The Role of Semantic Memory Networks in Crystallized Intelligence and Creative Thinking Ability

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Abstract

Crystallized intelligence (*Gc*)—knowledge acquired through education and experience—supports creativity. Yet whether *Gc* contributes to creativity beyond providing access to more knowledge, remains unclear. We explore the role of a "flexible" semantic memory network structure as a potential shared mechanism of *Gc* and creativity. Across two studies (N = 506 and N = 161) participants completed *Gc* tests of vocabulary knowledge and were divided into low, medium, and high *Gc* groups. They also completed two alternate uses tasks, to assess verbal creativity, and a semantic fluency task, to estimate semantic memory networks. Across both studies, the semantic memory network structure of the high *Gc* group was more flexible—less structured, more clustered, and more interconnected—than that of the low *Gc* group. The high *Gc* group also outperformed the low *Gc* group on the creativity tasks. Our results suggest that flexible access to semantic memory supports both verbal intelligence and creativity.

Keywords: crystallized intelligence, divergent thinking, knowledge, semantic network, verbal creativity

Educational relevance statement

Crystallized intelligence (*Gc*)—knowledge acquired through education and experience—supports creativity, yet whether *Gc* contributes to creativity beyond providing access to more knowledge (semantic memory), remains unclear. In this two-part study, we find that individuals with higher *Gc* tended to have a more flexible semantic memory structure, which in turn supported greater verbal creativity. This finding suggests that building students' vocabulary knowledge and verbal skills may not just expand their knowledge base, but also increase creativity through enabling more flexible access to that knowledge. If supported by further research, this could mean educational interventions targeting growth in *Gc* and semantic flexibility may foster students' creative capacities beyond just improving content mastery. Overall, this research highlights the interplay between building domain knowledge and cultivating creative thinking, suggesting educators should aim to develop both abilities in tandem rather than treating them separately.

1. Introduction

As a primary component of human intelligence, crystallized intelligence (*Gc*) refers to the ability to learn, retain, structure and apply acquired knowledge to solve real-life problems (Cattell, 1963). *Gc* is developed through education and experience across the lifespan, and it is often measured by tests of vocabulary knowledge (Kan et al., 2011; Schipolowski et al., 2014). *Gc* has repeatedly been shown to positively correlate with another important ability—creative thinking (Cho et al., 2010; Frith et al., 2021; Runco & Acar, 2010; Shi et al., 2017; Silvia, 2015; Sligh et al., 2005)—ostensibly by providing access to more information (i.e., the quantity of knowledge) that can be combined in new ways to solve problems. In the present research, we explore another potential mechanism underlying *Gc's* association with creative thinking: the organization of concepts in semantic memory, which plays an important role in facilitating memory retrieval and has been linked to higher creative ability (Benedek et al., 2023). We thus aim to understand how semantic memory network structure relates to *Gc* and whether any differences may explain *Gc's* association with creative thinking.

1.1. Knowledge and Creativity

Decades of factor analytic research has linked *Gc* to semantic memory, particularly broad retrieval ability (*Gr*), i.e., the ability to efficiently retrieve information from long-term memory (Carroll, 1993) and knowledge (Beauducel & Kersting, 2002). Perhaps unsurprisingly, *Gc* and *Gr* are strongly correlated: people who know the meaning of more concepts tend to be better able to retrieve more concepts when asked to do so (Beauducel & Kersting, 2002; Carroll, 1993). A recent meta-analysis also found broad retrieval ability moderately correlated with divergent thinking ($r = .48$; Miroshnik et al., 2023). Both intelligence facets have also been associated with creativity, such as divergent thinking (e.g., Benedek et al., 2012; Forthmann et al., 2019; Silvia et al., 2013; Sligh et al., 2005), creative writing (Avitia & Kaufman, 2014; Tan & Grigorenko, 2013; Taylor & Barbot, 2021), and metaphor production (Beaty & Silvia, 2013; Kenett et al., 2018; Stamenkovic & Holyoak, 2018). Yet how *Gc* and *Gr* contribute to creativity, beyond simply providing access to more knowledge, remains unclear.

Researchers have long explored the question of how concepts in semantic memory are interconnected, activated, and retrieved (Collins & Loftus, 1975; Kumar, 2021). Two classic models of semantic processing are the complexity model and the connectivity model (Klimesch, 1987; Kroll & Klimesch, 1992). At the core of both models is the assumption that meaning is represented by a set or network of semantic features (Kintsch, 1980).

A controversial issue between the two theories arises when considering how individual features, or entire networks, may influence processing speeds and memory performance. On one hand, the complexity model assumes that processing capacity is limited. As such, with more semantic components to be processed—as with high *Gc*—memory load should increase, thus slowing overall processing time (Gentner, 1981). In contrast, the connectivity model places more emphasis on the underlying memory structure, and holds that indirect activation will become increasingly effective as the number of interconnected nodes (higher *Gc*) increases (Klimesch, 1987). Indeed, concepts with more features are judged faster than those with only a few (Klimesch, 1987; Kroll & Klimesch, 1992).

The spread of information across a highly interconnected semantic memory structure should thus be more efficient under the connection model rather than the complexity model. Yet, empirically testing these competing models has been challenging, due to challenges in quantifying semantic memory (Kumar, 2021; Kumar et al., 2022). Recently, the application of computational network science methods (Hills & Kenett, 2022; Siew et al., 2019) to study cognition allows modelling semantic memory as networks, and assess how variation in semantic organization relates to higher cognitive abilities, such as intelligence and creativity.

1.2 Mapping Knowledge Organization Using Computational Network Science Methods

Advances in network science methodologies have allowed researchers to quantitatively examine the organization of different knowledge structures (e.g., semantic memory; Hills & Kenett, 2022; Siew et al., 2019). Network science is based on graph theory, offering quantitative methods for the representation of complex systems (e.g., semantic memory) as networks (Siew et al., 2019). A network is made up of nodes (e.g., individual concepts or representations), and edges that signify the relations between them (e.g., semantic similarity).

Semantic memory network modelling has provided insight into language and memory structure (Siew et al., 2019), cognition across clinical populations (Castro, 2022), aging (Cosgrove et al., 2023; Cosgrove et al., 2021; Wulff et al., 2019), memory restructuring and development (Bieth et al., 2021; Kenett & Thompson-Schill, 2020), language development (Hills et al., 2009a, 2009b), bilingualism (Borodkin et al., 2016; Fernández-Fontecha & Kenett, 2022), and creativity (Kenett & Faust, 2019).

To study semantic memory as a network, researchers commonly administer verbal fluency tasks (e.g., listing as many animals as possible in 1-2 minutes; Ardila et al., 2006), and use the responses to estimate memory structure across groups (e.g., high and low creative individuals; Kenett, Beaty, et al., 2016). Several widely adopted methods have been proposed to analyze semantic fluency data as group-based semantic memory networks (Christensen & Kenett, 2023; Zemla & Austerweil, 2018). More recently, other methods have also been proposed that can estimate individual-based semantic memory networks (Wulff et al., 2022). One such approach is based on semantic relatedness judgments, combining a series of pairwise judgments of semantic relatedness between words to represent ones' organization of concepts in memory (Benedek et al., 2017; He et al., 2021; Ovando-Tellez, Kenett, et al., 2022).

