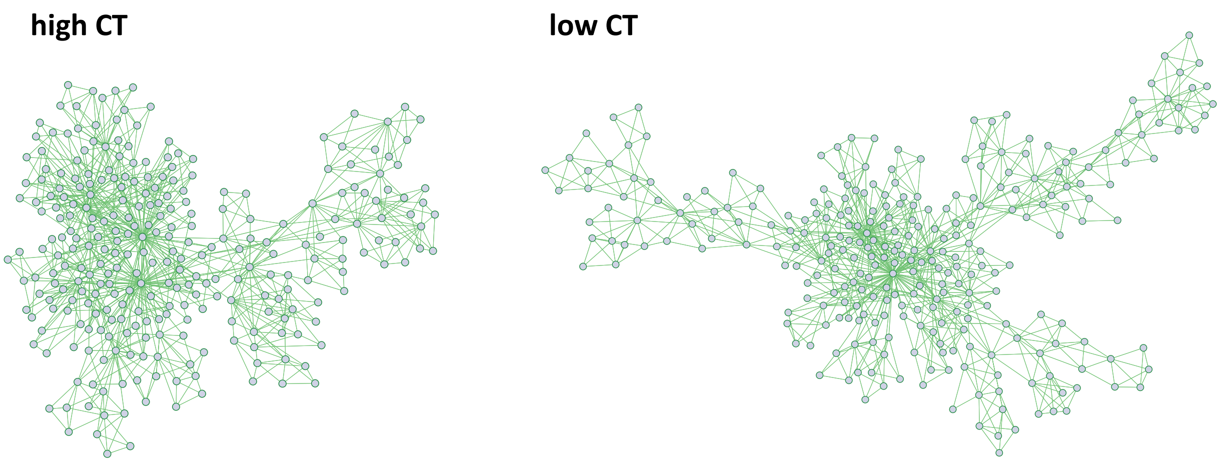

Figure 2. *A 2D visualization of the semantic network of individuals with high convergent thinking (CT) and low CT ability.*

Note. Circles represent nodes (i.e., concepts) which are connected by edges based on the strength of the semantic associations between concepts in each group.

We first tested whether the semantic networks of the low- and high- CT groups were significantly different from random networks with the same number of nodes and edges. This random network analysis revealed that, for both groups, and for all network metrics (CC, ASPL, & Q), the empirically generated semantic networks were significantly different from randomly generated networks (all p's < .001).

We then conducted the critical test of whether the low- and high- CT ability groups were significantly different from each other (**Table 2**). An independent-samples *t*-test revealed that the high CT group exhibited a shorter ASPL (M = 4.24) than the low CT group (M = 4.87), t (1998) = 33.09, $p < .001$, $d = 1.48$. Further, the high CT group had a significantly higher CC (M = 0.73) than the low CT group (M = 0.72), t (1998) = -34.62, $p < .001$, $d = 1.55$. Lastly, the high CT group had a significantly lower Q (M = 0.72) than the low CT group (M = 0.74), t (1998) = 39.56, $p < .001$, $d = 1.77$.

Altogether, compared to the low CT group, the semantic memory network of the high CT group was significantly more connected (higher CC), with shorter average paths (lower ASPL) and fewer communities (lower Q).

Problem Solving Strategy-based Semantic Network Analysis

Next, we examined semantic memory networks in the problem solving strategy groups. As noted above, because the sample sizes across our four problem solving groups were unequal, we ran a pairwise comparison of semantic networks across only two of the problem solving groups: the high-insight/low-analysis and low-insight/high-analysis groups. Of note, these two groups were largely matched in terms of sample sizes, N = 132 and N = 133 respectively, and they are the most informative for drawing comparisons between insight and analysis strategies. Because high-insight participants tended to solve more CRA problems overall, we controlled for accuracy when computing semantic memory networks and the associated parameters of these two networks, leading to semantic memory networks with 251 nodes. The networks were visualized via Cytoscape 3.9.1 (**Figure 3**), generating 2D representations of unweighted and undirected networks.

