Fostering Creativity in Science Education Reshapes Semantic Memory

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Abstract

Fostering creativity is vital for tackling 21st-century challenges, and education plays a key role in nurturing this skill. According to the associative theory, creativity involves connecting distant concepts in semantic memory. Here, we explore how semantic memory changes following an educational intervention intended to promote creativity. Specifically, we examine how a scientific education curriculum—Scientific Creativity in Practice (SCIP) program—impacts the semantic memory networks of 10–18-year-old students in a chemistry class ($n = 176$). Students in an Intervention group who received the SCIP intervention, and a Control group who did not, completed creative thinking tests, as well as verbal fluency tasks to estimate semantic networks in science-specific (chemistry) and domain-general (animal) categories. Results showed that the SCIP intervention enhanced performance on one test of scientific creative thinking but showed no significant difference on another. Using network science methods, we observed increased interconnectedness in both science-specific and domain-general categories, with lower path distances between concepts and reduced modularity. These traits define a 'small-world' network, balancing connections between closely related and remote concepts. Notably, the chemistry semantic network showed substantially more reorganization, consistent with the chemistry contents of the SCIP intervention. The findings suggest that semantic memory reorganization may be a cognitive mechanism underlying successful creativity interventions in science education.

Keywords: creativity, science, semantic network, knowledge

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Creativity is pivotal in tackling complex contemporary challenges (Newton & Newton, 2014). Education initiatives increasingly aim to cultivate creativity among students, including science education (Pllana, 2019), by teaching students how to generate and evaluate scientific hypotheses and experiments. Although specific educational programs have been shown to promote creative thinking in students (Denervaud et al., 2021), the cognitive mechanisms underlying creative learning are less understood. According to the associative theory, creativity involves connecting remote concepts (Mednick, 1962), and the ability to forge such connections relies on the organization of knowledge stored in semantic memory (Kenett & Faust, 2019). In this study, we explore the impact of a science education curriculum previously shown to enhance creative thinking—Scientific Creativity in Practice (SCIP) program (previously known as flex-based learning) (Haim & Aschauer, 2022)—on the semantic memory organization of middle- and secondary-school students. Using network science tools, we studied whether the SCIP program changed how science concepts were organized in semantic memory, which could explain improvements in scientific creative thinking.

Creativity

Creativity is vital for addressing the multifaceted challenges of the 21st century. Solutions to problems such as climate change, increasing wealth inequality, and the rapid spread of misinformation require innovative scientific solutions. Like other forms of creative thinking, scientific creativity involves both divergent thinking (generating many ideas; Guilford, 1950) and convergent thinking (narrowing down to a solution; de Vries & Lubart, 2019; Guilford, 1967; Kind & Kind, 2007). While both general creativity and scientific creativity involve divergent and convergent thinking, they differ in terms of the domains in which they are applied, and the level of domain-specific knowledge required (e.g., chemistry, physics; Hu & Adey, 2002; Mukhopadhyay, 2013). Theories of scientific creativity have emphasized a range of cognitive skills, from combinatorial ideation (Simonton, 2003) to abstract reasoning and analogical transfer (Kind & Kind, 2007). Identifying the specific cognitive components of scientific creativity can inform educational practices aimed at fostering this critical 21st century skill.

The associative theory of creativity posits that creativity involves forging connections between remotely associated concepts in semantic memory (Mednick, 1962; Kenett, 2019; Kenett & Faust, 2019). Semantic memory—knowledge of words and concepts—is thought to be organized as an interconnected network in the mind (Siew, 2019). In a semantic network, concepts are represented as nodes and relationships between them are the links, whereby nodes that are “closer” share more meaning (e.g., dog and cat; Collins & Loftus, 1975). Highly creative individuals are found to have a distinctly different semantic structure that facilitates such conceptual connections as compared to individuals lower in creativity (Mednick, 1962).

Recent advances in cognitive network science have provided new tools to explore the role of memory structure in creativity. For example, compared to individuals with lower creativity, those with higher creativity—as evidenced by more creative achievements and better performance on creative thinking tests—exhibit a more "flexible" structure to their semantic memory networks (Kenett et al., 2014; Kenett & Faust, 2019), i.e., their networks exhibit more connections and shorter paths linking concepts. This flexible network configuration appears to promote creative thought, as it allows people to efficiently connect seemingly unrelated concepts to generate novel ideas.

Education and Scientific Creativity

Education may influence creativity by re-organizing semantic memory—expanding, refining, and modifying the connectivity between concepts. Despite the importance of education in creative thinking, limited research has examined the cognitive mechanisms behind this relationship. Education could support creative thinking through two key pathways: 1) acquiring new conceptual knowledge (memory content) and 2) modifying the representation of memory itself (memory structure).

One recent study compared two educational systems, traditional and Montessori, and found that Montessori students had more “flexible” semantic memory networks, with many connections between concepts and shorter distances between them. The Montessori method is a child-centered educational approach that emphasizes self-directed learning, hands-on exploration, and collaborative play. Students engage with self-chosen learning materials under the guidance of teachers (Marshall, 2017). Montessori students also performed better on assessments of creative thinking (Denervaud et al., 2021). These findings highlight how education shapes the organization of semantic memory, and suggest educational experiences have the potential to mold advanced cognitive functions like creative thinking.