Common network measures include the clustering coefficient (CC), average shortest path length (ASPL), and modularity (Q). CC refers to the extent that two neighbors of a node will themselves be neighbors (i.e., a neighbor is a node i that is connected through an edge to node j), averaged across all nodes in the network. A higher CC relates to greater overall connectivity in the network. In semantic memory networks, such connectivity denotes the similarity between concepts (nodes) and has been related to creativity (Kenett & Faust, 2019). ASPL refers to the average shortest number of steps (i.e., traversed edges) required to travel between any pair of nodes, thus marking the overall spread of a network. In semantic memory networks, ASPL is correlated with a participants' judgment on the degree of relatedness between two concepts, with more closely related concepts associated with a lower ASPL (Kenett et al., 2017; Kumar et al., 2020). Q measures the degree to which a network breaks apart into smaller clusters or communities, with a higher Q denoting more distinct and separate communities in a network (Fortunato, 2010; Newman, 2006); thus, communities will often represent specific semantic categories (e.g., fruits and vegetables, animals, buildings). In semantic memory networks, higher Q has been related to higher structure and rigidity (Kenett, Beaty, et al., 2016; Kenett, Gold, et al., 2016). Critically, the larger the CC, and the smaller the Q and ASPL, the more flexible and efficient the semantic memory network is, which facilitates information processing and cognitive operations in the network (Kenett et al., 2014; Kenett, Beaty, et al., 2016; Kenett & Faust, 2019).

Within the creativity domain, Kenett et al. (2014) examined semantic memory networks of individuals with lower and higher levels of verbal creative ability. More creative individuals were found to exhibit a more flexible, clustered, and condensed semantic memory network (higher CC, lower Q and ASPL) compared to lower creative individuals—a finding that replicated using continuous, individual-based semantic memory networks methodology (Benedek et al., 2017; He et al., 2021; Ovando-Tellez, Kenett, et al., 2022). More recently, Li et al. (2021) found that individuals producing more highly original metaphors possessed more clustered and interconnected semantic networks.

Studies have also applied semantic memory network modeling to examine the link between intelligence and creativity. Kenett, Beaty et al. (2016) explored how fluid intelligence (*Gf*) and creative achievement relate to the structure of semantic memory networks. High *Gf* was associated with more “rigid” semantic memory networks (i.e., highly structured networks with lower CC, higher Q and ASPL), while high creative achievement was associated with more “flexible” semantic memory networks (higher CC, lower Q and ASPL). These results were replicated in children by Rastelli et al. (2020), who found a similar pattern in children who showed high levels of intelligence and divergent thinking ability.

Together, these studies suggest that intelligence and creativity may differ at the level of semantic memory networks, with intelligence (especially *Gf*) related to more structured networks and creativity related to less structured networks. Yet whether this finding extends to *Gc*—which relates to the volume of knowledge and may thus be even more relevant to understanding knowledge organization—remains unknown.

1.3 The Current Study

In the current study, we conducted two studies (Study 1 n = 506; Study 2 n = 161) to test whether *Gc* relates to variation in the organization of concepts within semantic memory networks, as well as individual differences in creative thinking ability (assessed via divergent thinking tasks). We predict that high *Gc* individuals, who have more knowledge to retrieve, will show a more flexible, interconnected, and clustered semantic memory network (higher CC, lower ASPL and Q; Hypothesis 1), consistent with past research on creative thinking ability (Kenett & Faust, 2019). Furthermore, we predict that high *Gc* individuals will show higher divergent thinking scores (Hypothesis 2), replicating past work (Cho et al., 2010; Sligh et al., 2005).

2. Study 1

In Study 1, we reanalyzed existing data to test for differences in the structure of semantic memory networks of individuals varying in *Gc*. In addition, we examined whether these individuals also vary in their creative thinking abilities, assessed via the alternate uses task (AUT)—a typical task used to assess divergent thinking (Acar & Runco, 2019). Participants completed two tests of vocabulary knowledge to assess *Gc*, and a semantic fluency task for the estimation of their group-based semantic memory networks; only a subset of participants in this dataset completed the AUT. *Gc* scores were then used to separate participants into low, medium, and high *Gc* groups to compare their semantic memory networks. Considering past research that has shown that flexible semantic memory network structure is related to creativity, we expected the same for *Gc*. We further expected to replicate past work pointing to a relation between *Gc* and creativity (e.g., Cho et al., 2010; Gerver et al., 2023; Sligh et al., 2005).

2.1. Materials and Methods

2.1.1. Participants

Participants (*N* = 506, 402 women, mean age = 19.86 years, *SD* = 3.87 years) were recruited from various studies conducted at the MASKED University. All participants provided written informed consent prior to the data collection. This study was approved by the MASKED Institutional Review Board.

Our aim was to estimate group-based semantic memory networks, which requires splitting participants into groups for network estimation (Christensen & Kenett, 2023). Participants were thus divided into three groups in accordance with their *Gc* scores (Christensen et al., 2018), to assess a linear relationship between *Gc* and semantic memory network organization (compared to extreme low vs. high groups). This was done by dividing the sample into three thirds, according to their *Gc* score distribution (lower, middle, and top third; Altman & Bland, 1994). We conducted a one-way ANOVA on the *Gc* scores of participants in low, medium, and high *Gc* groups (**Table 1**) and confirmed that the groups were significantly different from each other.

Table 1. *Descriptive statistics for the three Gc groups.*

Group	***Gc***					**AUT**			
	Age	**N**	**Gc_ Adv**	**Gc_ Extend**	***Gc***	**Age**	**N**	**Fluency**	**Originality**
Low	18.79 (1.82)	169	5.72 (1.75)	6.94 (2.02)	12.66 (2.39)	21.60 (3.70)	15	6.37 (2.31)	1.34 (.19)
Medium	19.41 (2.94)	168	7.51 (1.64)	10.25 (1.54)	17.76 (1.26)	20.61 (2.67)	41	8.55 (3.78)	1.52 (.26)
High	21.37 (5.43)	169	10.22 (2.01)	13.58 (2.41)	23.80 (3.46)	22.96 (6.18)	89	8.94 (4.61)	1.61 (.33)
Full	19.86 (3.87)	506	7.82 (2.59)	10.26 (3.38)	18.08 (5.22)	22.15 (5.27)	145	8.57 (4.25)	1.56 (.31)

Notes. Gc_Adv represents the score of advanced vocabulary test; Gc_Extend represents the score of extended range vocabulary test. *Gc*: Crystallized intelligence. *Gc* represents the total score of the two *Gc* tasks (advanced vocabulary test and extended range vocabulary test). *AUT* = alternate uses task; *N* = the number of subjects in the sample; The data in parentheses represents the square deviation.

2.1.2 Materials

2.1.2.1. *Gc* Assessment

All participants completed two widely used tests of vocabulary knowledge (Kan et al., 2011): the advanced vocabulary test (18 items) and the extended range vocabulary test (24 items; ETS Kit of Factor-Referenced Cognitive Tests; Ekstrom et al., 1976). In each task, participants were asked to select the synonym of a target word from a list of possible answers. Participants had eight minutes to complete both tasks and instructed that only the correct responses would count towards the final score. The total score of the two tests was computed. The Cronbach alpha value for *Gc* in this Study was found to be of 0.685.