We first tested whether the semantic networks of the high-insight/low-analysis and low-insight/high-analysis groups were significantly different from random networks. This random network analysis revealed that for both groups, and for all network metrics (CC, ASPL, & Q), the empirically

Parameter	*M*		F	p	η^2
	high-insight/ low-analysis	low-insight/ high-analysis			
ASPL	4.56	5.14	42.37	< .001	= 0.021
CC	0.718	0.718	0.08	= .777	< 0.001
Q	0.74	0.75	3.69	= .055	= 0.002

Table 3. Results from a 1000 iteration bootstrapping and ANCOVA controlling for accuracy.

Note. Means of each group are presented for all network parameters. t-statistics and effect sizes are presented; η^2, partial eta squared. ASPL, average shortest path length; CC, clustering coefficient; Q, modularity.

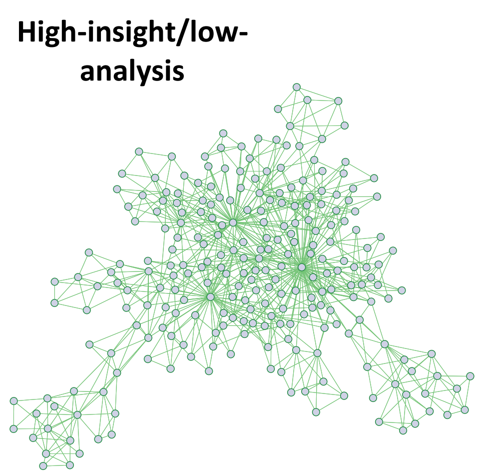

Figure 3. *A 2D visualization of the semantic network of individuals in the high-insight/low-analysis and high-insight/low-analysis groups.* Circles represent nodes (i.e., concepts) which are connected by edges based on the strength of the semantic associations between concepts in each group.

generated semantic networks were significantly different from randomly generated networks (all p's < .001). We then compared the semantic networks with a series of between-groups ANCOVAs, controlling for CRA accuracy, running pairwise comparisons networks across only two of the problem solving groups: the high-insight/low-analysis and low-insight/high-analysis groups (**Table 3**).

An ANCOVA, controlling for accuracy, revealed that the high-insight/low-analysis group exhibited a shorter ASPL (M = 4.56) than the low-insight/high-analysis group (M = 5.14), F (1996) = 42.37, $p < .001$, $\eta^2 = 0.021$. No significant difference in CC was observed between the high-insight/low-analysis (M = 0.718) and the low-insight/high-analysis group (M = 0.718), F (1996) = 0.08, $p = .777$, $\eta^2 < 0.001$. We further observed no significant difference in Q between the high-insight/low-analysis group (M = 0.74) and the low-insight/high-analysis group (M = 0.75), F (1996) = 3.69, $p = .055$, $\eta^2 = 0.002$. Thus, people who tended to solve problems with insight exhibited a semantic memory network with shorter paths between concepts than people who tended to solve problems with analysis.

Discussion

The associative theory of creativity proposes that people's ability to think creatively is based on their ability to connect distant concepts stored in a more flexible semantic memory structure. Network science has provided empirical support for this view, showing that semantic memory structure supports DT ability (Benedek et al., 2017; He et al., 2021; Kenett et al., 2014; Kenett & Faust, 2019). Yet how semantic memory structure relates to CT, and the phenomenon of insight, remain unclear. The present study addressed this question by examining semantic memory networks related to CT and insight. We administered the CRA and a semantic fluency task (to estimate semantic memory networks) to a large sample of participants and separated them into groups based on their CRA performance (i.e., accuracy) and problem solving strategy (i.e., insight vs. analysis). We found that high-accuracy was characterized by a more flexible semantic memory network structure, with short paths and high connectivity between concepts, alongside reduced network modularity. We also found that high-insight (compared to high-analysis) was associated with shorter paths between concepts—even after controlling for accuracy. Our findings extend the growing literature on the role of semantic memory networks in creativity to the domain of CT, and suggest that shorter paths between concepts in semantic memory networks may support people's ability to solve CT problems with insight.