Creativity in the scientific process relies upon the ability to make new connections between concepts (Kenett et al., 2016) and educational interventions aid budding scientists in navigating this process (Hadzigeorgiou et al., 2012). One intervention is the Scientific Creativity in Practice (SCIP) program (previously known as flex-based learning), which aims to develop students’ flexibility in navigating different perspectives and applying varied strategies to scientific problems (Haim & Aschauer, 2022; School of Creative Solutions, 2021).

The Scientific Creativity in Practice (SCIP) program, developed at the Center for Science Teaching at Upper Austrian University of Education using a design-based research approach (Barab & Squire, 2004), and is implemented in approximately 50 schools in Austria. SCIP targets key aspects of scientific creativity through techniques such as divergent thinking, bisociation, original association, imagination visualization, and metacognition. The program emphasizes both domain-specific science competencies and domain-general creative skills, employing activities like clustering for original associations and WoSeCo (word-sentence-construction) for verbal creativity (see Method). Many SCIP learning activities are social in nature, such as the "Listen-Think-Pair-Share" technique, where students work individually before collaborating in small groups.

Central to SCIP is the focus on metacognition, comprising cognitive knowledge and cognitive regulation. The program integrates various interventions to promote metacognitive skills (see Method). For instance, the 'Thinkflex Tasks' (Haim & Aschauer, 2022) foster divergent thinking through a structured process of brainstorming, exchange, and reflection. In these tasks, students might list advantages and disadvantages of fireworks, considering multiple perspectives such as visual appeal, cultural significance, environmental impact, and safety. This approach enhances students' ability to view problems from various angles, generate diverse solutions, and critically reflect on their thinking processes. Further descriptions and examples of activities in the intervention program can be found in the Scientific Creativity in Practice (SCIP) intervention section under Materials and Methods and in prior papers (Haim & Aschauer, 2022, 2024).

To measure improvement in scientific creativity among adolescents, SCIP employs the Divergent Problem-solving Ability in Science-Test (DPAS-TEST; Aschauer et al., 2022). This validated tool complements the program's activities designed to develop scientific creativity. SCIP's focus on both domain-specific science competencies and domain-general creative skills is evident in its various activities (see Method). For example, clustering activities train original associations by tasking students to organize and link concepts, while WoSeCo activities enhance verbal creativity through sentence construction using technical terms. These activities support the creation of meaningful connections between scientific concepts, improving understanding and retention while developing flexibility in combining terms.

A recent large-scale study examined the effects of the SCIP program. The study involved 104 teachers and 3,516 Austrian secondary school students aged 10-18 years in both laboratory and real-world classroom settings. It found that the SCIP program boosted scientific creativity compared to traditional instruction (Haim & Aschauer, 2022). Although these findings highlight the potential of educational interventions for cultivating scientific creativity across, the cognitive mechanisms behind these benefits remain unknown. Elucidating the mechanisms of interventions like SCIP is critical for understanding how learning cultivates creative thinking.

To address this critical gap, the present study examined the impact of the SCIP scientific creativity intervention on students' semantic memory networks. We compared demographically similar students who did or did not undergo the SCIP intervention (N = 176). To estimate semantic networks, we used network science methods applied to verbal fluency tasks. In these tasks, students generate concepts belonging to specific categories. Students completed a chemistry fluency task to capture domain-specific knowledge, as well as an animal fluency task as a domain-general comparison. We hypothesized that students who participated in the SCIP program would exhibit more flexible semantic networks—with short path distances and high connectivity—resembling the networks associated with high creativity. Analyzing fluency-based networks allowed us to investigate whether and how the SCIP program shapes the structure of semantic memory to promote creative thinking.

Materials and Methods

Participants

A total of 176 students (47 females; 46 males; 83 unspecified) from four schools participated in the study. The schools included two academic secondary schools and two middle schools. Academic secondary schools and middle schools are institutional education options for students in Austria. Academic secondary schools prepare students ages 10-18 for tertiary education, while middle schools prepare students ages 10-14 for vocational careers. Compared to academic schools, middle schools tend to have more students from lower socioeconomic backgrounds and migrant families. On national standardized assessments, middle school students also typically score below the national average (Luciak, 2008; Schreiner et al., 2020). The control and intervention group both contained one academic secondary school and one middle school class.

The students were from four schools located near each other in Linz, Upper Austria. The schools had similar teaching requirements. Two classes of 25-35 students each were sampled from each school (eight classes total). Four classes were from the 3rd grade of academic secondary schools, with students aged 13. The other four classes were from the 4th grade of middle school, with students aged 14. Due to technical issues, data from 9 students was lost, resulting in a sample of 167 students. Parental consent was obtained for all students. The study was approved by the institutional review board of the Upper Austrian Department of Education.

Scientific Creativity in Practice (SCIP) intervention

The SCIP intervention spanned six weeks during the student's chemistry class. Students participated in intensive training sessions once a week, completing a total of six intervention sessions. Detailed records of individual session attendance were unavailable for the intervention. However, as the training took place during regular chemistry lessons and students were not permitted to miss more than a few classes, this ensured consistent participation across the group. Due to time restrictions, the entire SCIP program was not conducted. Rather, students were introduced to and trained in four creativity methods: *Thinkflex*, *Flexperiment*, *Clustering*, and *WoSeCo*. Each session focused on one or two of these methods. In total, students in the intervention class were trained with two Thinkflex tasks, one Flexperiment, four Clustering and four WoSeCo tasks.