2.1.2.2. Semantic Fluency Task

All participants completed a classic categorical verbal fluency task: animal fluency, requiring them to list as many animals as possible in 60 seconds. We used the animal category for its high cross-cultural and cross-linguistic reliability. This task has been shown to effectively reflect people’s ability to retrieve semantic information from long-term memory (Ardila et al., 2006; Goñi et al., 2011), and has been widely adopted for the modelling of group-based semantic memory networks (Siew et al., 2019; Zemla & Austerweil, 2018).

2.1.2.3. Creative Thinking Assessment

A subset of participants (*N* = 145; 106 females; mean age = 22.15 years, *SD* = 5.27 years) completed the Alternative Uses Task (AUT; Guilford et al., 1978)—a widely adopted task for the assessment of creative thinking—to evaluate the verbal creative ability of participants. Participants were given three minutes to type as many creative uses as they could think of for each of two common objects (“box” and “rope”). Their answers were recorded via MediaLab and were later scored in terms of their originality, a critical measure of divergent thinking ability. A subjective scoring approach (Silvia et al., 2008) was adopted, with four trained raters providing originality scores on a Likert scale ranging from 1 (*not at all creative*) to 5 (*very creative*; Silvia et al., 2008) to all responses. For each AUT response, fluency and originality were calculated. Fluency refers to the average number of answers generated by participants for the two objects. The originality score was calculated by averaging the averaged originality scores for both objects. These two indicators of creativity are commonly used in creativity research (Beaty et al., 2018; Silvia et al., 2008). Raters had a high inter-rater agreement (ICC = .81), which meets the high level (ICC > 0.7) of reliability as per the standard outlined by Hinton et al. (2004).

2.1.3 Network Analysis

Semantic fluency data from the three *Gc* groups was analyzed via a group-based semantic memory network approach (Borodkin et al., 2016; Kenett et al., 2013). Here, each node represents a category exemplar (e.g., *cat*) and edges quantitatively represent the associations between two exemplars. These associations are computed as the tendency of the sample to generate exemplar b (e.g., *fish*) when exemplar a (e.g., *cat*) was also generated. All network analyses were performed in R (3.6.1). The pipeline that was adopted for the network analysis of semantic fluency data was reproduced from Christensen and Kenett (2023).

2.1.3.1. Network estimation

First, the R packages of SemNetDictionaries (Christensen, 2019b) and SemNetCleaner (Christensen, 2019a) were used to preprocess participants' verbal fluency data. Repetitions (i.e., responses given more than once by the same participant) and non-category members (e.g., for the animal category: *carrot*, *tree*, *toy*) were removed in this phase. Typing errors were also corrected, including spelling errors (e.g., *dig* to *dog*), word root variations (e.g., *cats* to *cat*), and continuous strings (i.e., multiple responses entered as a single response). Next, the data was transformed into a verb response matrix, where columns represented the different unique verbal fluency exemplars, and rows represented all the participants. The response matrix was then transformed into a binary response matrix, with each cell containing the values 1 or 0. A 1 indicates that a participant generated the specific exemplar, while 0 indicates that the exemplar was not generated by the participant.

The SemNetCleaner package (Christensen, 2019a) was used to further process the binary response matrix into a finalized format for network estimation, as well as to control for possible confounding factors when comparing networks. To exclude spurious associations, only responses that were given by at least two participants in each group were included in the binary response matrix (Christensen et al., 2018; Kenett et al., 2013). Furthermore, responses in the binary matrix were equated to ensure that the networks of all groups were compared using an equal number of nodes (van Wijk et al., 2010). A total of 20, 39, and 89 nodes were excluded from the low, medium, and high *Gc* groups respectively. This left 116 matched nodes in each group for the subsequent network analysis. Next, the SemNeT package (Christensen & Kenett, 2023) was used to compute the association profiles of verbal fluency responses. Network estimation was accomplished via a correlation-based approach, specifically by approximating how responses co-occur across each group.

The word similarity matrix was then transformed into an n x n weighted and undirected adjacency matrix, where each word represents a node and the edge between two nodes is the similarity between them. The triangulated maximally filtered graph (Christensen et al., 2018; Massara et al., 2016) was then used to minimize spurious relations between nodes in the network, via the NetworkToolbox package (Christensen, 2018) in R (3.6.1). An equal number of edges was left across all groups to avoid comparing networks with different structures (Christensen, 2018; van Wijk et al., 2010). To examine the structure of the networks, the edges were binarized so that they were all converted to a uniform weight (i.e., 1). All networks were analyzed as unweighted (i.e., all weights are treated as being equal) and undirected (i.e. bidirectional relations are assumed between all nodes) networks (Christensen, 2018; Christensen et al., 2018).

2.1.3.2. Network analysis

We used the NetworkToolbox package (Christensen, 2018; Christensen et al., 2018) to analyze global network properties and computed the CC, ASPL, and Q of the networks of the three groups. Two complementary approaches were used to statistically examine the validity of the results. We first simulated a set of random networks for each *Gc* group, allowing us to test whether the network measures could be owed to the null hypothesis, i.e., whether the network parameters observed across the three *Gc* groups differ from a random network with an equal number of nodes and edges (Beckage et al., 2011; Steyvers & Tenenbaum, 2005). To this end, Erdős-Rényi random networks were simulated with a fixed edge probability and equal number of nodes and edges (Erdös & Rényi, 1960). The global network measures (i.e., CC, ASPL, and Q) were then computed for each random network, resulting in separate sampling distributions. Each empirical network measure was then compared to its reference distribution to evaluate the statistical significance, assessed via a one-sample Z-test for each network parameter.

Next, to allow for the statistical comparison of any two networks, a bootstrapping approach (Efron, 1979) was used to simulate and compare partial semantic memory networks for the three groups. This method involves the random selection of a subset of nodes in the semantic network (Borodkin et al., 2016) for the construction of distinct partial networks for each group. In this study, partial semantic networks were generated by sampling 50% of the total nodes in a single semantic network. The CC, ASPL, and Q measures were then computed for each partial network. This procedure was repeated with 1,000 iterations for each partial bootstrapping analysis, leading to a distribution of values for each network measure. A between-subject ANOVA was then conducted to compare differences in the measures across the three groups. Additionally, Tukey's HSD pairwise comparison was conducted for post-hoc multiple comparisons. Figures corresponding to the bootstrapping approach were generated using the SemNetCleaner package in R (Christensen, 2019a).

2.1.4 Procedure

Participants completed all tasks on computers using MediaLab. After signing the informed consent, they were instructed how to complete the cognitive tasks, and they received research credit or money for their participation after the test. The first subsample of participants (n = 356) completed *Gc* tests (the advanced vocabulary test and the extended range vocabulary test) and the semantic fluency task (listing animals). The second subsample (n = 145) completed the *Gc* tasks, the semantic fluency task, and the AUT.