The semantic memory network of the high CT group was more connected (higher CC) and less structured (shorter ASPL and lower Q) than that of the low CT group. This network structure mirrors that of high DT ability (Benedek et al., 2017; He et al., 2021; Kenett et al., 2014; Kenett & Faust, 2019), as well as higher real-life creative achievements (Ovando-Tellez et al., 2022), indicating that a flexible semantic memory structure may contribute to both DT and CT. Cognitive search during the RAT has been compared to a multiply constrained problem, wherein an individual engages in a local search strategy and sequentially compares candidate solutions to small batches of features afforded by each cue word (Smith et al., 2013). In this light, CT problems are reliant on bottom-up influences defining the directed memory search occurring over a memory network. This aspect of CT problems highlights a similarity with DT problems, as both types of problems rely on an initial divergent thinking process for the generation of candidate ideas, while later stages require a convergent process for selecting the best idea, differentiated by the idiosyncratic influence of executive functions and memory networks (Smith, 2013). In other words, DT tasks involve CT during later stages, while CT tasks involve DT during early stages. Given this relationship between DT and CT, it is unsurprising that a similar semantic network structure relates to both forms of creative thinking.

Interestingly, our results for high CT ability stand in contrast to the network structure found for individuals higher in fluid intelligence, which tends to be relatively more rigidly structured (Kenett et al., 2016)—an intriguing contrast, given the strong and well-established links between CT and fluid intelligence (Akbari Chermahini et al., 2012; Lee et al., 2014; Taft & Rossiter, 1966), as well as CT and working memory capacity (Lee & Therriault, 2013). Investigations of fluid intelligence and real-life creative achievement have indicated that while creativity may depend on network flexibility—with shorter path lengths and a lesser separation of concepts into structured communities—fluid intelligence depends more on the structuring of semantic memory into ordered neighborhoods of concepts with high global clustering (Kenett et al., 2016). It may thus be that the missing link between our present findings and past research involving fluid intelligence and working memory may lie within the influence of executive processes operating over these memory networks. In this context, our findings have implications for dual process theories of creativity that emphasize the contribution of both associative and executive cognitive processes in creative performance (Beaty et al., 2021; Beaty, Silvia et al., 2014).

Our findings also have implications for the associative theory of creativity. Mednick promoted the idea of “associative hierarchies” that focused primarily on the strength of associations between concepts: highly creative individuals should have more connections between semantically distant concepts, relative to less creative individuals. Here, we extend this theorizing with empirical evidence from network science, showing that high CT ability is related to a semantic network structure that may facilitate the retrieval of weakly associated concepts, as these concepts are themselves embedded in a more interconnected and flexible structure—high CT networks were characterized not only by high connectivity (CC), but also by shorter paths between concepts (ASPL) and reduced modularity (Q).

A shorter average path length may facilitate remote conceptual combination necessary for solving CT problems via spreading activation (cf. Schilling, 2005). Likewise, lower network modularity may facilitate problem solving by reducing the boundaries of otherwise well-defined semantic communities that may cause fixation (Smith & Ward, 2012). Benedek & Neubauer (2013) investigated the associative hierarchy theory and concluded that highly creative individuals and low creative individuals did not differ in their associative hierarchies, at least in terms of common concepts. Later studies demonstrated that semantic structures, measured through latent-semantic analysis, and executive processes both contribute to creativity (Beaty et al., 2021; Beaty, Silvia et al., 2014). Accounting for the present findings, it remains likely that the structural properties of semantic memory play a role in creative thinking, facilitating CT in problem solving. These interpretations remain speculative, however, and future work is required to more directly examine how specific network metrics facilitate and constrain problem solving performance.