Thinkflex (think-flexibly) encourages creative and open-minded thinking in students, with the goal of broadening students' thinking. Thinkflex activities aim to generate many diverse answers by approaching tasks from multiple perspectives. Common type of *thinkflex* task includes prompting students to ask questions, investigate why something is not working, and consider impacts of decisions (Haim & Aschauer, 2022). An example of such a task may ask students to "*List as many advantages and disadvantages of fireworks as possible. At the end, assign all your answers to specific categories and also think of alternatives to fireworks.*"

Flexperiment (flexible-experiment) involves open-ended experiments with diverse possible solutions. Key objectives include encouraging divergent thinking, building tolerance for mistakes, enhancing teamwork, boosting confidence in problem-solving, and avoiding fixed ways of thinking. These activities are aligned with the subject's curriculum. For science subjects, activities can include testing hypotheses, identifying errors, separating/synthesizing substances, exploring possibilities, and recognizing features (Haim & Aschauer, 2022). An example of a task is to "*Find as many ways as possible to make a candle flame go out using only gasses.*"

In *Clustering*, students organize concepts for a topic into clusters around main themes and subthemes. Clustering supports associative thinking and verbal fluency in a given subject in two key ways. First, it helps students organize and structure subject content. Second, it encourages understanding and connecting relevant technical terms. Clustering prepares students for later tasks like WoSeCo that require comprehending subject matter and terminology.

WoSeCo (word-sentence-construction) aims to build students' verbal creativity within a specific subject. The teacher provides a technical term, then students take turns making accurate sentences using that term plus their own term. Each subsequent student incorporates a new technical term, and this cycle continues until all students have participated once or twice. The main aim of WoSeCo is to encourage students to creatively merge technical terms into form meaningful contextual sentences, promoting a deeper understanding of the subject matter (Haim & Aschauer, 2022).

Procedures

The study used a quasi-experimental non-equivalent groups design between-subjects design with an intervention group and control group. Only the intervention group experienced the six weeks SCIP intervention during their chemistry class while the control group followed their regular class routine. Students were tested between May 26 and June 7, 2023, with each session lasting approximately 1-1.5 hours. All tasks were completed online using computers or tablets in the computer room or auditorium at the school. The sessions were conducted in German. A researcher was present in each class, and a teacher was present in 6 out of the 8 classes. To ensure uniformity of instruction, the same researcher explained the verbal fluency task at the start of each session. Students then engaged in 5 minutes of physical exercises like circling their arms or jumping which they also repeated after finishing the first part of the study. These exercises are not typically part of the SCIP program, but were incorporated specifically for the 45 minute long study to mitigate potential fatigue and raise attentiveness. These physical exercises were carried out for both the intervention and the control classes to ensure comparability. The 5-minute verbal fluency task was conducted for two topics for 2 minutes each and was administered using PsychoPy (version 2022.2.5). Students took a 5-minute break with more physical exercises to combat potential fatigue before the researcher explained the 30-35 minutes DPAS task, administered using SosciSurvey. After finishing the verbal fluency and DPAS tasks, students completed a short demographic survey to conclude the session.

Materials

Animal Fluency Task

The animal fluency task (Ardila et al., 2006) was administered first. It is the most common fluency task used to estimate domain-general, group-based semantic networks (A. P. Christensen & Kenett, 2021). Students were given 2 minutes to generate as many nouns as possible related to a given topic. 'Plants' was used as the practice topic, followed by 'animals' as the test topic The topic remained at the top of the screen while students typed and submitted each response by hitting the ‘Enter’ key.

Chemistry Fluency Task

To estimate domain-specific semantic memory networks (Siew & Guru, 2023), the topic ‘chemistry’ was presented to the students. Identical to the animal fluency task, students were given two minutes to generate as many words related to chemistry as possible. This approach follows the method of Siew and Guru (2023), who assessed science-related memory networks by administering fluency tasks for various science topics (biology, chemistry, mathematics, physics, psychology).

Divergent Problem-solving Ability in Science test (DPAS)

The DPAS was implemented to assess students’ scientific creativity in problem-solving and evaluate the effectiveness of the program intervention. The DPAS has been validated as a reliable measure of scientific creativity both longitudinally and between groups (Aschauer et al., 2022). It was administered on SosciSurvey (Leiner, 2019).

The DPAS task consists of two subtests: divergent ideation in science task (DIST) and divergent ideation in experiment task (DIET). For DIST, students generated potential alternative solutions and explanations for a given empirical observation. For DIET, students used a provided list of items/materials to determine a specific scientific quantity or distinguish between two quantities.

A total of six DPAS items were presented: three DIST items (reasons for temperature change in a classroom, protecting sheep from UV radiation, reasons for non-frozen ice cream) and three DIET items (determine height of 150cm, determine time period of 30 min, distinguish mass of two cans). Students completed the task in 30-35 minutes.

Responses were rated by an author of this paper based on a scoring guide (Aschauer et al., 2022) and the dataset was blinded prior to scoring. Furthermore, the responses were sorted alphabetically rather than grouped by individual participant, which ensured that the scorer did not evaluate all answers from a single participant in sequence. This process facilitated unbiased scoring and helped maintain consistency in evaluating similar responses with the same criteria. For each item, the sum of appropriate responses assessed the fluency score.