2.2. Results

Before estimating semantic memory networks, we first examined the uniqueness and number of responses in the semantic fluency task across the three groups (**Table 2**). A one-way ANOVA was conducted to examine the effect of *Gc* on fluency, revealing a significant main effect of *Gc* group, F (2, 503) = 20.243, p < .001, $\eta_p{}^2$ = .075: individuals with higher *Gc* produced more responses, as expected. A post hoc *t*-test analyses was then conducted, exposing significant differences between all group pairings, all *p*'s < .05 (**Table 2**). McNemar's chi-square tests were applied to test the differences of the number of the unique responses between two of the three groups and were all found to be significant (**Table 2**). These results show that higher *Gc* participants produced more (and more unique) verbal fluency responses.

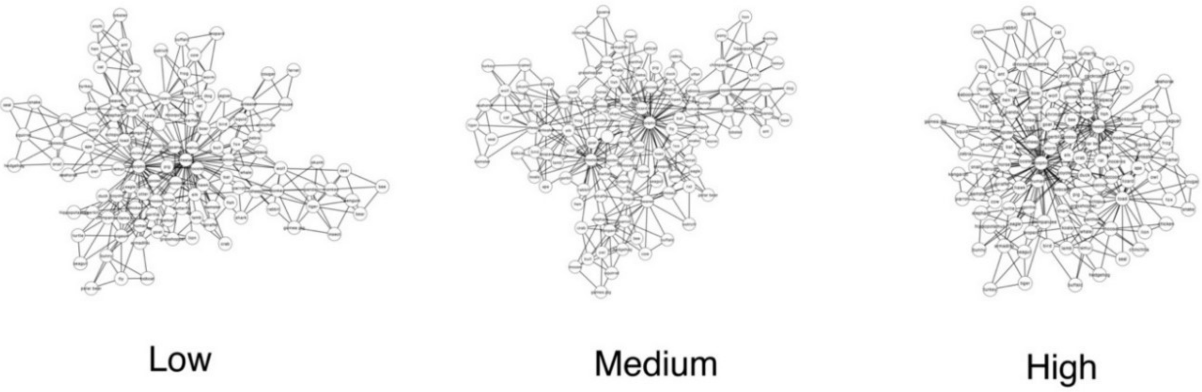
Table 2. *Descriptive statistics and analysis of the average and unique responses data for the three Gc groups.*

Groups	***n* (average)**		***t***	***df***	***p***	***d***	***n* (total)**	***n* (unique)**	***N***	**χ^2 *df* = 1**	***p***	***φ***
	M (*SD*)	Range										
Low	15.25 (4.03)	3-26	-3.437	335	.001	.374	266	203	37	6.25	.012	.224
Medium	16.76 (4.03)	7-28						229	63			
Low	15.25 (4.03)	3-26	-5.897	336	< .001	.642	346	203	28	76	< .001	.249
High	18.05 (4.69)	2-34						318	143			
Medium	16.76 (4.03)	7-28	-2.723	335	.007	.297	350	229	32	50.61	< .001	.231
High	18.05 (4.69)	2-34						318	121			

Notes: *n* (average) = mean average and range of the number of responses in each group; *n* (total) = total number of unique responses; *n* (unique) = the number of unique responses in each group; *n* = the number of unique responses from the total not given by the other group. χ^2 refers to the McNemar's test; φ is the effect size of the McNemar's test.

We then estimated and compared the semantic memory networks constructed from the animal category responses of the low, medium, and high *Gc* groups. The network measures (CC, ASPL, and Q) for these three networks were computed (**Table** 3) with R (Christensen & Kenett, 2023) and the semantic memory networks of the three groups were visualized (**Figure 1**) via the force-directed layout of the Cytoscape software (Fruchterman & Reingold, 1991; Shannon et al., 2003). In these 2D visualizations, the nodes represent the examples given by participants and edges convey symmetrical (i.e., bidirectional) similarities between two nodes because these networks are undirected and unweighted.

Figure 1. A 2D visualization of the semantic memory networks for the three Gc groups.



Notes. Nodes denote the matched animal names generated by all three groups. Edges denote binary, symmetrical relations between nodes.

Upon visual inspection of the networks, the semantic memory network of the high *Gc* group appears more condensed than that of the medium and low *Gc* groups. This observation is consistent with the network measures presented **in Table 3**, with the high *Gc* group showing a higher CC, and lower ASPL and Q, compared to the networks of the medium and low *Gc* groups.

Table 2. *Network measures for each of the three Gc groups*

Groups	**CC**	**ASPL**	**Q**
Low	.75	2.78	.60
Medium	.76	2.78	.59
High	.77	2.47	.52

Notes. ASPL, average shortest path length; CC, clustering coefficient; Q, modularity.

To exclude the possibility that the network differences between the three groups derive from a null model, we conducted a simulated random network analysis (Christensen & Kenett, 2023). This analysis revealed that all empirical network measures for the low, medium, and high *Gc* groups were significantly different from their random counterparts (all *p'*s < .001), thus yielding a rejection of the null hypothesis.

Next, we conducted the bootstrapping analysis to examine the statistical significance of the differences found in the network measures across the three groups. Half of the total nodes within each network were selected for the bootstrapping partial networks analysis (58 out of 116 nodes). A one-way ANOVA analysis was conducted on the effect of group on each of the partial networks' measures.

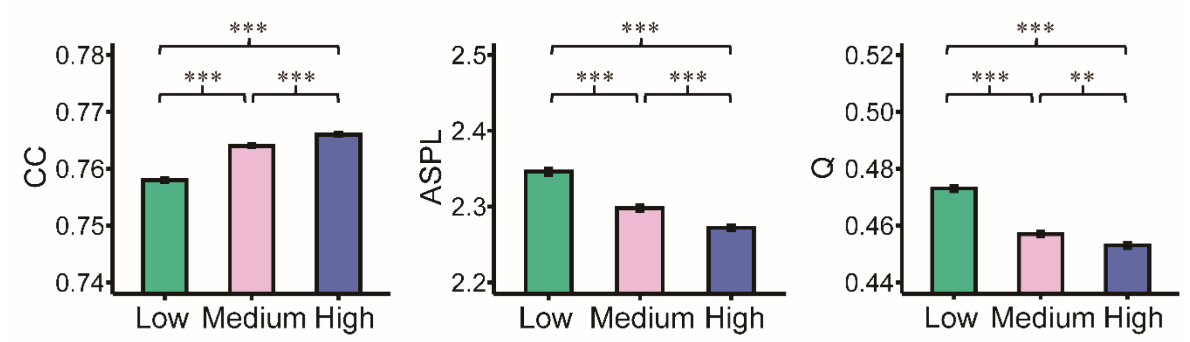
Post-hoc Tukey's HSD pairwise comparison revealed significant differences between the network measures in the three groups (all *p's* < .001; **Table 4**). Consistent with our Hypothesis 1, ASPL and Q were significantly smaller for partial networks of the high *Gc* group compared to the other two groups. In contrast, CC was significantly larger for partial networks of the high *Gc* group compared to the low and medium *Gc* groups (**Figure 2**). These results indicate that the semantic memory networks of participants in the high *Gc* group are characterized by higher connectivity (higher CC), shorter paths (lower ASPL), and lower modularity (lower Q; **Figure 2**).