Turning to insight and analysis, we conducted separate network analyses to examine whether semantic memory networks differ as a function of problem solving strategy. Because we found that the two groups of interest, the high-insight/low-analysis and the low-insight/high-analysis groups, statistically differed in terms of accuracy on the CRA, we controlled for the possible confounding role of accuracy in our analysis. We observed an effect for ASPL: the semantic memory network of individuals in the high-insight/low-analysis had shorter path distances than those in the low-insight/high-analysis group. Notably, the effect for Q was only marginally non-significant (p = .055), where the average Q for the high-insight/low-analysis group was numerically lower than that of the low-insight/high-analysis group. Our findings overall support the small-world theory of insight proposed by Schilling (2005)—a small-world network structure, marked by high CC and low ASPL, may be more conducive to facilitating "shortcuts" in semantic memory networks by decreasing the steps needed to connect remote concepts, thus resulting in insight. Our results also compliment a recent study by Bieth et al. (2021), who found that solving CT problems (i.e., riddles) relates to restructuring concepts within semantic memory networks by decreasing path length between solution-related concepts in the semantic memory network of people who solved these riddles (see also Durso et al., 1994). Interestingly, we only observed an effect of insight on ASPL, potentially indicating that only short paths between concepts, and not a small-world network structure as previously hypothesized (Schilling, 2005), are beneficial to insight problem solving.

Limitations and Future Directions

A limitation of the current study is the semantic memory network group-based approach. We analyzed existing data from a semantic fluency task, which are commonly used to model aggregated group-based semantic memory networks (but see Zemla et al., 2020). A growing number of studies are also modeling semantic networks continuously (Benedek et al., 2017; He et al., 2020; Morais et al., 2013; Ovando-Tellez et al., 2022; Wulff et al., 2022). Future studies using such continuous network methods could replicate our findings to determine whether the patterns observed here hold when treating CT ability and insight as continuous variables. This would prevent one from dichotomizing the grouping variable, avoiding issues such as the loss of power, effect size, the loss of information on individual differences, and the possible overlooking of nonlinear trends in the data (MacCallum et al., 2002). It is plausible that the marginally non-significant effect of problem solving strategy on Q (p = .055) resulted from the adoption of a median split, and the loss of statistical power associated with this technique. Future studies should thus further investigate whether Q is truly unrelated to problem solving strategy.

Further, it is worth mentioning that the measure of insight and analysis adopted in this paper relies on self-reports from participants, and thus likely carry a degree of inaccuracy (see Paulhus & Vazire, 2007). A more objective measure of insight could be adopted in future research, less emphasis on the phenomenological aspect of the "aha" moment, and operationalizing insight as the overcoming of an impasse (Ash et al., 2012; Knoblich et al., 1999). Of note, in the present paper we didn't include working memory capacity, nor fluid intelligence, both of which have been shown to be strongly predictive of CT ability, and may thus be considered across future studies in combination with CT ability and insight (Akbari Chermahini et al., 2012; Lee et al., 2014; Lee & Therriault, 2013; Taft & Rossiter, 1966). Further studies may thus investigate the moderating effects of these variables on the relationship between CT ability and semantic memory networks.

Conclusion

Altogether, the present study provides novel evidence in support of the associative theory of creativity and suggests that the structure of semantic memory supports CT and insight problem solving. Our findings extend the growing literature on the role of semantic memory networks in creative thinking, indicating that semantic memory networks characterized by high connectivity, short path distances, and reduced modularity are linked to several aspects of creativity, such as DT and real-world creative achievement (Benedek et al., 2017; Denervaud et al., 2021; He et al., 2020; Kenett et al., 2014; Kenett et al., 2016; Li et al., 2021; Ovando-Tellez et al., 2022). Specifically, we found that CT ability was associated with a more interconnected and flexible semantic network structure (i.e., higher CC and lower ASPL and Q), consistent with previous findings on DT ability, while insight problem solving (controlling for CRA accuracy) was related to shorter distances between concepts (i.e., lower ASPL). Future research should continue to examine relationships between semantic networks and creativity, including how dynamic reorganization of semantic network structure may impact creativity (cf. Bieth et al., 2021), to better understand how semantic memory structure may support creative performance. Taken together, research on semantic networks is highly valuable for understanding the links between semantic memory and creativity, and may also provide a promising approach for developing translational applications which enhance creative thinking abilities, such as DT, CT, and insight problem solving.

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