Group Construction

Comparisons between the control and intervention group were made by constructing group-based semantic memory networks from the animal (domain-general) and chemistry (domain-specific) fluency task responses (A. P. Christensen & Kenett, 2021). Participants’ responses were aggregated into the two groups (control N = 78, intervention N = 89).

Semantic Memory Network Estimation

The SemNA toolbox (A. P. Christensen & Kenett, 2021) was used for the preprocessing, network construction, and analysis comparing the control and intervention groups for the two fluency tasks. SemNA comprises three R packages—*SemNetDictionaris, SemNetCleaner, and SemNeT*—that standardize semantic network analysis. All analyses were performed in R v4.3.1 (R Core Team, 2023) through RStudio v2023.06.0 ("Mountain Hydrangea").

Preprocessing

Participants' responses from the two semantic fluency tasks were automatically preprocessed using SemNetDictionaries v0.2.0 (A. P. Christensen, 2022) and SemNetCleaner v1.3.4 (A. P. Christensen, 2021). Identical preprocessing steps were conducted for the animal and chemistry fluency task data. Prior to processing, participants' responses were translated from German to English. Swear words, within-participant repetitions (i.e., duplicated responses), and non-category members (e.g., dragon, ant colony, moon for the animals) were removed. The data was then cleaned by addressing issues like spelling errors, compound responses, root word variations, and continuous strings. Unrecognized words underwent manual spell-checking and correction to standard English.

To create a binary response matrix, the cleaned data was transformed. Each unique participant response was assigned as a column, and individual participants were assigned as rows. The frequency of response occurrence within participants populated the matrix, with 1 indicating the participant generated the exemplar, and 0 indicating they did not. To enable direct network comparison and control potential confounds (e.g., differences in nodes/edges; Wijk et al., 2010), all unique animal responses were matched between the groups. Following semantic network analysis conventions (A. P. Christensen et al., 2018; Kenett et al., 2016), only exemplars provided by at least two participants overall were included in the response matrix. This criterion is necessary to allow a direct comparison between the networks. Network parameters are sensitive to variations in node numbers; comparing these parameters directly between networks could lead to misleading conclusions, such as attributing network properties to specific nodes rather than broader network characteristics. This constraint ensures there's enough data (responses from at least two participants) to calculate correlations between groups accurately. Responses from a single person might be influenced by individual idiosyncrasies or biases. By requiring data from multiple participants, the approach aims to reduce the impact of these individual variations on the connections between groups, thus minimizing the likelihood of creating misleading associations (Borodkin et al., 2016). For each group, only the responses provided by the other group were retained. Thus, all semantic memory network comparisons focused solely on organization differences of the same nodes.

Network Construction

The same network analysis steps were conducted separately for the animal and chemistry fluency tasks, comparing the control and intervention groups. Using the SemNeT package (version 1.4.4; A. Christensen, 2017/2023), association profiles between the fluency responses were created. The cosine similarity function, which estimates the co-occurrence probability between two words by calculating the angle between their word vectors, determined the network edges. This constructed an n x n adjacency matrix representing associations between each response within each group (A. P. Christensen et al., 2018). Cosine similarity values range between 0-1, with 1 indicating two words always co-occur and 0 indicating they never co-occur. This technique mirrors corpus-based methods in text analysis such as latent semantic analysis (Landauer & Dumais, 1997) and semantic distance (Beaty & Johnson, 2021).

The adjacency matrix was then used to implement the Triangulated Maximally Filtered Graph (TMFG) method, which aimed to maximize node association strength while ensuring the network planarity, allowing the network to be depicted on a 2D surface without crossing edges (Tumminello et al., 2005). To meet this structural constraint, the resulting network retains 3n - 6 edges, where n is the number of nodes in the network.

Network Analysis

The clustering coefficient (CC), average shortest path length (ASPL), and modularity (Q) were calculated for the control and intervention group networks for both animal and chemistry fluency tasks. CC measures local connectivity and the degree to which a network clusters together. It is calculated by determining the proportion of connections between neighboring nodes out of all possible connections. Higher CC indicates a more interconnected, cohesive network, while lower CC suggests a more dispersed, less clustered network (Siew, 2019). ASPL indicates network efficiency and concept relatedness, calculated as the shortest number of steps/edges between any two nodes. Lower ASPL indicates greater node closeness (Kleinberg, 2000). Q assesses network segregation by comparing connection density within versus between communities (Fortunato, 2010). Higher Q indicates robust, well-defined community structure, with more within-community than between-community connections (Newman, 2006).

The correlation-based network measure estimation method was used to estimate semantic networks for each group (control, intervention) across the two fluency tasks (i.e. animals, chemistry), resulting in four networks. Random network and bootstrap analyses then compared the network matrices (CC, ASPL, Q). Random network analysis is an important first step to establish that the fluency networks exhibit greater structure than would be expected by chance alone before comparing the group-based networks (via bootstrap analyses). For the random network analyses, the fluency-derived networks were compared against randomly generated networks with equal nodes and edges. For the bootstrap analyses, a case-wise bootstrap method (Efron, 1979) with 1000 iterations per network was used to compare control versus intervention networks. The group network matrices were compared via independent-samples t-test using the SemNeT R package (A. P. Christensen & Kenett, 2021).

Results

Demographics and Descriptive Statistics

First, we tested for demographic differences between the control and intervention groups on the animal fluency and chemistry fluency tasks (Table 1). There was no significant difference in gender distribution between the groups (p = .24). However, there were significant differences in the proportion of participants born in Austria, X^2 (2, N = 167) = 9.31, p = .009 and those with German as their first language, X^2 (2, N = 167) = 10.13, p = .006.