Table 3. *One-way ANOVA on the partial networks bootstrap analyses.*

	Group	***M***	***SD***	***F* (2, 2997)**	***P***	***ηp2***	**Contrast Groups**	***p***	**HSD Results**
CC	low	.758	.01	206.83	< .001	.121	low-high	< .001	low < high
	medium	.764	.01				medium-high	< .001	medium < high
	high	.766	.01				medium-low	< .001	medium > low
ASPL	low	2.346	.13	98.638	< .001	.062	low-high	< .001	low > high
	medium	2.298	.12				medium-high	< .001	medium > high
	high	2.272	.11				medium-low	< .001	medium < low
Q	low	.473	.03	139.79	< .001	.085	low-high	< .001	low > high
	medium	.457	.03				medium-high	< .01	medium > high
	high	.453	.03				medium-low	< .001	medium < low

Notes. ASPL, average shortest path length; CC, clustering coefficient; Q, modularity.

Figure 2. *Means for the Gc groups on CC, ASPL, and Q.*



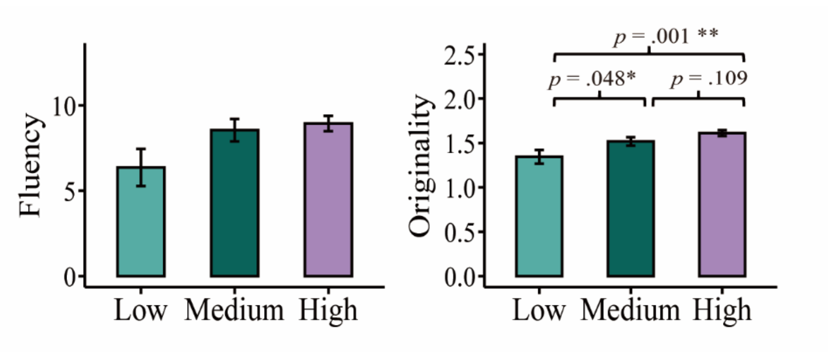
Note - The data represents 50% of selected nodes. Error bar represents *SE*.

2.2.1 Creative thinking

Due to the low sample of participants who completed the AUT in the low *Gc* group, as well as the samples of the three *Gc* groups being of unequal sizes, we conducted a series tests of normality. A Kolmogorov-Smirnov test of normality revealed that the high *Gc* group was not normally distributed (p = .008). We thus used a one-way Kruskal-Wallis test, which does not assume equal sample sizes between groups, to assess the differences of fluency and originality between the low, medium, and high *Gc* groups.

This analysis revealed that there was no significant difference in fluency between the three groups, W = 5.187, p =.075. However, in terms of originality, significant differences were observed among the three groups, W = 11.239, p = .004. The comparative analyses showed that the scores for the high *Gc* group (M = 1.61, SD = .33) were significantly higher than that of the low *Gc* group (M = 1.34, SD = .19), W = 3.219, p < .001, d = 1.002, as predicted by Hypothesis 2. Similarly, the medium *Gc* group exhibited significantly higher scores (M = 1.52, SD = .26) compared to the low *Gc* group, W = 1.975, p = .048, d = .790. The scores for the medium *Gc* group were not significantly different compared to the high *Gc* group, W = -1.602, p = .109, d =.303 (**Figure 3**).

Figure 3. *The differences in fluency and originality of AUT scores for the three Gc groups.*



Note. Error bar represents *SE*.

Furthermore, the relation between *Gc* and DT were examined via Pearson's correlation analysis (**Table 5**). The results showed significant correlation between *Gc* and originality.

Table 5. *Pearson's correlations of Gc and originality in study 1*

Variable		Gc_Adv	Gc_Extend	Gc	Fluency	Originality
*Gc*_Adv	Pearson's r	—				
	p-value	—				
	N	506				
*Gc*_Extend	Pearson's r	.521**	—			
	p-value	< .000	—			
	N	506	506			
Gc	Pearson's r	.833**	.906**	—		
	p-value	< .000	< .000	—		
	N	506	506	506		
Fluency	Pearson's r	.014	.067	.048	—	
	p-value	.869	.425	.563	—	
	N	145	145	145	145	
Originality	Pearson's r	.279**	.350**	.364**	-.226**	—
	p-value	.001	< .000	< .000	.006	—
	N	145	145	145	145	145

Notes: * - $p < .05$; ** - $p < .01$. *Gc*_Adv represents the score of advanced vocabulary test; *Gc*_Extend represents the score of extended range vocabulary test. *Gc* means the sum of *Gc*_Adv and *Gc*_Extend. Fluency refers to the average number of answers generated by participants for the two objects. The originality score was calculated by averaging the averaged originality scores for both objects.

2.3. Discussion

Study 1 examined whether *Gc* relates to the underlying organization of concepts within semantic memory networks. Our Hypothesis 1 was confirmed: the high *Gc* group exhibited a more flexible, interconnected, and clustered semantic memory network, and also a significantly higher originality score on the verbal creative thinking task (AUT), replicating past work (e.g., Cho et al., 2010; Sligh et al., 2005). These results indicate that a flexible semantic memory network structure may be a shared mechanism underlying verbal intelligence and verbal creativity. However, the limited sample of participants across the three groups that also completed the AUT, particularly in the low *Gc* group, requires replication to test the robustness of our findings. This was the aim of Study 2.

3. Study 2

In Study 2, we aimed to replicate and extend Study 1 in a new sample. Most notably, all participants in Study 2 completed the AUT, unlike the smaller subset of participants in Study 1. Additionally, we separated participants into equally sized groups, whereas Study 1 had unequal groups. Thus, although Study 1 supported our hypotheses, we conducted a second study to ensure that the results were stable in a new sample with complete data. Given that *Gf* and *Gc* are strongly correlated (Stamenkovic & Holyoak, 2018), Study 2 further aimed to replicate the findings of Study 1 after controlling for a possible confound effect of *Gf* on *Gc*. To do so, in Study 2 we also collected *Gf* data via the series completion task (Cattell & Cattell, 1961/2008).

3.1. Materials and Methods

3.1.1 Participants

One hundred sixty-one participants (94 female; M_{age} = 19.02 years, *SD* = 2.49 years) were recruited from MASKED University. All participants provided written informed consent prior to the data collection. The study was approved by MASKED Institutional Review Board.

Participants were divided into three groups based on the *Gc* values (Christensen et al., 2018). One-way ANOVA were conducted on the *Gc* scores of participants in the low, medium, and high groups, $F\ (2, 158) = 264.023$, $p < .001$, $\eta_p^2 = .770$, confirming the appropriateness of the groups (**Table 6**).

Table 6. *Descriptive statistics for age, number of subjects, Gc and AUT scores across the three groups.*

Group	Age	N	*Gc*_Adv	*Gc*_Extend	*Gc*	AUT Fluency	AUT Originality
Low	18.67 (0.80)	54	8.13	5.83	13.96 (2.51)	7.50 (2.54)	2.05 (.17)
Medium	18.85 (.92)	54	11.26	8.02	19.28 (1.29)	7.69 (2.31)	2.12 (.22)
High	19.55 (4.13)	53	14.47	10.15	24.40 (2.97)	8.34 (1.80)	2.15 (.18)
Full	19.02 (2.49)	161	11.27	7.99	19.22 (4.86)	7.84 (2.26)	2.10 (.19)

Notes. AUT = alternate uses task; *Gc*: Crystallized intelligence. *N* = the number of subjects in the sample. *Gc* represents the total scores of the two Gc tasks (advanced vocabulary test and the extended range vocabulary test).