Table 1. Descriptive statistics for control and intervention groups

	Overall	Control	Intervention	*p*
n	167	78	89	
Gender (%)				0.237
Female	45 (26.9)	22 (28.2)	23 (25.8)	
Male	45 (26.9)	25 (32.1)	20 (22.5)	
Unspecified	76 (45.5)	30 (38.5)	46 (51.7)	
NA	1 (0.6)	1 (1.3)	0 (0.0)	
Country (%)				0.009
Austria	126 (75.4)	52 (66.7)	74 (83.1)	
Others	29 (17.4)	21 (26.9)	8 (9.0)	
NA	12 (7.2)	5 (6.4)	7 (7.9)	
German (%)				0.006
No	48 (28.7)	31 (39.7)	17 (19.1)	
Yes	118 (70.7)	46 (59.0)	72 (80.9)	
NA	1 (0.6)	1 (1.3)	0 (0.0)	

Scientific Creativity (DPAS)

Responses to the Divergent Problem-solving Ability in Science test (DPAS) test underwent rigorous cleaning. Each response was evaluated for suitability, feasibility, and accuracy, while nonsense responses were excluded from analysis.

Results showed separate patterns across the two subtests—DIST (divergent ideation in science task) and DIET (divergent ideation in experimental task). For the DIST, the SCIP program had a significant intervention effect (independent samples t-test, $t(165) = 1.76$, $p = .04$). Intervention students ($M = 4.27$, $SD = 2.50$) outperformed controls ($M = 3.64$, $SD = 2.08$) in fluency scores. No significant effect was observed for the DIET. Thus, in this sample, the SCIP program significantly improved scientific creativity on open-ended verbal tasks (DIST) but not complex experiments (DIET).

Verbal Fluency Performance

Significant correlations were found between both DPAS subtests and verbal fluency scores (see Table 2). Students with better DPAS performance also achieved higher verbal fluency scores for both topics (animals, chemistry). A Steiger's Z-test was then conducted to compare the dependent correlations between the animal verbal fluency score and DIST fluency score ($r = .543$) with chemistry verbal fluency score and DIST fluency score ($r = .595$) while accounting for the correlation between the animal and chemistry verbal fluency score themselves ($r = 0.64$). The test revealed no significant difference between the two correlations, $t(162) = -1.00$, $p = .32$. The same test was also used to compare the dependent correlations between the animal verbal fluency score and DIET fluency score ($r = .410$) with chemistry verbal fluency score and DIET fluency score ($r = .544$) while accounting for same correlation and found a significant difference between them $t(162) = -2.39$, $p = .018$. The correlation with DPAS subtests was numerically larger for chemistry than animals in the DIET subtest, which may indicate that the chemistry fluency task likely measures domain-specific semantic memory (relevant for scientific creativity), while the animal fluency task assesses more general semantic memory.

Table 2. Pearson correlation coefficient between DPAS subtests and verbal fluency scores

PCC	**DIST fluency score**	**DIET fluency score**
Animal verbal fluency score	.543**	.410**
Chemistry verbal fluency score	.595**	.544**

** … p < .001

Table 3 shows fluency performance for control and intervention groups on the animal and chemistry fluency tasks. There were no significant differences in animal fluency between the control ($M = 18.13$, $SD = 5.96$) and intervention ($M = 19.72$, $SD = 7.39$) groups, $t(164) = -1.54$, $p = .063$, $d = -.235$, 95% CI [-3.631, 0.449]. However, on the chemistry fluency task, the intervention group generated significantly more responses ($M = 13.96$, $SD = 5.30$) than controls ($M = 11.51$, $SD = 5.33$), $t(165) = -2.965$, $p = .002$, $d = -.460$, 95% CI [-4.069, -0.815]. This indicates the SCIP program not only improved scientific creativity but also science-specific verbal fluency.

Table 3. Descriptive statistics for the animal and chemistry fluency tasks

	Animal Fluency Task				Chemistry Fluency Task			
	n (average)		*n* (within)	*n* (between)	*n* (average)		*n* (within)	*n* (between)
Group	*M (SD)*	Range			*M (SD)*	Range		
Control	18.13 (5.96)	5-32	226	71	11.51 (5.33)	1-26	282	157
Intervention	19.72 (7.39)	6-35	273	118	13.96 (5.30)	2-31	269	144

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

Semantic Network Analysis

Semantic memory networks were constructed for the control and intervention groups. The animal semantic memory network had 99 nodes and the chemistry semantic memory network had 66 nodes (Figure 1). Cytoscape 3.10.0 (Shannon et al., 2003) generated 2D representations of these unweighted, undirected networks. Circles represent participant responses and lines represent links between them.

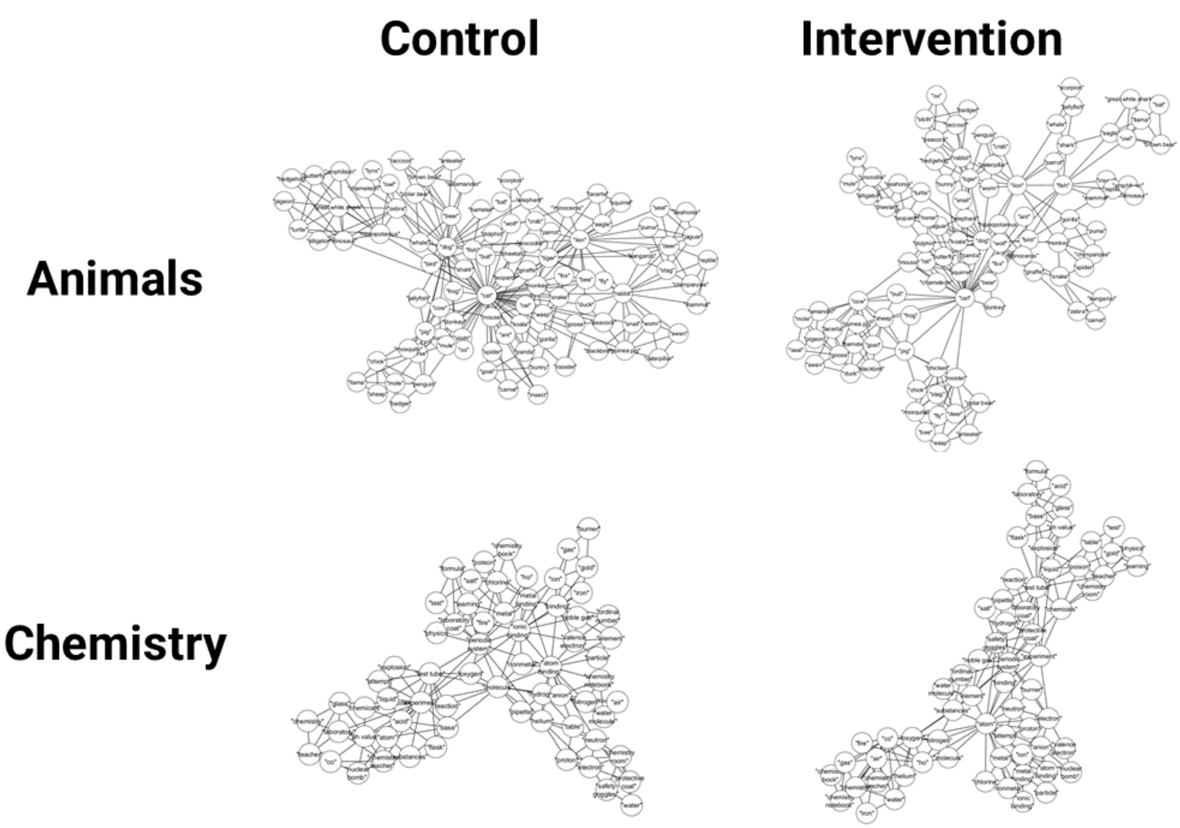

Figure 1. A 2D visualization of the animal and chemistry semantic networks of individuals in control and intervention group. Nodes were adjusted slightly manually to ensure no overlapping. Random network analysis, matched on the number of nodes and edges, revealed the semantic networks differed from random networks across all metrics (ASPL, CC, Q; all $p < .001$). Thus, the fluency networks exhibit greater structure than would be expected by chance alone.

Next, bootstrapped network analysis compared the control and intervention networks for the animal and chemistry fluency tasks (Table 4 and Figure 1).

Table 4. Comparison of semantic memory networks between groups

		M (SD)				
	Parameter	Control Group	Intervention Group	*t-value*	*p-value*	*d*
Animal Fluency	ASPL	3.282 (0.223)	3.209 (0.211)	7.482	< .001	0.335
	CC	0.718 (0.009)	0.721 (0.009)	-9.852	< .001	0.441
	Q	0.627 (0.019)	0.624 (0.02)	3.565	< .001	0.159
Chemistry Fluency	ASPL	3.331 (0.287)	3.048 (0.233)	24.214	< .001	1.083
	CC	0.694 (0.016)	0.71 (0.013)	-26.178	< .001	1.171
	Q	0.596 (0.021)	0.580 (0.025)	16.385	<. 001	0.733

Note. Results from bootstrapping and two-samples t-tests comparing the animal and chemistry fluency semantic memory networks between control and intervention groups. Bootstrapping was performed over 1000 iterations. Means (*M*) of all network parameters (ASPL, CC, Q), *t-value*, *p*-value, and effect size in Cohen's *d* (Cohen, 1962) are presented. 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.

Regarding animal semantic networks, an independent-samples *t*-test revealed the intervention group had significantly shorter average shortest path length (ASPL; $M = 3.209$, $SD = .211$) compared to controls ($M = 3.28$, $SD = .223$), $t(1998) = 7.48$, $p < .001$, $d = .34$, 95% CI [0.054, 0.092]. In addition, the intervention group also showed significantly larger clustering coefficient (CC; $M = 0.721$, $SD = 0.009$) than controls ($M = 0.72$, $SD = 0.009$), $t(1998) = -9.85$, $p < .001$, $d = .44$, 95% CI [-0.005, -0.003]. Modularity (Q) was also significantly lower in the intervention group ($M = 0.62$, $SD = 0.02$) than controls ($M = 0.63$, $SD = 0.019$), $t(1998) = 3.57$, $p < .001$, $d = .16$, 95% CI [0.001, 0.005]. In summary, the intervention group showed more interconnected (higher CC; lower ASPL) and less modular (lower Q) animal semantic networks.