3.1.2. Materials

The same tasks from Study 1 were administered in Study 2: *Gc* (vocabulary tests), semantic fluency task (animals), and AUT creative thinking task (box and rope). The Cronbach alpha value for *Gc* in this study was found to be 0.402. The subjective scoring approach (Silvia et al., 2008) was adopted for AUT, with three trained raters providing originality scores on a Likert scale ranging from 1 (*not at all creative*) to 5 (*Extremely creative*; Silvia et al., 2008). Participants' AUT originality score was computed similarly as in Study 1. AUT Raters had a high inter-rater agreement (ICC = .72), which meets the high level (ICC > 0.7) of reliability as per the standard outlined by Hinton et al. (2004). *Gf* score was assessed via the series completion task, which was adopted from Cattell's Culture Fair Intelligence Test

(Cattell & Cattell, 1961/2008). Participants were presented a series of images drawn within small boxes that changed in succession: they had to discover the rule guiding the changing images and determine the next item in the series (13 items, 3 min). *Gf* was calculated by summing up the number of correct responses.

3.1.3. Procedure

All participants completed the tasks online using Pavlovia. They received research credit their participation after the test.

3.2 Results

As in Study 1, we began by comparing the uniqueness and number of responses in the semantic fluency task across the three *Gc* groups (**Table 7**). A one-way ANOVA between *Gc* and fluency exposed significant differences in fluency between the three groups, F (2, 158) = 7.424, $p < .001$, $\eta_p^2 = .086$. The post hoc *t*-test analyses revealed significant differences between two of the three groups, *p'*s < .05 (see **Table 7** for detailed results). Further, the McNemar's chi-square tests showed the unique responses between two of the three groups were all significant (**Table 7**). These results replicate Study 1: higher *Gc* participants produced more (and more unique) verbal fluency responses.

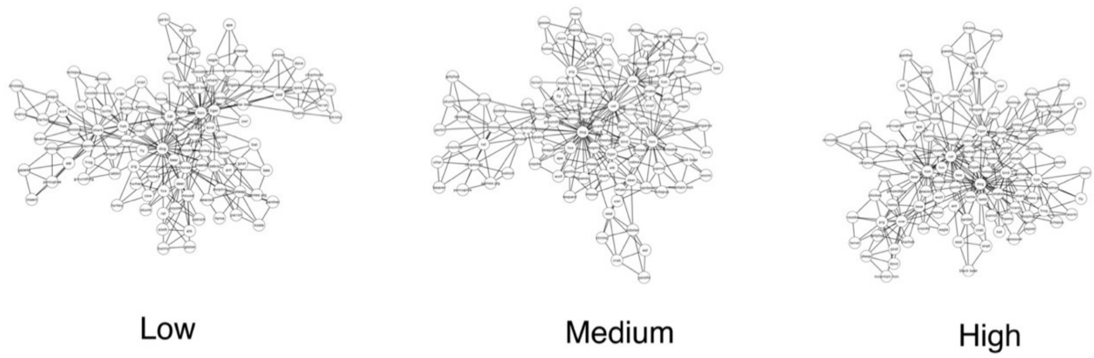
***Table** 7. Descriptive statistics and analysis of the average and unique responses data for the three Gc groups.*

Groups	***n* (average)**		***t***	***Df***	***p***	***d***	***n* (total)**	***n* (unique)**	***n***	**χ^2 *df* = 1**	***p***	***φ***
	***M* (*SD*)**	**Range**										
Low	21.87 (10.91)	1-38	-2.947	106	.004	.567	259	201	43	1.941	.164	.240
Medium	27.59 (9.20)	3-47						216	58			
Low	21.87 (10.91)	1-38	-3.447	105	.001	.668	282	201	28	24.807	< .001	.211
High	28.23 (7.90)	1-43						254	81			
Medium	27.59 (9.20)	3-47	-.382	105	.703	.642	292	216	38	12.009	.001	.229
High	28.23 (7.90)	1-43						254	76			

Notes. n (average) = mean average and range of the number of responses in each group; *n* (total) = total number of unique responses; *n* (unique) = the number of unique responses in each group; *n* = the number of unique responses from the total not given by the other group. χ^2 refers to the McNemar's test; *φ* is the effect size of the McNemar's test.

Next, we estimated and compared the semantic memory networks of the three groups**.** A total of 24, 45, and 58 nodes were excluded from the low, medium, and high *Gc* groups respectively. This left 105 matched nodes in each group for the subsequent network analysis. The networks were visualized (**Figure 4**) and the network measures (CC, ASPL, and Q) for these three networks were computed (**Table 8**) with R (Christensen & Kenett, 2023).

Figure 4. A 2D visualization of the semantic networks for the low, medium, and high Gc groups.



Note. Nodes denote the matched animal names generated by all three groups. Edges denote binary, symmetrical relations between nodes.

Upon visual inspection, the semantic memory network of the high *Gc* group appears more condensed than that of the medium and low *Gc* groups. This observation is consistent with Study 1 and the network measures presented in **Table 8**, with the high *Gc* group showing a higher CC, and lower ASPL and Q, compared to the networks of the medium and low *Gc* groups.

Table 8. *Network measures for each of the three Gc groups*

Groups	CC	ASPL	Q
Low	.742	2.989	.611
Medium	.744	2.839	.626
High	.756	2.798	.605

Notes. ASPL, average shortest path length; CC, clustering coefficient; Q, modularity.

Similarly, the simulated random network analysis revealed that all empirical network measures for the low, medium, and high *Gc* groups were significantly different from their random counterparts (all *p'*s < .001).

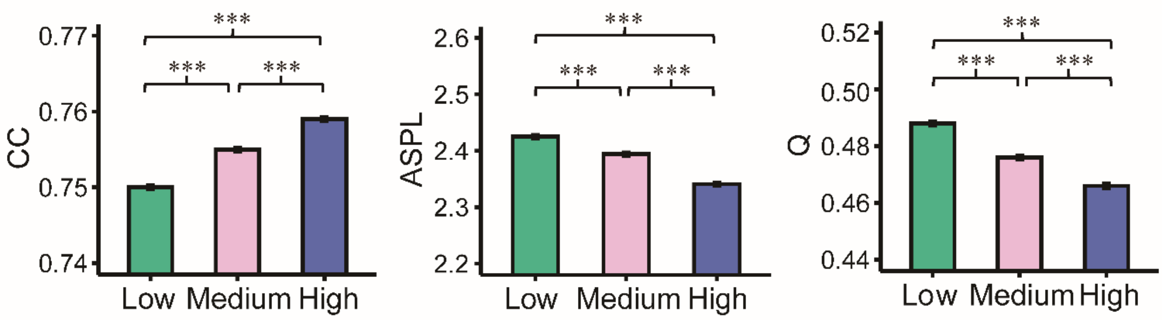
Finally, we conducted the partial-network bootstrapping analysis. Half of the total nodes within each network were selected for bootstrapping partial networks analysis (52 out of 105 nodes). A one-way ANOVA analysis exposed significant differences between the three groups on the partial network measures. Tukey's HSD pairwise comparison showed significant differences between the three groups (all *p's* < .001; detailed in **Table 9**). Consistent with our Hypothesis 1 and Study 1, the high *Gc* group showed significantly smaller ASPL and Q for partial networks compared to the other two groups. In contrast, CC was significantly larger for partial networks of the high *Gc* group compared to the low and medium *Gc* groups (**Figure 5**).