Regarding chemistry semantic networks, a similar pattern emerged, albeit with much larger effect sizes than the animal networks. An independent-samples t-test showed the intervention group had significantly shorter ASPL ($M = 3.048$, $SD = .233$) than controls ($M = 3.331$, $SD = .287$), $t(1998) = 24.214$, $p < .001$, $d = 1.083$, 95% *CI* [0.26, 0.306]. The intervention group also had larger CC (Intervention: $M = 0.71$, $SD = .013$; *Control*: $M = 0.694$, $SD = .016$), $t(1998) = -26.178$, $p < .001$, $d = 1.171$, 95% *CI* [-0.018, -0.015]. Q was also significantly lower in the intervention group ($M = 0.58$, $SD = .025$) than controls ($M = 0.596$, $SD = .021$), $t(1998) = 16.385$, $p < .001$, $d = 0.733$, 95% *CI* [0.015, 0.019].

In summary, the chemistry network results suggest the intervention group was more interconnected (higher CC; lower ASPL) and less modular (lower Q), with effect sizes orders of magnitude larger than the animal networks (range: 2.65 - 4.61 times). The SCIP program thus impacted both domain-general and domain-specific semantic memory networks, but had a substantially greater effect on domain-specific semantic structures with science concepts.

Discussion

Past research has shown that educational interventions like SCIP (formally known as flex-based learning) can successfully foster scientific creative thinking in students. However, less is known about how these creativity interventions may impact the cognitive mechanisms that underlie creativity. The present research investigated how SCIP impacts students' semantic memory organization, which is critical for creative thinking (Beaty & Kenett, 2023). Students' verbal fluency responses were used to construct semantic networks in both domain-general (animal) and domain-specific (chemistry) categories. As expected, the results showed SCIP boosted the open-ended and divergent aspect of scientific creativity (DIST), replicating previous findings (Haim & Aschauer, 2022) but found no significance in the more convergent aspect (DIET). More importantly, SCIP seems to have restructured the semantic memory networks in the intervention group. These changes were observed across both domain-general and domain-specific networks, with the greatest reorganization occurring within the domain-specific chemistry networks. Taken together, these results provide some evidence that reorganizing semantic memory may be a key cognitive mechanism by which effective scientific creativity interventions like SCIP enhance creative thinking.

Firstly, the key finding of our study is that participation in the SCIP program is associated with changes in the underlying semantic network of students. Results were consistent with our hypothesis. We found a significant difference between the intervention and control groups across both domain-general (animal) and domain-specific (chemistry) semantic networks. In both domains, students in the intervention group displayed a more highly connected semantic network, with lower average shortest path length (ASPL), greater clustering coefficient (CC), and less modularity (Q), aligned with prior research. Comparison between traditional and Montessori education found that Montessori students exhibited more flexible semantic memory networks and performed better in creative thinking assessments (Denervaud et al., 2021).

According to the associative theory, creativity involves forming connections between concepts in memory (Kenett & Faust, 2019). Our findings mirror typical characteristics of highly creative people, who tend to have a more flexible, “small-world” semantic memory network defined by greater cohesion and integration. A small-world structure enables efficient communication across the network and spreading activation between concepts, critical for connecting ideas during creative thinking (He et al., 2020; Kenett et al., 2014). This small-world network was found in students after undergoing SCIP, suggesting the intervention may have enhanced their creative thinking by making it easier for them to link concepts in semantic memory. The emergence of small-world properties implies an optimal balance of local clustering of related concepts and global reachability of distant concepts that could facilitate creative idea generation and knowledge integration.

A key finding was the lower average shortest path length (ASPL) in the intervention compared to the control group. ASPL measures the number of steps between nodes in a network. Shorter paths in semantic networks relate to closer semantic distance, faster reaction time, and higher judged relatedness between words (Kenett et al., 2017; Kumar et al., 2020). The reduced ASPL suggests students who underwent the intervention could navigate and search conceptual knowledge more efficiently. Within creativity, enhanced conceptual navigation can facilitate idea generation. Shorter paths are often influenced by 'bridge' links between clusters (Schilling, 2005), which may promote creativity by enabling novel combinations of concepts by ‘jumping’ between more remote concepts.

Additionally, the intervention group showed a higher clustering coefficient, reflecting the tendency for connected concepts to cluster together, akin to network density (He et al., 2020; Marko & Riečanský, 2021). A high clustering coefficient implies concepts are interconnected and form close-knit neighborhoods (Siew et al., 2019). After the intervention, students may have developed knowledge structures with tighter connections between related concepts, improving search through spreading activation and flexible switching (Marko & Riečanský, 2021).

Finally, the intervention group had lower modularity (Q), implying their networks were less divided into distinct, non-overlapping modules. This structure is more inclusive, with blurrier category boundaries. Low-Q networks integrate diverse knowledge and can link seemingly unrelated concepts, which is beneficial for creativity, as well as interdisciplinary research, where concepts from different domains are interconnected. Unexpected or novel semantic associations between concepts may emerge, as there are fewer constraints on how concepts are grouped together. Together with a high CC, a low Q is also indicative of a resilient network. Percolation analysis of semantic networks from previous research suggests that the semantic network of highly creative individuals exhibits greater resilience against simulated network attacks. This resilience is evidenced by the slower disintegration of the network, and it aligns with the findings from our current result of higher CC and lower Q (Cosgrove et al., 2021, 2023; Kenett et al., 2018).

The results also revealed differences in semantic memory networks for both the domain-specific (chemistry) and domain-general (animals) categories. Critically, the effect size was over two to four times larger in the domain-specific chemistry network across all network measures. This substantial effect indicates that the SCIP intervention had a greater impact on science-specific memory structures compared to general knowledge. The reorganization of the chemistry network aligns with the long-established research on the recency effect (Baddeley & Hitch, 1993; Greene, 1986) showing newly learned vocabulary concepts exhibit higher activation and salience (Wiswede et al., 2007). In this study, students learned the chemistry concepts more recently than animals. Therefore, these domain-specific representations may be more susceptible to restructuring from the learning intervention.

However, there could be several potential explanations for concurrent changes in the animal knowledge semantic network. Firstly, the effect sizes are consistent with the theoretical expectations from transfer learning. According to the generalization theory of transfer learning, learning performance in one context can be generalized to performance in another context (Perkins & Salomon, 1992). However, transferring skills or knowledge between distinct contexts (far transfer) is less likely than within related ones (near transfer). Education interventions have been shown to alter the semantic knowledge networks of students (Denervaud et al., 2021). Under the SCIP intervention, students may perceive mental concepts in general to be more flexible, dynamic, and connected. The educational intervention's emphasis on scientific concepts explains the notably larger effect size observed in the domain-specific (chemistry) network compared to the domain-general (animal) network, aligning with the principles of near and far transfer. Next, the difference in effect size could also be interpreted as the impact of changing a smaller part of the network (chemistry) on the larger network (animal). The domain-specific network could be embedded within a larger domain-general network such that by changing a portion of the network through learning, the changes reverberate throughout (Y. Kenett & Thompson-Schill, 2023).

As per prior literature, the Divergent Problem-solving Ability in Science test (DPAS) scientific creativity task provided evidence for the effectiveness of SCIP (formally known as flex-based learning) (Aschauer, Haim & Weber, 2022). Students who underwent the intervention showed higher fluency on the open-ended divergent ideation in science task (DIST) compared to controls. This aligns with the core aims of the SCIP activities like Thinkflex and WoSeCo to boost divergent thinking and verbal fluency. However, no significant difference was found between groups on the more constrained divergent ideation in experiment task (DIET). A potential explanation in the discrepancy could stem from students' lack of hands-on experimental training. Due to time constraints, teachers in the intervention classes conducted only one flexperiment—an open-ended experiment with multiple possible solutions. This appears insufficient to improve experimental creativity. In contrast, verbal tasks like Clustering and WoSeCo were practiced more often (four times each), which improved DIST performance.

In addition, while the DIST requires flexible solutions, reasons, or consequences for a provided situation without restricting students to specific materials, the DIET focuses on practical problems with constraints on available materials. Hence, the DIET requires more complex domain knowledge and practical skills that the students may not have time to acquire yet. Still, overall, the DPAS results demonstrate that the SCIP program significantly enhanced scientific creativity, specifically for open-ended verbal divergent thinking.

Limitations and Future Research

Our study has limitations that can inform future research directions. Firstly, it is important to consider potential between-group differences in language use. Differences in language could theoretically influence semantic networks. The absence of a pre-test and the non-randomized design (quasi-experimental) also weakens strong causal inferences. A non-equivalent group design (Shadish et al., 2002) is the lack of random assignment to treatment and control groups. Despite that, the design was chosen for its real-world applicability. We hence urge caution in interpretation and future research with pre-tests that would theoretically not be modified by the intervention (i.e. fluid intelligence test) to solidify these findings. Another alternative way to address this limitation would be to conduct a delayed intervention for a group.

Next, the relationship between learning, semantic network changes, and creativity remains uncertain. While we suspect more flexible networks underlie creativity by allowing efficient concept access and flexible combination, we could not directly link these variables given the group-based network analysis. Group-based network estimation precludes a dynamic, individual assessment of semantic memory structure. Additionally, contextual effects like prior-knowledge and present goals affect conceptual activation (Yee & Thompson-Schill, 2016). Future research should employ individual-based network approaches (Y. N. Kenett et al., 2017) to directly examine how interventions impact semantic network structure and creativity within individual students. Researchers can use the semantic relatedness judgment task (RJT), presenting participants with pairs of words and asking them to judge their semantic relatedness; this approach yields continuous data and enables the estimation of semantic networks at the individual level. They can then apply a linear mixed model to account for any possible hierarchical structure in the data and a mediation analysis to explore if the relationship between the educational intervention and scientific creativity can be explained by the participants' semantic networks.

Another limitation concerns potential age-related differences in the malleability of semantic memory, making certain ages potentially particularly receptive to learning-induced modifications. Future studies could examine the effect of SCIP across age groups. Additionally, although we presume SCIP directly altered semantic networks, this effect could be mediated by other factors relevant to creativity, such as metacognition (Armbruster, 1989), fluid intelligence (Y. N. Kenett et al., 2016), self-efficacy (Haase et al., 2018), motivation (Harackiewicz & Priniski, 2018). Future studies could also compare the effect that education has on creativity by directly measuring changes in memory content on top of its structure in the acquisition of new concepts through recall and recognition tasks. Finally, we cannot deduce which specific intervention activities changed semantic networks. Future studies should explore isolating intervention components to provide insights into cultivating flexible knowledge structures. This can help create learning environments that promote improved concept understanding and creativity.

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