Table 9. *One-way ANOVA on the partial networks' bootstrap analyses.*

	Group	***M***	***SD***	***F* (2, 2997)**	***P***	***ηp2***	**Contrast Groups**	***p***	**HSD Results**
CC	low	.750	.01	305.431	< .001	.169	low-high	< .001	low < high
	medium	.755	.01				medium-high	< .001	medium < high
	high	.759	.01				medium-low	< .001	medium > low
ASPL	low	2.425	.10	205.896	< .001	.121	low-high	< .001	low > high
	medium	2.394	.09				medium-high	< .001	medium > high
	high	2.341	.09				medium-low	< .001	medium < low
Q	low	.488	.03	185.223	< .001	.110	low-high	< .001	low > high
	medium	.476	.02				medium-high	< .001	medium > high
	high	.466	.03				medium-low	< .001	medium < low

Notes. ASPL, average shortest path length; CC, clustering coefficient; Q, modularity.

Figure 5. *Means for the Gc groups on CC, ASPL, and Q*

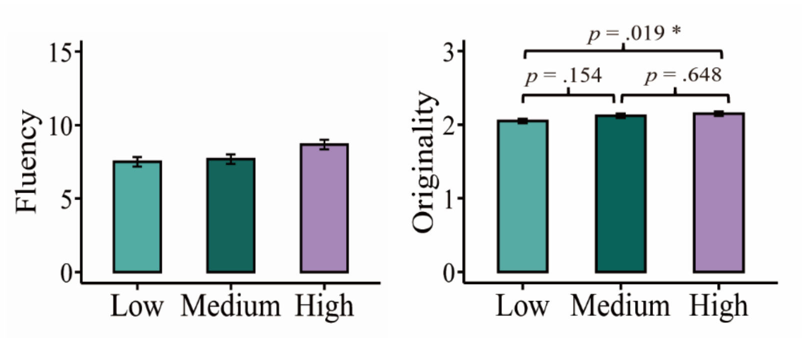


Note. The data represents 50% of selected nodes. Error bar represents *SE*.

3.2.1 Creative Thinking

Finally, we concocted separate one-way ANOVA's to examine the effect of *Gc* group AUT fluency and originality. This analysis revealed that there was no significant difference in fluency between the three groups, F (2, 158) = 2.065, p = .130, η_p^2 = .025. Due to the lack of significant differences observed among the samples in the overall test, multiple comparisons were not performed. However, in terms of originality, the one-way ANOVA revealed a significant main effect of Group, F (2, 158) = 3.914, p = .022, η_p^2 = .047. Tukey-HSD post-hoc test exposed significantly higher originality scores for the high *Gc* group (M = 2.15, SD = .18) compared to the low *Gc* group (M = 2.05, SD = .17), $t_{(105)}$ = 2.964, p = .019, d = .571, as predicted by Hypothesis 2. The differences of originality scores between the medium *Gc* group (M = 2.12, SD = .22) and high *Gc* group were not significant $t_{(105)}$ = -.850, p = .648, d = .149. Similarly, there were no significant differences observed between the medium group and the low Gc group, $t_{(106)}$ = 1.813, p = .154, d = .170 (**Figure 6**).

Figure 6. *The differences in fluency and originality of AUT scores between the Gc groups.*



Note. Error bar represents *SE*.

Finally, to account for the possible confound of *Gf*, we conducted an ANCOVA with *Gf* as a covariate, *Gc* Group as the independent variable, and AUT originality as the dependent variable. This analysis revealed that even after controlling for *Gf*, the effect of *Gc* Group on AUT originality remains significant, $F_{(2, 158)} = 3.062$, $p = .049$, $\eta_p^2 = .038$. This suggests that the effects observed in this study are primarily specific to *Gc*.

Furthermore, the relation between *Gc* and DT were examined via Pearson's correlation analysis (**Table 10)**. The results revealed significant correlation between *Gc* and originality.

Table 10. *Pearson's correlations of Gc and originality in study 2*

Variable		Gc_Adv	Gc_Extend	GC	Fluency	Originality
*Gc*_Adv	Pearson's r	—				
	p-value	—				
	N	161				
*Gc*_Extend	Pearson's r	.235**	—			
	p-value	.003	—			
	N	161	161			
Gc	Pearson's r	.859	.699**	—		
	p-value	.000	.000	—		
	N	161	161	161		
Fluency	Pearson's r	.110	.139	.154	—	
	p-value	.165	.079	.051	—	
	N	161	161	161	161	
Originality	Pearson's r	.221**	.126	.229**	.092	—
	p-value	.005	.111	.004	.247	—
	N	161	161	161	161	161

Notes. * - $p < .05$; ** - $p < .01$. *Gc*_Adv represents the score of advanced vocabulary test; *Gc*_Extend represents the score of extended range vocabulary test. *Gc* means the sum of *Gc*_Adv and *Gc*_Extend. Fluency means the number of the alternate uses task answers generated by participants. The originality means the sum of the originality scores for both objects.

3.3. Discussion

Study 2 replicated the results of Study 1: the semantic memory network of the high *Gc* group is more flexible, interconnected, and clustered. In addition, we found that the higher the *Gc*, the higher the verbal creativity.

4. General Discussion

Across two studies, we examined whether *Gc* relates to the structure of semantic memory networks and verbal creativity. Consistent results from both samples showed that the high *Gc* group exhibited a more flexible semantic memory network, characterized by less structure, greater clustering, and increased interconnectedness, in comparison to the low *Gc* group. Moreover, the high *Gc* group outperformed the low *Gc* group on verbal creativity, providing a robust replication of prior work. These findings suggest that the structure of semantic memory supports both verbal intelligence and creative ability, suggesting that a shared mechanism may underlie these two cognitive abilities.

4.1 *Gc* and Semantic Memory Networks

We found that high *Gc* individuals have a more efficient, flexible, clustered, and interconnected semantic memory network (reflected by a higher CC, and smaller ASPL and Q) than low *Gc* individuals. A shorter ASPL implies that, on average, fewer steps are required to travel between any two nodes in a network (Latora & Marchiori, 2001). A smaller Q reflects the presence of highly interconnected communities, and indicates a higher efficiency for long-range network communication (Fortunato, 2010). CC measures the extent to which the nodes of a network cluster together (Siew et al., 2019). Within semantic memory networks, a higher CC has been related to stronger associative abilities like associational fluency and associational flexibility (He et al., 2021).

Altogether, the present study suggests that a highly interconnected semantic memory network is beneficial for verbal intelligence, supporting the classic connectivity model of semantic processing (Klimesch, 1987). One possibility is that the more interconnected semantic memory network of high *Gc* individuals may facilitate searching through indirect pathways, thus improving their overall search efficiency on verbal intelligence and creativity tasks (see also Marko & Riečanský, 2021; Michalko et al., 2023). This network structure may increase the possibility of finding both correct and creative solutions, depending on the task, rather than fixating on non-related information. Conversely, our results do not seem to support the complexity model (Gentner, 1981), which holds that the processing capacity for accessing and comparing features is limited, and that, with increased semantic components, memory load will in turn increase, slowing processing efficiency and thus task performance.

High *Gc* individuals may also be able to better connect different branches or communities, evidenced by a lower Q in the high *Gc* network. In other words, having less overall structure in a network, as quantified by Q, may make it easier to navigate and connect different subcategories in the network (e.g., farm animals vs. marine animals; Michalko et al., 2023). This finding is notable, however, as one might expect high *Gc* individuals to have more structured networks, with discrete clusters for semantic subcategories (e.g., Cosgrove et al., 2023)—which has also been shown for high fluid intelligence (Kenett, Beaty, et al., 2016). Yet this structure is consistent with research on creativity, which consistently shows less structure in the semantic memory networks of highly creative groups (Benedek et al., 2017; Kenett et al., 2014; Li et al., 2021). These results provide additional theoretical support for the connectivity model of semantic processing (Klimesch, 1987), as processing efficiency does not seem to decrease with an increase in semantic complexity.

4.2 *Gc*, Creativity, and Semantic Memory Networks

Compared to the other groups, the high *Gc* individuals showed the highest creative abilities, consistent with past research reporting correlations between these two cognitive abilities (e.g., Cho et al., 2010; Gerver et al., 2023; Sligh et al., 2005). But why do high *Gc* individuals tend to be more creative? High *Gc* reflects a more unique knowledge base, i.e., having a richer vocabulary obtained through education and experience (Beauducel & Kersting, 2002). Further, a previous study found personal and social experience explained 65% of originality scores for alternative uses tasks (Runco & Acar, 2010), which supported the claim that divergent thinking tests may depend heavily on experience.

Here, we show that high *Gc* is also related to a more flexible, clustered, and interconnected semantic memory network—a semantic structure associated with high creative thinking ability across a range of tasks, including divergent thinking (Benedek et al., 2017; He et al., 2021; Ovando-Tellez, Kenett, et al., 2022), convergent thinking (Luchini et al., 2023), and novel metaphor production (Beaty & Silvia, 2013; Li et al., 2021). Moreover, the present research demonstrates that increased semantic memory network flexibility, across the three *Gc* groups, is accompanied by increased verbal creativity. We thus suggest that a flexible semantic memory network helps to explain why high *Gc* individuals are more creative: both verbal intelligence and creative thinking ability are characterized by a flexible organization of semantic memory.

Moreover, considering the CHC theory of intelligence, which posits that intelligence includes *Gf*, *Gc*, *Glr* (long-term retrieval), and other abilities (Horn & Blankson, 2005), Both *Gc* and semantic memory (retrieval ability) are integral components of general intelligence (*g*). While semantic memory may statistically mediate the relationship between *Gc* and DT, both *Gc* and semantic memory contribute to the generation of unique ideas in distinct ways. For example, high *Gc* reflects a wealth of information retrieval, while a more flexible semantic memory network may enhance retrieval efficiency and offer greater potential to generate original or novel ideas by identifying weaker connections within the network. Besides, the ANCOVA conducted in Study 2 showed that when *Gf* was controlled, the effect of *Gc* on originality is still significant, which indicates that the effects observed in this study are primarily specific to *Gc*.

Interestingly, high *Gc* individuals also produced more unique verbal fluency responses, which may also help to explain *Gc's* link to creativity. Although *Gc* is robustly related to verbal fluency, i.e., producing more responses (Silvia et al., 2013), to our knowledge, the present study is the first demonstration that high *Gc* individuals produce more unique responses. This finding makes intuitive sense: knowing more words (high *Gc*) should increase the likelihood of producing more unique words on a fluency task. Yet, the semantic memory network analysis provides additional insight: high *Gc* individuals have a more flexible semantic memory network structure, which may facilitate search processes when retrieving (uncommon) words on a verbal fluency task—even when they are not instructed to do so (Ovando-Tellez, Benedek, et al., 2022). Indeed, highly creative individuals produce more unique responses on verbal fluency tasks (Kenett et al., 2014), and they show a similar memory structure. This result provides another angle for understanding the interrelations among verbal intelligence, verbal ability, and the organization of the semantic system.

4.3. Limitations and Future Directions

A few limitations exist in our study. First, our creativity and semantic fluency tasks were "domain general" and did not evaluate individuals on a specific domain (e.g., creative writing). Thus, future studies are encouraged to extend these results in specific domains (e.g., Merseal et al., 2023). Second, our sample predominantly includes undergraduate students, who may not represent a larger population of domain experts or the general population. Our participants were all younger adults, which makes it challenging to generalize findings to older adults, who are likely to possess a broader vocabulary and semantic knowledge base (Cosgrove et al., 2023; Cosgrove et al., 2021). Future studies should extend the current investigation to address the issues of age and expertise, examining whether differences in domain knowledge and experience relate to differences in creative abilities and the underlying semantic network.

Additionally, the present research analyzed group differences by dichotomizing a continuous variable (i.e., vocabulary knowledge). This is a necessary procedure that is widely used to estimate group-based semantic memory networks when using the verbal fluency task (Christensen & Kenett, 2023; Zemla & Austerweil, 2018). Future studies should aim to replicate and extend our findings by using a semantic relatedness judgment task (Benedek et al., 2017; He et al., 2021; Ovando-Tellez, Kenett, et al., 2022) to construct individual-based semantic memory networks, which could elucidate the effects of individual differences in semantic memory network structure on both *Gc* and creativity. Importantly, our research was limited in its ability to triangulate the relationships between all three variables: *Gc*, creative ability, and semantic memory networks. Nevertheless, given prior work separately linking these three systems, we expect that analyzing individual-based semantic memory networks will replicate the group findings reported in this work. Importantly, such a future study examining the relation between individual-based semantic memory networks, *Gc*, and DT, will allow a mediation analysis to be conducted, testing the mediating effect of semantic memory on the relation between *Gc* and DT.

4.5. Conclusion

In summary, the current study quantitatively investigated the semantic memory network structure of people with different levels of *Gc* and explored how it may underly the relationship between *Gc* and verbal creativity. The novelty of our study lies in the outcomes that we obtained via a computational network science approach and the significance of these findings in relation to existing theories. In particular, our study applies computational network science methods to empirically and directly examine the support for either the complexity model or the connectivity model.

Our findings suggest that individuals with high *Gc* possess more efficient semantic memory networks that are less segregated into distinct communities, exhibiting greater flexibility in the semantic system. Additionally, the high *Gc* group showed higher creative abilities than the low *Gc* group. Our results offer preliminary evidence to suggest that a rich and flexible semantic memory network could form the foundation for understanding the link between verbal intelligence and creativity. This study provides the first empirical evidence supporting the classic connectivity model of semantic processing with computational network science methods.

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